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PRICING OF TIME-VARYING LIQUIDITY RISK IN THE FRANKFURT STOCK EXCHANGE

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ABSTRACT

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This thesis examines the effect of stock-level liquidity and systematic liquidity risk on stock excess returns in the Frankfurt Stock Exchange. Additionally, systematic liquidity risk is examined for a time trend. This study uses two proxies for liquidity, *PQS* to measure the quoted bid-ask spread and *AdjILLIQ* to measure price impact, enabling comparison of the results between the two proxies. The sample consists of all stocks quoted at the Frankfurt Stock Exchange between 01/2000 and 12/2018. Methodologically, a variety of prior studies are followed (Lee, 2011; Kim and Lee, 2014; Saad and Samet, 2015; Vu, Chai, and Do, 2015). Conditional, time-varying liquidity risks are estimated at the portfolio level with a quadvariate DCC-GARCH(1,1) estimator. The liquidity risks measured at the portfolio level are used to estimate the pricing of liquidity risk at the stock-level. Pricing is examined by using a fixed effects panel regression to estimate a conditional version of the LCAPM of Acharya and Pedersen (2005).

The results suggest that a hypothesized illiquidity premium is subsumed by other factors, such as size and the book-to-market ratio. Return premia are found for stocks which: (i) become illiquid with the market, (ii) earn lower returns during illiquid markets, and (iii) are illiquid during down markets. Total annualized premia for systematic liquidity risk are 3.07 percent using *AdjILLIQ* and 3.66 percent using *PQS*. No time trend is found in liquidity risk. The results are generally similar between the proxies. Premia (i) and (iii) are robust to an alternative method in Fama-MacBeth (1973) regressions, and the results concerning *AdjILLIQ* are robust to holding period. Dividing the sample into size groups implies that pricing of liquidity risk may vary between small, medium-sized, and large stocks.

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Tämä pro gradu -tutkielma tutkii osakkeen likviditeetin sekä systemaattisen likviditeettiriskin vaikutusta osakkeiden ylituottoihin Frankfurtin pörssissä. Lisäksi tarkastellaan, onko likviditeettiriskissä havaittavaa trendiä. Tutkimuksessa käytetään kahta likviditeetin mittaria, *PQS* ja *AdjILLIQ*, joka mahdollistaa tulosten vertailun mittareiden välillä. Tutkimuksen aineisto kattaa kaikki Frankfurtin pörssissä noteeratut osakkeet aikavälillä 01/2000-12/2018. Tutkielma mukailee metodologisesti useita aiempia tutkimuksia (Lee, 2011; Kim ja Lee, 2014; Saad ja Samet, 2015; Vu, Chai ja Do, 2015). Ehdollisia, ajassa muuttuvia likviditeettiriskejä mallinnetaan portfoliotasolla monimuuttujaisella DCC-GARCH(1,1)-mallilla. Portfoliotasolla mallinnettuja likviditeettiriskejä käytetään likviditeettiriskin hinnoittelun arvioinnissa osaketasolla. Hinnoittelua tutkitaan arvioimalla Acharyan ja Pedersenin (2005) likviditeettimukautettu CAPM-malli kiinteiden vaikutusten paneeliregressiolla.

Tulokset vihjaavat, että hypotesoitu epälikvidien osakkeiden tuottopreemio peittyy muiden muuttujien kuten markkina-arvon ja B/M-luvun vaikutuksiin. Tuottopreemio löytyy osakkeista jotka: (i) ovat epälikvidejä epälikvideillä markkinoilla, (ii) tarjoavat alhaisempia tuottoja epälikvideillä markkinoilla ja (iii) ovat epälikvidejä, kun markkinoiden tuotto on alhainen. Annualisoidut preemiot systemaattiselle likviditeettiriskille kokonaisuudessaan ovat 3.07 (*AdjILLIQ*) ja 3.66 prosenttia (*PQS*). Likviditeettiriskissä ei ole havaittavissa trendiä. Tulokset ovat yleisesti ottaen samankaltaisia likviditeetin mittareiden välillä. Preemiot (i) ja (iii) ovat robusteja vaihtoehtoiselle estimaatiomenetelmälle (Fama ja MacBeth, 1973) ja *AdjILLIQ*:lla mitattuna myös eri pitoajoille. Aineiston jaotteleminen kokoluokkien mukaan vihjaa, että likviditeettiriskin hinnoittelu vaihtelee pienten, keskisuurien ja suurien osakkeiden välillä.

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Lappeenranta, 16.5.2020
Lauri Kuosmanen

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

ADF	Augmented Dickey-Fuller (test)
AIC	Akaike information criterion
AMEX	American Stock Exchange
AR	Autoregressive
ARCH	Autoregressive conditional heteroskedasticity
ARD	Autoregressive with drift
BIC	Bayesian information criterion
CCC	Constant conditional correlation
DCC	Dynamic conditional correlation
EGARCH	Exponential generalized autoregressive conditional heteroskedasticity
FSE	Frankfurt Stock Exchange
GARCH	Generalized autoregressive conditional heteroskedasticity
KPSS	Kwiatkowski, Phillips, Schmidt, and Shin (test)
LM	Lagrange multiplier
NYSE	New York Stock Exchange
OLS	Ordinary least squares
PP	Phillips-Perron (test)

1 INTRODUCTION

Liquidity is a complex and elusive concept, defined in the context of asset pricing as the ability to trade a significant quantity of a security at a low cost within a short time (Holden, Jacobsen, and Subrahmanyam, 2013). Kyle (1985) notes similar characteristics in defining market liquidity. Tight markets enable turning around a position within a short timeframe, whereas deep markets are able to accommodate large orders with little price response, and resilient markets recover quickly from random, uninformative shocks. Conversely, illiquidity can be considered in terms of costs (Amihud and Mendelson, 1991). The bid-ask spread increases in illiquidity and entails a price concession for sellers and a price premium for buyers. Furthermore, market impact costs entail larger price concessions and premia for larger orders. Lastly, the inability to find a suitable trading partner or favorable trading terms may impose delay and search costs. All of the above definitions share the notions of cost, quantity, and time, highlighting the complexity of the phenomenon. As a multi-faceted phenomenon, liquidity is of interest to all market participants. Traders, institutional investors, capital issuers, the exchanges, as well as regulators and policy makers all benefit from liquid markets, which tend to be well-functioning, less volatile, and facilitate efficient risk sharing (Harris, 2003; Foucault, Pagano, and Röell, 2013).

Literature on the relationship between liquidity and asset returns is extensive and can be divided into two strands: one focusing on the asset-specific liquidity level and another on systematic liquidity risk. Regarding liquidity level and asset returns, Amihud and Mendelson (1986) both theorize and provide evidence that returns increase in illiquidity. Further evidence of the illiquidity premium is abundant (e.g. Brennan and Subrahmanyam, 1996; Eleswarapu, 1997; Amihud, 2002). The literature focusing on systematic liquidity risk has identified three risks: commonality in liquidity, flight to liquidity, and the depressed wealth effect. Commonality in liquidity relates to the co-movement of asset liquidity with liquidity at a larger scale, such as at the industry or market level and even internationally. Evidence of the phenomenon is extensive both in the US market (Chordia, Roll, and Subrahmanyam, 2000; Huberman and Halka, 2001; Korajczyk and Sadka, 2008) and internationally (Fabre and Frino, 2004; Brockman, Chung, and Pérignon, 2009; Foran, Hutchinson, and O'Sullivan, 2015). Flight to liquidity refers to a phenomenon where, during an illiquid market, investors seek to substitute illiquid or otherwise undesirable assets with more liquid or desirable ones, consequently causing a greater decline in the value of the undesirable assets. US evidence of the phenomenon is abundant (Amihud, 2002; Pástor and Stambaugh, 2003; Korajczyk and Sadka, 2008), whereas Liang and Wei (2012) find evidence in further 10 developed markets. Lastly, the depressed wealth effect refers to a situation where an asset becomes illiquid during a declining market. During market downturns, investors tend to face wealth problems and seek to exit their positions. Holding an illiquid asset in such a situation may exacerbate the wealth problems. Again, US evidence is extensive (Acharya and Pedersen, 2005; Hagströmer, Hansson, and Nilsson, 2013; Kim and Lee, 2014), whereas international studies mainly group markets by region (Lee, 2011) or degree of development (Lee, 2011; Saad and Samet, 2015).

Extensive literature points to time-variance of the phenomena. Amihud et al. (2015) find the illiquidity premium to increase in declining markets. Commonality in liquidity has also been found to increase during periods of volatility and market decline (Karolyi, Lee, and van Dijk, 2012; Johann et al., 2019). More generally, Vu, Chai, and Do (2015) find the premium for aggregate liquidity risk to be substantially higher in bearish markets. Although time-variance of liquidity risk is well-documented, Hagströmer, Hansson, and Nilsson (2013) do not find a decreasing trend in liquidity risk premia, nor do Saad and Samet (2015) find decreasing trends in liquidity risks.

The liquidity-adjusted capital asset pricing model (LCAPM) of Acharya and Pedersen (2005) is the first theoretical model to incorporate liquidity level and the three liquidity risks into a unified framework. Moreover, the LCAPM allows for conditional estimation whereby the liquidity risks are allowed to vary over time. The model has been used in empirical studies both on the US market (Acharya and Pedersen, 2005; Hagströmer, Hansson, and Nilsson, 2013; Kim and Lee, 2014) and internationally (Lee, 2011; Saad and Samet, 2015; Vu, Chai, and Do, 2015), both in conditional and unconditional specifications.

1.1 Research gap and objectives

Despite its prominence among stock markets, literature on systematic liquidity risk in the German market remains relatively scarce. The literature documents an illiquidity premium among German stocks (Hagemeister and Kempf, 2010; Koch, 2010). Liang and Wei (2010) in turn find a premium related to flight to liquidity. Commonality in liquidity has also been found among German stocks, and between US and German markets (Kempf and Mayston, 2008; Brockman, Chung, and Pérignon, 2009; Johann et al., 2019). Moreover, commonality has been found to vary over time and to increase during market declines (Kempf and Mayston, 2008; Johann et al., 2019). However, none of the studies report a pricing implication. The unified framework of the LCAPM is applied to German stocks unconditionally by Lee (2011) and conditionally by Saad and Samet (2015). Hagemeister and Kempf (2010, p. 156) also estimate the full LCAPM unreported, and state that only one of the liquidity betas is significantly different from zero at the 1 percent level.

This study fills a gap by estimating a conditional version the LCAPM using a sample of all stocks listed in the Frankfurt Stock Exchange (FSE) between 1.1.2000 and 31.12.2018. The FSE is a natural choice as it is by far the largest exchange in the country (Deutsche Börse Group, 2020). Moreover, the 19-year timeframe is long enough to capture the time before, during, and after the financial crisis of 2008. This study uses two illiquidity proxies: closing percent quoted spread (*PQS*) of Chung and Zhang (2014) and the adjusted Amihud (2002) proxy (*AdjILLIQ*) of Kang and Zhang (2014) to proxy the spread and price impact, respectively.

The method of this study follows various prior studies. Similar to Lee (2011) and Kim and Lee (2014), stocks are grouped into portfolios based on pre-ranking betas. Following Saad and Samet (2015), the time-varying conditional liquidity risks are estimated at the portfolio level using the dynamic conditional correlation and generalized autoregressive conditional heteroskedasticity (DCC-GARCH) estimator of Engle (2002). This approach allows for the liquidity risks to vary over time, which is presumable based on prior findings. Possible trends in the liquidity risks are examined with trend tests of Vogelsang (1998) and Bunzel and Vogelsang (2005), similar to Saad and Samet (2015). Following Lee (2011) and Kim and Lee (2014), the time-varying conditional liquidity risks are assigned to the portfolio constituents, and the LCAPM is estimated using individual stocks as test assets. This approach lends power to the test and allows controlling for stock-specific characteristics. Following Vu, Chai, and Do (2015), the LCAPM specifications are estimated with a fixed effects panel regression to avoid potentially biased estimates of the conventional Fama and MacBeth (1973) regressions.

This study aims to answer the following questions:

1) Is the stock-specific liquidity level and systematic liquidity risk priced in the FSE?
2) Is there a time trend in the liquidity risks?
3) Do the results differ between the illiquidity proxies used?

The first question determines whether investors are compensated for holding illiquid assets and seeks to confirm the findings of Koch (2010) and Hagemeister and Kempf (2010). Moreover, it sheds light on whether systematic liquidity risks are priced, and consequently, whether investors should consider said risks in portfolio formation. The answers partly extend the findings of Johann et al. (2019) with a pricing implication related to commonality and add detail to the findings of Saad and Samet (2015) with country-specific estimates. In estimating the pricing of systematic liquidity risks, this study also adds to the literature by considering the free float of a stock, which has an idiosyncratic effect on liquidity through limiting the number of shares available for trading. Therefore, its confounding effect on the pricing of the liquidity risks is controlled for. As this study examines time-varying liquidity risks, the second question provides further insight on the time-variance. Lastly, the use of two illiquidity proxies allows for a comparison between the measures. This is of particular interest because the LCAPM considers the illiquidity cost as a cost of sale. *PQS* proxies this directly, whereas *AdjILLIQ* does not but is rather assumed to be a valid proxy (Acharya and Pedersen, 2005). Therefore, similar results between the proxies can be seen as a validation of this assumption.

1.2 Structure

The rest of this study is structured as follows. Section 2 describes the theoretical background, gives an overview of prior literature on the topic, and presents the hypotheses of this study. Section 3 describes the sampling and methodology. Empirical results related to each step in the methodology as well as robustness tests of the pricing of liquidity risk are presented in Section 4. Section 5 discusses the economic implications of the results, as well as their generalizability and limitations. Section 6 concludes.

2 THEORETICAL BACKGROUND

2.1 Defining liquidity

Liquidity is a complex and elusive concept. In the context of asset pricing, Holden, Jacobsen, and Subrahmanyam (2013, p. 4) define it shortly as the ability to trade a significant quantity of a security at a low cost within a short time. This highlights the complexity as quantity, cost, and time are to be considered.

To better understand the nature of liquidity and illiquidity costs, it is useful to consider the market as the interaction of groups of liquidity suppliers and liquidity demanders. The liquidity suppliers offer to buy assets at the bid price and sell assets at the ask price. Conversely, liquidity demanders agree to sell assets at the bid price and buy at the ask price. Both groups are subject to illiquidity costs in transacting. Aside from direct, exogenous transaction costs, such as brokerage fees and order processing costs, Amihud and Mendelson (1991, pp. 56-57) identify three types of illiquidity costs. Firstly, the bid-ask spread is inversely related to liquidity; liquid assets can be bought or sold at prices close to each other. Secondly, market impact costs are incurred when a transaction for a large quantity affects the transaction price. Large orders typically entail a larger price concession when selling or a larger price premium when buying. Lastly, delay and search costs are incurred when delaying a trade to find a counterparty or in anticipation of better trading terms, such as a better price or a lower market impact cost.

In defining market liquidity, Kyle (1985, p. 1316) highlights three key characteristics. Tightness of the market refers to the costs associated with turning around a position within a short timeframe. This touches upon the bid-ask spread as well as the delay and search costs discussed by Amihud and Mendelson (1991). Market depth refers to the price response to large orders; a deep market is able to accommodate a large order with relatively little price response. The link to the market impact costs of Amihud and Mendelson (1991) is evident. Lastly, the resiliency of a market refers to the speed of price recovery from random, uninformative shocks.

Generally, liquidity is a sign of a well-functioning market and as such, facilitates efficient risk sharing. Seeing that it is a broad concept, it is relevant to all market participants. For traders, liquidity is of interest simply because illiquid assets are costlier (Foucault, Pagano, and Röell, 2013, p. 4). In terms of the bid-ask spread, illiquid assets sell for less and are costlier to buy. Moreover, especially for institutional investors who generally trade in large quantities, delay and search costs as well as market impact costs are a consideration. Liquidity is also of interest to capital issuers. As liquidity affects security prices, the cost of capital and consequent capital expenditure decisions of the issuers may also be affected (Foucault, Pagano, and Röell, 2013, p. 5). Liquidity is also of interest to the exchanges themselves, as it stimulates trading activity and attracts investors. And lastly, regulators and policy makers should prefer liquidity because liquid markets tend to be less volatile (Harris, 2003, p. 394).

2.2 Measuring liquidity

As liquidity is a broad concept, it is difficult to capture in a single measure (Amihud, 2002). Consequently, a large number of liquidity measures have been proposed in the literature. Conceptually, the measures can be categorized into two distinct groups. Spread-based measures measure the direct cost of a trade and generally relate to the tightness of the market, whereas price impact measures focus on price response to trading volume, and generally relate to market depth and resiliency. Moreover, the two groups of measures can further be divided into two categories: high-frequency measures based on intraday transaction data and low-frequency proxies which are generally based on daily data.

By design, high-frequency measures have an advantage in terms of precision as they account for each individual transaction. A downside to their use is the scarcity of data required. For the US market, data is generally available only from 1983 onwards, and many countries lack data altogether (Goyenko, Holden, and Trzcinka, 2009, p. 153). For German stocks, high-frequency data is available for research over the period of 1999-2013.[1] Moreover, constructing long time series of illiquidity measures using intraday data, where available, can be computationally heavy due to the large amount of transactions (Amihud, 2002, p. 32).

[1] Market Microstructure Database Xetra (MMDB-Xetra) is provided by the Center for Financial Studies (CFS) at Goethe University Frankfurt am Main. The data set covers the years 1999-2013 and contains various high-frequency liquidity measures for all CDAX index constituents that are traded on Xetra. Xetra is an electronic trading venue of the Frankfurt Stock Exchange. For the database, see CFS (2014).

Low-frequency proxies are naturally less precise, as typically closing prices and end-of-day figures are used. As such, they do not directly measure transaction costs but rather approximate the illiquidity cost (Goyenko, Holden, and Trzcinka, 2009). A natural advantage of the low-frequency proxies is the general availability of data for long periods of time and the relative ease in constructing long time series from daily observations. As Goyenko, Holden, and Trzcinka (2009) point out, low-frequency proxies generally tend to measure liquidity, providing a compromise between precision, computational ease, and availability of data. This study employs one low-frequency proxy each for spread and price impact. The following subsections give a brief overview of each class of measures, justify the choice of proxy, and describe the chosen proxies in more detail.

2.2.1 Spread-based measures

Perhaps the simplest and most widely used high-frequency spread-based measure is the *effective spread*. It is commonly calculated as two times the absolute difference between the transaction price and preceding bid-ask midpoint (Chordia, Roll, and Subrahmanyam, 2000; Goyenko, Holden, and Trzcinka, 2009). This represents the cost of a roundtrip on the asset, assuming the midpoint remains unchanged. The *effective spread* can also be expressed in relative terms, proportional to, for example, the price of the actual transaction (Chordia, Roll, and Subrahmanyam, 2000). Seeing that a *proportional effective spread* is ideal for comparison between securities, it is used as a benchmark for selecting a low-frequency proxy for this study.

Among low-frequency proxies, the measure of Roll (1984) is widely used (e.g. Lesmond, 2005; Kim and Lee, 2014). In short, *Roll* proxies the effective spread based on the autocovariance of price changes. The model has also seen several extensions. Hasbrouck (2004) computes a measure (*Gibbs*) by taking a Bayesian estimation approach and using a Gibbs sampler to estimate a variant of the *Roll* measure. The measure of *Roll* is also extended by Holden (2009), by using the framework of Huang and Stoll (1997) to combine the autocovariance of price changes with observable price clustering. The measure is commonly referred to as *Holden*. Holden (2009) also uses the observable price clustering separately to propose a measure called *effective tick*. Two conceptually independent proxies are also proposed by Lesmond, Ogden, and Trzcinka (1999). Their proxy commonly referred to as *LOT* measures effective spread as the difference in percentage buying and selling costs, whereas *Zeros* is simply a ratio of days with zero returns to total trading days. Most recently, Chung and Zhang (2014) propose a simple closing percent quote spread (*PQS*), the spread proportional to the midpoint, to approximate quoted spreads.

Goyenko, Holden, and Trzcinka (2009) compare the abovementioned low-frequency proxies, with the exception of *PQS*, to their high-frequency counterparts using US market data. In terms of both cross-sectional and time series correlation, *Holden* dominates the sample, with *effective tick* and *Gibbs* as distant runners up. In a similar comparison of Chung and Zhang (2014), *Holden* is excluded, but *PQS* dominates both *effective tick* and *Gibbs*. The results are largely similar in Fong, Holden, and Trzcinka (2017), where *PQS* dominates *effective tick*. Although it appears that *Holden* performs well where tested, it is acknowledged that it is very computationally intensive. Therefore, *PQS* is chosen as the spread-based proxy for this study due to computational ease and good performance.

2.2.2 Price impact measures

In terms of high-frequency price impact measures, the seminal paper of Kyle (1985) introduces *Lambda* as a measure of price impact in an equilibrium. The *Lambda*, measured as the slope coefficient of a regression of price change on trading volume, remains constant in the model of Kyle (1985). Hasbrouck (2009) takes a similar approach and estimates *Lambda* by periodic regressions of log price changes against signed square root Dollar trading volume. Commonly 5-minute time intervals are used (Goyenko, Holden, and Trzcinka, 2009; Hasbrouck, 2009). This measures the cost of demanding a certain amount of liquidity over a five-minute period. Another pertinent high-frequency measure is the *5-minute price impact* proposed by Goyenko, Holden, and Trzcinka (2009), measured as the change in the log bid-ask midpoints over a 5-minute interval.[2] The choice of a low-frequency proxy for this study is based on correlation to the *Lambda* of Hasbrouck (2009).

[2] Goyenko, Holden, and Trzcinka also compute a static price impact, the data for which is available due to Securities and Exchange Commission (SEC) Rule 605. The measure is not considered in this study, as rules in other markets may differ from SEC rules.

The literature regarding low-frequency price impact proxies is relatively scarce compared to spread-based proxies. Datar, Naik, and Radcliffe (1998) simply use a monthly turnover rate to proxy liquidity. Similarly, Liu (2006) also considers only trading volume in computing a monthly standardized turnover-adjusted number of zero-volume trading days. Pástor and Stambaugh (2003, pp. 646-647) adopt the slope coefficient approach and measure *Gamma* as the ordinary least squares (OLS) slope coefficient of a regression of returns against previous period returns, excess returns, and trading volume. This effectively measures the reversal of the order flow shock of the previous day. Amihud (2002) proxies illiquidity (*ILLIQ*) as the absolute percentage return divided by trading volume. The proxy has become widely used and several variations of *ILLIQ* have been proposed in the literature. Goyenko, Holden, and Trzcinka (2009) formulate an extended *ILLIQ* as a spread proxy divided by trading volume. Similarly, they define a *Roll Impact* measure as the *Roll* proxy divided by trading volume.

Goyenko, Holden, and Trzcinka (2009) find both *ILLIQ* and its extensions to perform best compared to their high-frequency counterparts both in terms of cross-sectional and time series correlation. However, their results pertain to the US market, which is much more actively traded than other markets. In an international setting, Fong, Holden, and Trzcinka (2017) show that *ILLIQ* performs equally well with other low-frequency proxies in terms of correlation, but none of them are able to capture the level of the *Lambda* of Hasbrouck (2009). Importantly, Kang and Zhang (2014) note that *ILLIQ* is ideal mainly for actively traded markets. As the proxy requires days with trading volume, its accuracy in proxying illiquidity in inactively traded markets, or differentiating between actively and inactively traded stocks, is limited. Therefore, Kang and Zhang (2014) propose an adjusted proxy (*AdjILLIQ*), multiplying the original proxy by the proportion of non-trading days. In the comparisons of Kang and Zhang (2014), *AdjILLIQ* generally outperforms *ILLIQ*, especially in thinly traded markets. An advantage of the proxy is its ability to combine the good performance of *ILLIQ* and to further consider the proportion of non-trading days. As the sample of this study contains a large proportion of small, thinly traded stocks, *AdjILLIQ* is a sound choice.

2.2.3 Proxies chosen for this study

Based on Section 2.2.1, *PQS* is chosen as the spread-based proxy for this study due to good performance and ease of computation. It is defined by Chung and Zhang (2014, p. 97) as

$$PQS_m^i = \frac{1}{N_m^i} \sum_{d=1}^{N_m^i} \frac{Ask_{m,d}^i - Bid_{m,d}^i}{M_{m,d}^i}, \tag{1}$$

where *N* is the number of days with data available for stock *i* in month *m*, and *M* is the mean of closing ask and bid prices for stock *i* on day *d*, in month *m*. Similar to Chung and Zhang (2014), *PQS* is computed for each stock-month with a minimum of 10 observations. As a larger spread indicates illiquidity, the values of *PQS* increase in illiquidity. Moreover, the values are bounded from below by 0, as bid-ask pairs with a negative spread are omitted as errors. As *PQS* proxies the *proportional effective spread*, it relates to the direct cost associated with a trade of any size. Brennan and Subrahmanyam (1996) liken this to a fixed component of the trading cost. Moreover, in terms of market characteristics, the proxy relates to the tightness of the market. As transaction size is not a consideration, the results obtained using *PQS* should be of particular interest to the private investors whose orders are not large enough to affect prices.

As explained in Section 2.2.2, *AdjILLIQ* is chosen as the price impact proxy for this study. The proxy is based on *ILLIQ*, which is defined by Amihud (2002, p. 34) as

$$ILLIQ_m^i = \frac{1}{N_m^i} \sum_{d=1}^{N_m^i} \frac{\left|Ret_{m,d}^i\right|}{Vol_{m,d}^i}, \tag{2}$$

where *N* is the number of days with data available for stock *i* in month *m*. *Ret* and *Vol* refer to the absolute percentage return and Euro trading volume for stock *i* on day *d*, in month *m*, respectively. Kang and Zhang (2014) extend the proxy with a *ZeroVol* modifier defined as

$$ZeroVol = \frac{Number\ of\ days\ with\ zero\ volumes\ in\ a\ month}{Total\ number\ of\ trading\ days\ in\ a\ month}. \tag{3}$$

The modifier is notably similar to *Zeros* proposed by Lesmond, Ogden, and Trzcinka (1999). Kang and Zhang (2014, p. 55) further log transform the original measure, and formulate *AdjILLIQ* as

$$AdjILLIQ_m^i = \left[ln \left(\frac{1}{N_m^i} \sum_{d=1}^{N_m^i} \frac{\left| Ret_{m,d}^i \right|}{Vol_{m,d}^i} \right) \right] \times \left(1 + ZeroVol_m^i \right). \tag{4}$$

N remains the number of days with data available for stock *i* in month *m*. *Ret* and *Vol* are the absolute percentage returns and Euro trading volume (in thousands) of stock *i* on day *d*, in month *m*.[3] Therefore, *AdjILLIQ* in this study represents a percentage cost per €1000 of trading volume. As such, the values begin from 0 and increase in illiquidity. Similar to Kang and Zhang (2014), the proxy is computed for each stock-month with a minimum of 5 trading days. Considering Equations (2) and (4), it is evident that the measure is highly correlated with *ILLIQ*; minor differences may occur from the log transformation, but the most drastic differences are due to the *ZeroVol* multiplier.

As *AdjILLIQ* proxies the cost per volume, it can be likened to the variable component in trading costs discussed in Brennan and Subrahmanyam (1996) and to the market characteristics of depth and resiliency. The results obtained using *AdjILLIQ* should therefore be of particular interest to the institutional investors whose orders are large enough to affect prices.

2.3 The liquidity-adjusted capital asset pricing model

In the traditional capital asset pricing model (CAPM), the expected return of an asset is dependent on a systematic risk factor: the covariance between asset and market returns. The liquidity-adjusted CAPM (LCAPM) of Acharya and Pedersen (2005) complements this model by incorporating a stochastic illiquidity cost and consequent liquidity risk. In this model, the expected return of an asset is dependent on the covariances of its returns and illiquidity with the returns and illiquidity of the market. The model accounts for a net systematic risk which includes illiquidity, and which can be further decomposed into a

[3] It should be noted that the log transformation denoted *ln* is computed as *ln*(1+*ILLIQ*).

conventional market beta adjusted for liquidity, and three illiquidity betas corresponding to commonality in liquidity, flight to liquidity, and the depressed wealth effect.

Acharya and Pedersen (2005) describe a simple overlapping generations economy where agents under a wealth constraint maximize their expected utility from trading securities. Thus, the agents buy assets at time *t* and must sell all their assets at time *t*+1. Similar to the conventional CAPM, the agents are assumed to be risk-averse and able to lend or borrow at a risk-free rate (Sharpe, 1964; Lintner, 1965). The frictionless economy of the CAPM is extended to include a stochastic trading cost. Essentially, the LCAPM seeks to explain how the expected gross return of an asset is dependent of its relative illiquidity cost. The two are defined as

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

and

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

where r_t^i is the expected gross return of asset *i* at time *t*, c_t^i the relative illiquidity cost, D_t^i a stochastic dividend, and P_t^i the ex-dividend price.[4] Market measures of the two, r_t^M and c_t^M, respectively, are computed as averages of the constituents. The LCAPM models the expected net return of a security as

$$E_t\left(r_{t+1}^i - c_{t+1}^i\right) = r^f + \lambda_t \frac{cov_t\left(r_{t+1}^i - c_{t+1}^i, r_{t+1}^M - c_{t+1}^M\right)}{var_t(r_{t+1}^M - c_{t+1}^M)}, \tag{7}$$

where r^f is the return of a risk-free asset and λ_t is the time-varying risk premium defined as

[4] The illiquidity cost in LCAPM represents a cost of selling. It is noted that *AdjILLIQ* does not measure this directly. Similar to Acharya and Pedersen (2005) who employ *ILLIQ*, *AdjILLIQ* is assumed to be an adequate proxy.

$$\lambda_t = E_t(r_{t+1}^M - c_{t+1}^M - r^f). \tag{8}$$

The subscript *t* implies that expectations are conditional on information available up to time *t*. As noted by Acharya and Pedersen (2005), it is evident from Equation (7) that the conditional CAPM of Jagannathan and Wang (1996) holds for expected net returns and can thus account for the covariances. Moreover, it is evident that the only adjustment of Acharya and Pedersen (2005) is to incorporate trading costs. Equivalent to Equation (7), the conditional expected gross return of a security can be expressed as

$$\begin{aligned} E_t\left(r_{t+1}^i\right) = r^f + E_t\left(c_{t+1}^i\right) + \lambda_t \frac{cov_t\left(r_{t+1}^i, r_{t+1}^M\right)}{var_t(r_{t+1}^M - c_{t+1}^M)} + \lambda_t \frac{cov_t\left(c_{t+1}^i, c_{t+1}^M\right)}{var_t(r_{t+1}^M - c_{t+1}^M)} \\ -\lambda_t \frac{cov_t\left(r_{t+1}^i, c_{t+1}^M\right)}{var_t(r_{t+1}^M - c_{t+1}^M)} - \lambda_t \frac{cov_t\left(c_{t+1}^i, r_{t+1}^M\right)}{var_t(r_{t+1}^M - c_{t+1}^M)}. \end{aligned} \tag{9}$$

By assuming time-varying conditional covariances, variances, and an equal risk premium for all risk factors, Equation (9) can be equivalently formulated as

$$E\left(r_t^i - r_t^f\right) = E\left(c_t^i\right) + \lambda_t \beta_t^{1i} + \lambda_t \beta_t^{2i} - \lambda_t \beta_t^{3i} - \lambda_t \beta_t^{4i}, \tag{10}$$

where

$$\beta_t^{1i} = \frac{cov_t\left(r_t^i, r_t^M\right)}{var_t(r_t^M - c_t^M)}, \tag{11}$$

$$\beta_t^{2i} = \frac{cov_t\left(c_t^i, c_t^M\right)}{var_t(r_t^M - c_t^M)}, \tag{12}$$

$$\beta_t^{3i} = \frac{cov_t\left(r_t^i, c_t^M\right)}{var_t(r_t^M - c_t^M)}, \tag{13}$$

$$\beta_t^{4i} = \frac{cov_t\left(c_t^i, r_t^M\right)}{var_t(r_t^M - c_t^M)}. \tag{14}$$

In Equations (11)–(14), β^{1i} measures the covariance of the return of an asset and market return, with a liquidity adjustment in the denominator. This corresponds to the conventional CAPM market risk factor adjusted for liquidity. The intuition is that investors expect higher returns from an asset with a higher sensitivity to market returns.

Commonality in liquidity is measured by β^{2i} as the covariance of the illiquidity of an asset and market illiquidity. As indicated by Equation (10), the beta is positively related to expected returns, meaning that investors expect higher returns from an asset that becomes illiquid when the market overall becomes illiquid. This is simply due to a higher illiquidity cost for which compensation is required. Although the LCAPM is a one-period model, Acharya and Pedersen (2005) postulate that this could potentially apply even in a more general setting where investors can choose which assets to sell. In such a setting, investors could choose to sell other similar assets with a lower illiquidity cost, unless a return premium is paid.

The covariance of the returns of an asset and market illiquidity, which corresponds to the risk of flight to liquidity, is measured by β^{3i}. During illiquid markets, investors may wish to substitute illiquid or otherwise undesirable assets with more liquid or desirable ones, causing a greater decline in the value (and a larger negative covariance) of the more illiquid or undesirable assets. Therefore, Equation (10) indicates a negative relation to expected returns, as investors are willing to accept lower returns from assets which tend to have higher returns when the market is illiquid.

Lastly, β^{4i} measures the covariance of the illiquidity of an asset and market returns, which corresponds to the depressed wealth effect. A negative covariance would indicate that an asset becomes illiquid during down markets. This presents a considerable risk, as investors tend to face wealth problems during down markets and consequently want to sell their assets (Acharya and Pedersen, 2005). As holding a liquid asset during a down market is valuable, the effect of the covariance on expected returns is negative, indicating that investors are willing to accept a lower expected return from assets which are liquid during down markets.

2.4 Literature review: Liquidity and stock returns

There is extensive literature on the multi-faceted relationship between liquidity and stock returns. The following four subsections briefly summarize previous empirical findings related to the relationship between asset liquidity and returns, as well as the three liquidity risks described in the previous section. Much of the literature focuses on the US market, international studies are fewer, and literature focusing on the German market is especially scarce.

2.4.1 Liquidity level

The idiosyncratic effect of stock liquidity on stock returns is perhaps the most extensively studied aspect of liquidity. In an early work, Amihud and Mendelson (1986) propose a theory that stock returns increase with illiquidity. They examine the bid-ask spreads of stocks listed in the New York Stock Exchange (NYSE) over the period of 1961-1980 and find that stock returns indeed increase with illiquidity, implying a premium for holding illiquid stocks. Moreover, Amihud and Mendelson (1986) postulate a clientele effect to drive the illiquidity premium; investors with longer investment horizons are more inclined to buy illiquid assets, consequently affecting their pricing. The clientele effect is further discussed in Amihud and Mendelson (1991). Chalmers and Kadlec (1998) further consider the length of the holding period in estimating the illiquidity premium. Their study considers US-domiciled stocks listed in the American Stock Exchange (AMEX) and NYSE over the period of 1983-1992 and find a premium for amortized spreads.

The findings of Amihud and Mendelson (1986) are further examined by Eleswarapu and Reinganum (1993). Their study considers the bid-ask spreads of NYSE-listed stocks between 1961 and 1990, and finds a strong seasonality in the illiquidity premium, similar to the January effect in the CAPM beta (Tinic and West, 1984). The illiquidity premium is reliably priced only in the month of January and indistinguishable from zero in other months (Eleswarapu and Reinganum, 1993). Eleswarapu (1997) further extends on the topic by considering the bid-ask spreads of Nasdaq-listed stocks over the period of 1973-1990. The findings support both Amihud and Mendelson (1986) and Eleswarapu and Reinganum (1993); strong support for the illiquidity premium is found throughout the year, with a stronger spread effect in January. Eleswarapu (1997) notes that differences between the results from Nasdaq and NYSE may be due to differences in what the quoted spreads represent in each exchange. This raises the notion that a simple bid-ask spread may not be an ideal representation of liquidity, especially in terms of generalizability. Lee (1993) further discusses the noisiness of the bid-ask spread and notes that large trades may occur outside the spread, whereas small trades may occur within it.

Consequently, Brennan and Subrahmanyam (1996) consider both the spread as well as market impact in examining the fixed and variable components of the illiquidity premium, respectively. Their study is in many ways a departure. The market is expanded to cover both AMEX and NYSE-listed stocks over the period of 1984-1991. Moreover, price impact is included to study the implications of adverse selection as discussed in Kyle (1985), and the three risk factors of Fama and French (1993) are controlled for in the estimation. The study finds a return premium associated with both the spread and price impact in both exchanges, without noticeable seasonality. Evidence supporting the clientele effect of Amihud and Mendelson (1986; 1991) is limited to the price impact, however. In addition to proposing *ILLIQ* to proxy price impact, Amihud (2002) further examines the illiquidity premium related to price impact. The study considers NYSE-listed stocks over the period of 1964-1997 and finds an illiquidity premium, even when January is excluded from the sample.

Importantly, empirical studies have been extended to markets outside the notably liquid US market. Chan and Faff (2003; 2005) study the illiquidity premium among Australian stocks over the period of 1989-1998, using share turnover to measure liquidity. Both studies find that returns increase in illiquidity, with the latter study estimating an annualized premium well above 20 percent. However, as the authors note, methodological issues in hypothesis testing cause difficulty in determining the exact nature of the premium (Chan and Faff, 2005, pp. 445-450). The illiquidity premium is also examined in the Tokyo Stock Exchange over the period of 1975-2004 by Chang, Faff, and Hwang (2010). The study uses various illiquidity measures including turnover, *ILLIQ*, *Zeros*, and the measure of Liu (2006) discussed in Sections 2.2.1 and 2.2.2. Overall, the results indicate an illiquidity premium mainly in expansionary phases of the business cycle and in the pre-1990 portion of the sample. After controlling for variability of liquidity, the evidence is strong across business cycles, different subperiods, and all sections of the exchange. In another study on Asian markets, Lam and

Tam (2011) study the Hong Kong Stock Exchange over the period of 1981-2004. The study employs a total of 9 illiquidity proxies, including turnover, *ILLIQ*, *Gamma*, and the measure of Liu (2006), and finds returns to increase with illiquidity. Moreover, the study highlights markedly varied results between the proxies. Of particular interest to this study are the results pertaining to the German market. Koch (2010) examines stocks traded at the Frankfurt Stock Exchange (FSE) between 1974 and 2006 and reports evidence of an illiquidity premium. A similar result is reported by Hagemeister and Kempf (2010), who examine 210 HDAX index constituent stocks between 1995 and 2006, using expected returns and the bid-ask spread.

Results to the contrary are also reported in the literature. Eun and Huang (2007) examine the illiquidity premium over the period of 1995-2004 in the Chinese stock market and find that Chinese investors appear to pay a premium for liquidity. Similar results are reported by Nguyen and Lo (2013) who study the New Zealand market over the period of 1996-2011. Their study employs both high- and low-frequency proxies and finds consistent and robust evidence of an illiquidity discount.

The results of Amihud et al. (2015) suggest that the illiquidity premium varies over time and by market conditions. The paper examines 45 markets over the period of 1990-2011 and finds an illiquidity premium in most of the markets. Moreover, the results indicate that the illiquidity premium is higher when market returns are lower.

2.4.2 Commonality in liquidity

As market-wide phenomena are often observed, it is a reasonable notion that liquidity is not solely determined at the stock level. Chordia, Roll, and Subrahmanyam (2000) study commonality in liquidity, which refers to the co-movement of stock liquidity with liquidity of other assets, or at a larger scale such as the industry or market-level. The authors note the cross-sectional positive relationship between illiquidity and returns as compensation for trading costs, and further argue that if commonality in liquidity cannot be fully anticipated and impacts stocks asymmetrically, it should constitute a systematic risk. Using 5 high-frequency liquidity measures to examine stocks listed at the NYSE during 1992, they regress stock-level liquidity against market averages and find a significant common component in liquidity. In a coinciding paper, Huberman and Halka (2001) use 4 liquidity proxies to study a random sample of 240 stocks traded at the NYSE during 1996. The study models unanticipated movements (innovations) in illiquidity and estimates their correlations among groups of stocks, finding a systematic, time-varying component of liquidity. In another coinciding paper, Hasbrouck and Seppi (2001) use principal component analysis (PCA) to study commonality among the 30 Dow Jones constituents during 1994. Contrary to the previous studies, they find no evidence of commonality in liquidity. Korajczyk and Sadka (2008) extend the timeframe and study AMEX and NYSE-listed stocks over 1983-2000 using PCA. Their results conform to those of Chordia, Roll, and Subrahmanyam (2000) and Huberman and Halka (2001) in finding commonality in liquidity.

In terms of pricing implications in the US market, Acharya and Pedersen (2005) study stocks listed in NYSE and AMEX during 1962-1999 and estimate an annualized premium of 0.08 percent attributable to the covariance of stock and market liquidity. Kim and Lee (2014) also study NYSE and AMEX-listed stocks over a longer timeframe of 1962-2011 and estimate a substantially larger annualized premium at 2.28 percent. The difference may arise partly due to the timeframe, but to a larger extent due to differences in defining liquidity.

Outside the US, Fabre and Frino (2004) study stocks listed at the Australian Stock Exchange (ASX) during 2000. Using a method similar to Chordia, Roll, and Subrahmanyam (2000), the study finds evidence of commonality, albeit less widespread and lower in significance. Moreover, Vu, Chai, and Do (2015) examine the pricing of liquidity risks among stocks listed in ASX between 1995 and 2010 and find commonality in liquidity both priced and the dominant liquidity risk. Focusing on UK stocks, Foran, Hutchinson, and O'Sullivan (2015) examine stocks listed at the London Stock Exchange (LSE) between 1991 and 2013. Using a method similar to Korajczyk and Sadka (2008), they find evidence of commonality in liquidity. Moreover, the study notes that commonality is associated with a positive premium in LSE but does not estimate its magnitude. Among Finnish stocks listed between 1997 and 2015, Ahmed, Hirvonen, and Hussain (2019) report annualized premia attributable to commonality in the range of 0.26-0.36 percent.

As commonality is found at the exchange level, a larger-scale, international commonality is a possibility. Brockman, Chung, and Pérignon (2009) examine intraday data of 47 exchanges in 38 countries between 2002 and 2004. Using and extending the method of Chordia, Roll, and Subrahmanyam (2000), the study finds both widespread exchange-level commonality, as well as a global component in liquidity. Moreover, the study finds that local rather than global factors contribute more to commonality. Similarly, Karolyi, Lee, and van Dijk (2012) examine daily data of stocks in 40 countries between 1995 and 2009 for commonality. The study finds substantial variance in commonality between countries; both the level and variance of commonality tends to be lower in developed countries. Moreover, the level of commonality tends to rise during financial crises and market downturns. The reaction to market conditions is asymmetric, indicating that reactions to market declines are stronger.

Related to the German market, Kempf and Mayston (2008) examine constituents of the DAX 30, the German blue-chip index, using intraday data covering the period of 2.1.2004-31.3.2004. The study notes commonality at the inside spread, and a much stronger commonality beyond the best prices in the order book. Moreover, they note intraday variance in commonality and a stronger commonality during market declines. Brockman, Chung, and Pérignon (2009) also note commonality among German stocks. Similarly, Johann et al. (2019) find commonality in the FSE during 1999-2013 with a method following Chordia, Roll, and Subrahmanyam (2000). The study also finds commonality to increase in times of distress, reaching its highest levels during the financial crisis in 2008, which aligns with the results of Karolyi, Lee, and van Dijk (2012). The study further examines commonality in liquidity between Germany and the US, finding both long- and short-term commonality which is particularly high during the financial crisis. Moreover, liquidity in Germany appears to react to liquidity in the US, but not vice versa.

2.4.3 Flight to liquidity

As discussed in Section 2.3, flight to liquidity refers to the covariance of stock returns and market liquidity. During an illiquid market, investors may wish to substitute illiquid or otherwise undesirable assets with more liquid or desirable ones, causing a greater decline in the value of more illiquid assets. Amihud (2002) examines this phenomenon among NYSE-listed stocks between 1962 and 1997, both cross-sectionally and over time. The study finds a positive relationship between expected market illiquidity and ex ante returns, as well as a negative relationship between unexpected market illiquidity and contemporaneous returns. Both relationships are stronger for small, illiquid stocks, implying a flight to liquidity. Pástor and Stambaugh (2003) further study the cross-section of stocks listed in AMEX, Nasdaq, and NYSE during 1966-1999, and find that stocks with a higher return sensitivity to market liquidity have higher expected returns, providing further evidence of flight to liquidity. Controlling for common factors such as size, value, momentum, and market return, but not the level of liquidity, the study estimates an annualized premium of 7.5 percent attributable to flight to liquidity. Studying AMEX and NYSE-listed stocks over the span of 1964-1999, Acharya and Pedersen (2005) find similar results, but a substantially smaller annualized premium at 0.16 percent. Further US-market evidence of flight to liquidity is provided by Liu (2006) who examines AMEX, Nasdaq, and NYSE-listed stocks during 1960-2003, Korajczyk and Sadka (2008), who study intraday data of AMEX and NYSE-listed stocks during 1983-2000, and Kim and Lee (2014), who examine stocks in AMEX and NYSE during 1962-2008.

Baradarannia and Peat (2013) extend the US evidence by examining NYSE-listed stocks over the period of 1926-2008. The study considers the pricing of both stock level liquidity using *effective tick*, as well as a market liquidity factor, constructed similar to the small minus big (SMB) factor of Fama and French (1993). The study finds that the market liquidity factor has a positive relationship with stock returns over the entire sample period. The study further considers subperiods of pre-1963 and post-1962; the market liquidity factor has a positive relationship with returns in the pre-1963 period, but its effect is subsumed by the liquidity level in the post-1962 sample. The authors argue that this is due to a shift in business cycle lengths; the contraction periods, during which flight to liquidity is most prevalent, are substantially longer during the pre-1963 period, affecting the pricing ability of the market liquidity factor (Baradarannia and Peat, 2013, p. 19).

Bekaert, Harvey, and Lundblad (2007) extend the literature beyond the US by examining 19 emerging markets over the span of 1987-2003. Systematic liquidity risk, which corresponds to flight to liquidity, is found to have a positive and significant relationship with stock returns, both under full segmentation and in a mixed model where the degree of integration varies by market. Moreover, this risk is found to be empirically more significant than local market risk. Liang and Wei (2012) further extend the research to cover 21 developed countries. The sample periods vary depending on availability of data, most commonly spanning from 1989 to 2005. Using *Gamma* of Pástor and Stambaugh (2003) and *ILLIQ* as proxies, the study finds local systematic liquidity risk priced in 11 markets after controlling for the local market, value, and size factors. Of most interest for this study is that *ILLIQ* finds a premium for local liquidity risk among German stocks.

Results to the contrary are also documented in the literature. Nguyen and Lo (2013) examine stocks in New Zealand during 1996-2011, using 7 proxies, and find no evidence of a premium after controlling for market returns, momentum, and size and value factors. Of the evidence to the contrary, the results of Saad and Samet (2015) are perhaps of most interest for this study. They find no evidence of a premium related to flight to liquidity neither globally, nor in developed or emerging markets. The result concerning developed countries is of particular interest, as Germany is grouped together with 22 other countries.

2.4.4 Depressed wealth effect

The depressed wealth effect is introduced as a testable liquidity risk by Acharya and Pedersen (2005). The intuition is based on the finding of Lynch and Tan (2004) that liquidity premia tend to be substantially larger when transaction costs covary negatively with wealth shocks. This poses a considerable risk to investors holding an illiquid asset during market downturns, as they tend to face wealth problems and may wish to sell their assets. A high cost or an inability to sell may exacerbate the wealth problems.

Acharya and Pedersen (2005) use market returns to proxy wealth shocks, and subsequent literature largely follows suit. In their empirical test, Acharya and Pedersen (2005) examine stocks listed in AMEX and NYSE during the span of 1962-1999 and find the depressed wealth effect to be the largest contributor to the total liquidity risk premium, with an annualized premium of 0.82 percent. Further US evidence is documented by Hagströmer, Hansson, and Nilsson (2013), who study AMEX and NYSE-listed stocks over the span of 1927-2010. Similar to Acharya and Pedersen (2005), the depressed wealth effect is found to be the most important liquidity risk empirically, with an annualized premium estimated in the range of 0.38-0.68 percent. Similar evidence is also documented by Kim and Lee (2014), who examine AMEX and NYSE-listed stocks over the period of 1962-2011 using 8 illiquidity proxies as well as their first principal component. Again, the results indicate that the depressed wealth effect is the largest contributor to the total liquidity risk premium; an annualized premium of 2.42 percent is estimated using the first principal component of the illiquidity proxies.

Studies outside the US market are relatively scarce. Vu, Chai, and Do (2015) test the LCAPM on Australian stocks over the span of 1995-2010 and find the depressed wealth effect priced in the full sample of stocks, as well as among large and medium-sized stocks. The authors do not estimate a premium for the risk, however. Ahmed, Hirvonen, and Hussain (2019) test the LCAPM on Finnish stocks over the span of 1997-2015 and find the depressed wealth effect to be the most substantial liquidity risk with annualized premia in the range of 0.52-0.98 percent.

Of interest for this study are the studies which cover German stocks. Studies specific to Germany are not available to the knowledge of the author, but the global studies of Lee (2011) and Saad and Samet (2015) include Germany, albeit grouping it with other developed markets. Lee (2011) examines stocks in 50 countries over the span of 1988-2007 and finds the depressed wealth effect widely priced as a local risk. Most notably, the local risk is priced in the full sample of countries, but not among developed markets where Germany is grouped. Moreover, using global covariates to estimate global liquidity risks, the depressed wealth effect is priced in both the full sample of countries as well as among developed markets. Lee (2011) further estimates a global annualized premium of 0.66 percent attributable to the depressed wealth effect. Saad and Samet (2015) examine stocks in 83 markets over the span of 1985-2012 and generally provide evidence of a premium for the depressed wealth effect. Under assumed full segmentation, the risk is priced in the full sample, but not among developed markets. Nevertheless, using the estimates of aggregate liquidity risk to compute a premium for the depressed wealth effect, the annualized premia are estimated at 0.71 percent globally, and at 0.49 percent among developed markets. Under the arguably more realistic assumption of partial integration and using local market covariates, the depressed wealth effect is found priced both globally and among developed countries. Moreover, the results indicate that the risk varies substantially over time.

2.5 Hypotheses

The LCAPM of Acharya and Pedersen (2005) innately gives rise to the first five hypotheses which are tested in this study. Hypothesis 1 corresponds to the illiquidity premium discussed in Section 2.4.1. Hypotheses 2-4 correspond to the liquidity risks outlined in the LCAPM and Equations (12)–(14). The risks are commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. Hypothesis 5 is tested by computing the aggregate liquidity risk as a linear combination of the betas in Equations (12)–(14) as per Acharya and Pedersen (2005). As premia related to both illiquidity and the respective liquidity risks are widely documented in the literature, this study expects to find both an illiquidity premium, as well as premia for the liquidity risks. Hypotheses 1-5 are formally stated as:

Hypothesis 1*: The level of expected illiquidity has a positive and significant relationship with stock returns.*
Hypothesis 2*: The covariance of stock and market illiquidity has a positive and significant relationship with stock returns.*
Hypothesis 3*: The covariance of stock returns and market illiquidity has a negative and significant relationship with stock returns.*
Hypothesis 4*: The covariance between stock illiquidity and market returns has a negative and significant relationship with stock returns.*
Hypothesis 5*: The aggregate liquidity risk has a positive and significant relationship with stock returns.*

As the literature discussed under Section 2.4 documents time-variance of the liquidity risks pertaining to hypotheses 2-5, the hypotheses are tested by estimating a conditional version of the LCAPM similar to Saad and Samet (2015). The conditional time-varying liquidity risks are estimated using dynamic conditional correlation (DCC) and generalized autoregressive conditional heteroskedasticity (GARCH). The liquidity risks are estimated at the (decile) portfolio level, and the estimates are assigned to each portfolio constituent. Pricing of the liquidity risks is examined with a fixed effects panel regression using individual stocks as test assets, similar to Vu, Chai, and Do (2014).

Moreover, as this study considers time-varying risks, it is worthwhile to examine them for trends. Based on the findings of Hagströmer, Hansson, and Nilsson (2013) as well as Saad and Samet (2015), it is expected that the liquidity risks do not exhibit a trend.

Hypothesis 6*: There is no time trend in illiquidity risks.*

The trend tests are conducted on the DCC-GARCH estimates using trend tests of Vogelsang (1998) and Bunzel and Vogelsang (2005). The tests are conducted for the decile portfolios with the lowest and highest ex ante risk. This approach is taken following Saad and Samet (2015).

3 DATA AND METHODOLOGY

3.1 Data and sampling

All data used in this study is extracted from Thomson Reuters Datastream. The data set consists of all stocks quoted at the Frankfurt Stock Exchange (FSE) between 1.1.2000 and 31.12.2018.[5] Dead and delisted stocks are included in the sample to avoid survivorship bias. Daily data includes closing price adjusted for dividends, stock splits, and other capital changes; closing ask and bid prices; and trading volume. Simple returns are computed from daily closing prices. The closing price of 31.12.1999, which reflects the last closing price of 1999 is included in the sample to compute the first value of returns. Additionally, monthly observations of the free float ratio, market capitalization, and market-to-book ratio are used to control for stock characteristics. Simple monthly returns are computed from end-of-month closing prices. The 12-month Euribor rate reported at the end of each month, converted into a monthly rate, is used as a proxy for the risk-free rate, and monthly observations of the CDAX index are used to compute a proxy for market returns.[6]

The initial sample contains 2390 stocks. The following screening procedure is used to build a reliable sample. Any stock with data for at least one variable entirely missing is dropped from the sample. Any day in which more than 90 percent of the stocks available for trading have zero returns is dropped as a non-trading day (Lee, 2011). Data errors highlighted by Ince and Porter (2006) are screened as follows. Daily returns that equal or exceed 100 percent and are reversed either on the following day or on the prior day by a preceding negative return are dropped (Lee, 2011; Saad and Samet, 2015).[7] Moreover, the omitted observations are excluded from computing the *ZeroVol* proportion of *AdjILLIQ* to avoid inflating the measure. Monthly returns that equal or exceed 300 percent and are reversed either in the following month or in the prior month by a preceding negative return are dropped (Lee,

[5] German non-voting shares (*Vorzugsaktien*) are considered equities yet are often incorrectly classified as preferred stock in Datastream (Brückner, 2013). Stocks labeled as preferred are therefore retained in the sample.
[6] Many studies on the German stock market use the DAFOX index and prolong it with the CDAX index if necessary (Brückner, 2013). This study does not use the DAFOX index because it is only available until 2004 and would thus cover a minor part of the sample.
[7] If R_t or R_{t-1} is greater than 100% and $(1+R_t)(1+R_{t-1}) - 1 < 50\%$, both R_t and R_{t-1} are dropped.

2011). Additionally, any negative bid or ask price and any pair of bid-ask observations where the spread is negative are dropped.

First partial stock-months are excluded from the sample as the stock is not available at any portfolio formation point which occur at the beginning of the month or year. To avoid a look-ahead bias, delisted stocks are allowed to remain in the sample until their delisting date. Moreover, a stock may have an illiquidity ratio in the month of delisting if it has enough daily data. In such instances, the *ZeroVol* proportion of *AdjILLIQ* is adjusted to reflect only those days on which the stock is available for trading to avoid inflating the measure. Returns are not adjusted for delisting returns.

Stocks which have a price of less than €1.00 and market capitalization of less than €5 million at the end of the previous period are excluded from the next period as penny stocks.[8] This study effectively uses two samples built from the data, and therefore penny stocks are screened as follows. The equally weighted market portfolio used to measure market illiquidity is rebalanced monthly (Acharya and Pedersen, 2005), and stocks which fail to meet the criteria at the end of month t-1 are excluded from the sample for month t. The sample used for stock-level analysis employs annually formed portfolios, and stocks which fail to meet the above criteria at the end of year y-1 are excluded from the sample for year y.

Lastly, any stock with less than 37 observations of both illiquidity proxies is dropped from the sample used for stock-level analysis. This corresponds to the requirements outlined in Section 3.2.2. This criterion does not apply to the sample used for market illiquidity, which is simply an equally weighted average of all valid stock-months. After the above screening, extreme values of *AdjILLIQ* are removed from both samples by deleting the 99th percentiles of observations (Amihud, 2002; Amihud et al., 2015).[9] In the sample used for stock-level analysis, the 99th percentile has a mean value of 61 percent and a maximum of 787 percent, which seems unreasonable for a price impact of €1000 of trading volume.

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[8] Many large German stocks trade at prices below €1.00 despite market capitalizations measured in millions. Therefore, the combination of a price threshold of €1.00 and market capitalization threshold of €5 million are used (Brückner, 2013). An additional observation of market capitalization at the end of 1999 is used for screening the data of January 2000.

[9] Amihud (2002) deletes the 1st and 99th percentiles of the full sample, whereas Amihud et al. (2015) delete the 99th percentile of a rolling 3-month window.

3.1.1 Descriptive statistics

A total of 1118 stocks comprise the sample used to measure market illiquidity. The sample used for stock-level analysis contains 911 stocks; due to the method outlined in Section 3.2.2, 699 and 770 of these stocks are used in analyses concerning *AdjILLIQ* and *PQS*, respectively. The sample period covers 4825 trading days over 228 months. Table 1 presents descriptive statistics of monthly observations of both illiquidity measures for the sample used to compute market illiquidity, and of both illiquidity measures and stock returns for the sample used for stock-level analysis. The counts for *AdjILLIQ* and *PQS* are naturally fewer than the amount of valid sample months, as they require at least 5 and 10 days of data per month, respectively. The omission of the 99^{th} percentile of observations of *AdjILLIQ* in both samples further reduces the number. When comparing the values of the illiquidity proxies between the two samples, it is worth noting that Sample B is more efficient in filtering out penny stocks. Sample B filters stock-months whereas Sample A filters stock-years based on beginning-of-year values. The correlation between market measures of illiquidity computed from Sample B is 0.854.

Table 1. Descriptive statistics.

This table provides descriptive statistics of monthly values of both illiquidity proxies for the sample used to compute market illiquidity, and of both illiquidity proxies and stock returns for the sample used for stock-level analysis. It is noted that some observations of Sample A may be omitted from the final analyses due to criteria detailed in Section 3.2.2.

	Sample A: Stock-level analysis			*Sample B: Market portfolio*	
	AdjILLIQ	*PQS*	*Returns*	*AdjILLIQ*	*PQS*
Valid sample months	142276	142276	142276	151178	151178
Number of observations	117552	131696	140382	120826	135463
Sample coverage (%)	82.62	92.56	98.67	79.92	89.61
Minimum (%)	0.00	0.00	-100.00	0.00	0.00
Maximum (%)	23.92	200.00	831.03	19.15	193.69
Range (%)	23.92	200.00	931.03	19.15	193.69
Median (%)	0.19	2.61	0.00	0.19	2.61
Mean (%)	1.05	3.84	0.27	0.96	3.69
Skewness	4.719	11.895	5.639	4.284	11.155
Standard error of mean	0.000	0.000	0.000	0.000	0.000
Mean standard deviation (%)	1.69	3.19	15.02	1.39	2.73
Min. standard deviation (%)	0.00	0.08	1.55	0.00	0.00
Max. standard deviation (%)	8.07	62.40	82.48	6.71	70.04

For the focus of this study, Sample A is of main interest. Naturally, monthly returns have the highest sample coverage at nearly 99 percent. *AdjILLIQ* and *PQS* both have lower coverages due to the abovementioned computational requirements, yet both are relatively well-covered at 82.62 and 92.56 percent, respectively. Monthly returns have the highest range from minus 100 percent to 831 percent, with a mean of 0.27 percent. There are 11 instances of returns of minus 100 percent; 9 stocks cease trading afterwards and delist within a year, whereas two stocks continue trading. Of the illiquidity proxies, *PQS* has the higher range from 0 to 200 percent with a mean of 3.84 percent. The maximum value of *PQS* is not due to a single observation; 4 stocks combine for a total of 8 observations of 200 percent, and 21 stocks combine for 90 observations above 100 percent.

All variables display a mean that is higher than the median, hinting at possibly right-skewed distributions, which is confirmed by the positive values of skewness. In terms of illiquidity, this indicates that relatively low values are most frequent in the sample. Standard deviations also uniformly follow the ranges; monthly returns with the highest range also display the highest minimum, maximum, and mean standard deviations, and *AdjILLIQ* is on the opposite end on all accounts. The mean correlation between stock-level time series of *AdjILLIQ* and *PQS* is 0.517.

Liquidity increases monotonically with size in the FSE. Table 2 presents the size, illiquidity, and standard deviations in illiquidity of size deciles using both illiquidity proxies. Sample B is used to examine the size effect, as penny stocks are filtered out monthly. Only contemporaneous observations of illiquidity and end-of-month market capitalization are considered, and stocks are sorted monthly into size deciles based on their market capitalization. Illiquidity and market capitalization of the deciles are computed as equally weighted averages, and the table presents time-series averages of the figures. With both proxies, illiquidity increases drastically as size decreases. Moreover, the small, illiquid stocks exhibit substantially larger standard deviations in illiquidity. Conversely, larger stocks, on average, are more liquid and their liquidity is more stable over time.

Table 2. Size effect in illiquidity.

The table lists the average illiquidity denoted by $\mu(c)$, standard deviation in illiquidity denoted by $\sigma(c)$, and average market capitalization of size deciles. Values of illiquidity are reported as percentages, and market capitalization in millions. The averages are time-series averages of the deciles.

Decile	1	2	3	4	5	6	7	8	9	10
Panel A: AdjILLIQ										
$\mu(c)$	3.77	2.12	1.33	0.90	0.65	0.47	0.30	0.16	0.09	0.03
$\sigma(c)$	1.43	1.12	0.72	0.51	0.40	0.25	0.20	0.08	0.04	0.02
Size	7	18	32	53	87	149	288	665	1983	18307
Panel B: PQS										
$\mu(c)$	9.74	6.15	4.68	3.79	3.35	2.91	2.40	1.90	1.37	0.68
$\sigma(c)$	2.90	1.70	1.26	0.94	0.75	0.73	0.56	0.54	0.43	0.26
Size	6	15	28	45	75	128	242	542	1651	16629

3.2 Methodology

Following prior studies (Lee, 2011; Kim and Lee, 2014; Vu, Chai, and Do, 2015), individual stocks are used as test assets because this approach provides several benefits. Firstly, the loss of information which is inherent in portfolio formation is minimized. Similarly, this ensures a larger number of observations which lends power to the test. Secondly, using individual stocks as test assets allows to control for characteristics of individual stocks, such as the size or value effect (Lee, 2011). Lastly, this approach helps avoid potentially spurious results caused by characteristic-based portfolio formation (Brennan, Chordia, and Subrahmanyam, 1998; Berk, 2000). The above benefits, however, come with the cost that the estimates for individual stocks tend to be noisier than those for portfolios (Lee, 2011).

The estimation procedure is generally as follows. Firstly, innovations in illiquidity are obtained to examine the unanticipated movements in illiquidity (Section 3.2.1). Pre-ranking betas are then computed for each stock, and the stocks are sorted annually into decile portfolios based on the pre-ranking betas (Section 3.2.2). The efficacy of the portfolio formation is examined by computing full-sample post ranking betas for each portfolio, and portfolio characteristics are computed for further insight. Time-varying conditional liquidity risks are then estimated for each portfolio, and the portfolio betas are assigned to constituent stocks (Section 3.2.3). The most liquid and illiquid portfolio deciles are also tested for a time trend in liquidity risk (Section 3.2.4). Finally, a panel regression using individual stocks as test assets is used to determine the pricing of the time-varying liquidity risks (3.2.5). Each section details both the theoretical motivation, as well as the exact method of the procedure. Results are presented in Section 4 under corresponding subsections.

3.2.1 Innovations in illiquidity

Liquidity has widely been shown to be persistent. Earlier studies often report first order autocorrelation (Acharya and Pedersen, 2005; Lee, 2011; Saad and Samet, 2015), which supports the notion of Amihud (2002, p.43) that investors can, to some extent, predict liquidity. The Breusch-Godfrey Lagrange Multiplier (LM) test is used to test the joint significance of autocorrelation up to second order (Breusch, 1978; Godfrey, 1978). The test is conducted for both market illiquidity series and for each individual stock-level series, and the results are found in Appendix 1. Due to the presence of both first and second order autocorrelation in most of the sample, prior studies (Acharya and Pedersen, 2005; Lee, 2011; Saad and Samet, 2015) are followed in obtaining innovations in illiquidity.[10]

The innovations are obtained by estimating an autoregressive (AR) model on the data; the residuals inferred from the model act as the innovations, which represent unanticipated movements in illiquidity. As AR coefficients cannot be estimated for some of the stock-level illiquidity series using maximum likelihood as the method of estimation, the models are estimated on first differences of the series, similar to Saad and Samet (2015). AR(1) of first differences does not fully remove second order autocorrelation from the sample. Moreover, Akaike (AIC) and Bayesian (BIC) information criteria tend to favor AR(2) over AR(1). BIC favors AR(2) over AR(1) for *AdjILLIQ*, and in total for 48 percent of the series, whereas AIC favors AR(2) for both *AdjILLIQ* and *PQS*, and in total for 71 percent of the series. Therefore, innovations are obtained by estimating an AR(2) model on first differences of the illiquidity series. The coefficients are freely determined for each series with the equation

$$\Delta c_t^i = \alpha_0 + \alpha_1 \Delta c_{t-1}^i + \alpha_2 \Delta c_{t-2}^i + u_t^i, \tag{15}$$

[10] The market return series is also tested for autocorrelation, but innovations are not obtained. This is unlike in Acharya and Pedersen (2005), but similar to Lee (2011) and Saad and Samet (2015). Moreover, some stock-level return series exhibit autocorrelation, but this does not bias the parameter estimates discussed in Section 3.2.2.

where Δ indicates first differences, c_t^i is the illiquidity of time series i at time t, $\alpha_{0,\dots,2}$ are the estimated coefficients, and u_t^i is the residual interpreted as the innovation.

It is noted that an ex-post fitting of the AR models may induce a look-ahead bias. As the coefficients used to infer the residuals are determined from data for the full sample period, the residuals may be based on information unavailable at the time. However, this approach is taken to follow prior studies (Saad and Samet, 2015; Vu, Chai, and Do, 2015) in estimating the model of Acharya and Pedersen (2005), all of which employ this method. Moreover, Kim and Lee (2014, p. 119) argue that liquidity events are more explicitly evident with this method.

3.2.2 Illiquidity portfolios

Despite the use of individual stocks as test assets in the regression analyses, portfolios are used in estimating liquidity risk, similar to Lee (2011), Kim and Lee (2014), and Vu, Chai, and Do (2015). The motivation for using portfolios at this stage originates from the errors-in-variables (EIV) problem highlighted by Blume (1970). The EIV problem relates to the use of betas as regressors when the betas of individual stocks contain some degree of error. If the errors are not perfectly correlated, Blume (1970, p.156) shows that using weighted averages of stock-level betas as portfolio betas reduces the total error. Assuming that both high and low estimates of betas exhibit larger errors and to mitigate consequent bunching of errors within portfolios, Fama and MacBeth (1973) advocate the computation of pre-ranking betas based on one sample period for portfolio formation, and computing portfolio betas using a subsequent sample period.

Therefore, this study sorts stocks into decile portfolios based on pre-ranking betas and estimates the liquidity risk at portfolio level before assigning the portfolio illiquidity betas to each portfolio constituent. The portfolios are formed using a one-dimensional sorting similar to the one described in Fama and French (1992). Although they also employ a two-dimensional sorting based on size and pre-ranking betas, this is forgone to avoid potential bias caused by characteristic-based sorting (Lee, 2011).

Following Lee (2011) and Saad and Samet (2015), portfolios are formed based on three pre-ranking illiquidity betas as per Equations (12)–(14). For each stock *i*, the pre-ranking illiquidity beta *k* (*k*=1,…,3) for year *y* is estimated based on years *y*-1 to *y*-5, using stock and market returns, as well as the innovation series in stock and market illiquidity. The 5-year window begins in January and rolls over annually. To have a pre-ranking beta for year *y*, a stock must have at least 36 contemporaneous observations of returns and innovations in illiquidity within the given 5-year window. Stocks which become delisted during the holding period are allowed into the portfolios to avoid a look-ahead bias. Should a stock receive a pre-ranking beta for a year in which it is flagged as a penny stock, the pre-ranking beta is naturally deleted.

Based on the pre-ranking betas, the stocks are sorted annually into decile portfolios using the method described by Fama and MacBeth (1973). This method ensures that the middle 8 portfolios are of equal size, and the first and last portfolios receive possible additional stocks. In short, if there are *n* stocks and int(*n*/10) is the integral part of *n*/10, the middle 8 portfolios receive int(*n*/10) stocks each. If *n* is even, the first and last portfolios each receive int(*n*/10)+0.5[*n*-10int(*n*/10)] stocks. If *n* is odd, the last portfolio receives an additional stock. This produces a total of 6 sets of decile portfolios. First, the three pre-ranking betas are computed using *AdjILLIQ* and stocks are sorted into three sets of portfolios based on the pre-ranking betas. The process is then repeated using *PQS* alternatively. Equally weighted returns and illiquidity for the portfolios are computed as

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

and

$$c_t^p = \frac{1}{n}\sum_{i=1}^{n} c_t^i\,, \tag{17}$$

where r_t^i is the return of stock *i* of portfolio *p*, at time *t*, c_t^i is the corresponding illiquidity, and *n* is the number of constituents in portfolio *p*. The weighting is predetermined for each portfolio-year based on the amount of stocks at portfolio formation and is unaffected by missing values of c_t^i or r_t^i to adhere to the 1-year holding period.

Portfolio illiquidity is defined using the stock-level illiquidity proxies instead of their innovations. Therefore, portfolio illiquidity is tested for up to second order autocorrelation with the Breusch-Godfrey LM test. All portfolios exhibit autocorrelation of either first or second order, and innovations in portfolio illiquidity are obtained by estimating an AR(2) model on first differences as per Equation (15).

For each portfolio sorted on the pre-ranking beta k (k=1,…,3), a full-sample post-ranking beta k is estimated using portfolio and market returns, as well as innovations in portfolio and market illiquidity. In other words, portfolios sorted on the commonality beta will receive a post-ranking commonality beta, and so forth. The post-ranking betas and portfolio characteristics are reported in Section 4.2.

Prerequisites to Section 3.2.3

The estimation of time-varying liquidity risks uses portfolio and market returns, and innovations in portfolio and market illiquidity as inputs. The inputs are required to be zero-mean series. As already stated, innovations are obtained for portfolio illiquidity. Portfolio returns are also tested for autocorrelation and first order autocorrelation is found in all series. However, a simplifying assumption of the returns being zero-mean series is made. The results for the Breusch-Godfrey LM test for autocorrelation in portfolio illiquidity and returns are found in Appendix 2.

The estimation method also requires all inputs to be stationary. All series are therefore tested for a unit root with the augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests. Both tests are conducted alternatively with two null models: AR and AR with drift. The lag order for all tests is set to 12, which is intuitive as the data has a monthly frequency.[11] Additionally, all series are tested for stationarity with the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The lag order is again set to 12, which is both intuitive and corresponds to a lag

[11] With 167-168 observations in each series, this loosely corresponds to the lag order of l = int[12(n/100)$^{1/4}$] suggested by Schwert (1989).

order deemed satisfactory in terms of size and power of the test by the authors (Kwiatkowski et al., 1992, p. 165). The results for stationarity and unit root tests for portfolio and market series are found in Appendices 3 and 4, respectively.

3.2.3 Time-varying liquidity risk

The tendency of financial and macroeconomic time series to exhibit nonlinear behavior has widely been documented in literature (Engle, 1982; Bollerslev, 1986). Perhaps two of the most significant phenomena for this study are non-constant variance or volatility clustering, and leverage effects where volatility increases asymmetrically after positive or negative shocks. Such features have given rise to a wealth of models designed to account for the nonlinear behavior of time series. The autoregressive conditional heteroskedasticity (ARCH) model of Engle (1982), and the generalized version (GARCH) of Bollerslev (1986), are designed to explain how volatility is influenced by past volatility. Additionally, the exponential GARCH (EGARCH) of Nelson (1991) extends the model to consider leverage effects.

As the timeframe of the portfolio analysis of this study is 14 years, the notion of constant variance, and consequently constant risk, seems implausible. Therefore, following Saad and Samet (2015), this study employs the dynamic conditional correlation (DCC) estimator to estimate conditional time-varying liquidity risks (Engle and Sheppard, 2001; Engle, 2002). The model essentially generalizes the constant conditional correlation (CCC) of Bollerslev (1990) by allowing correlations to vary over time. The estimation occurs in two steps. Firstly, univariate GARCH(1,1) models are used to estimate the conditional variance of each variable and subsequently, transformed residuals are used in estimating dynamic correlations.

Let *n* denote the number of variables in the model; in this case *n*=4. The set of variables among which conditional correlations are estimated is

$$Y_t = \left(c_t^i, c_t^M, r_t^i, r_t^M\right)', \qquad t = 1, \dots, T, \tag{18}$$

where *T* is the total number of observations for each variable. Considering

$$E(y_t|\Omega_{t-1}) = 0, \qquad Var(y_t|\Omega_{t-1}) = H_t, \tag{19}$$

the expected value of y_t, conditional on the information set Ω up to the previous period, is 0. H_t denotes an $n \times n$ conditional covariance matrix. As such, it must be positive definite. It is assumed to follow a quadvariate DCC-GARCH(1,1) similar to Engle (2002), whereby the conditional covariance matrix for the LCAPM can be expressed as

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

D_t is an $n \times n$ diagonal matrix of time-varying conditional standard deviations, $\sqrt{h_{it}}$, at time t. The conditional variances h_{it} used to form the diagonal are obtained from univariate GARCH(1,1) processes as

$$h_{it} = \alpha_{i0} + \alpha_{i1} u_{i,t-1}^2 + \beta_i h_{i,t-1}, \qquad i = 1, \dots, n, \tag{21}$$

where $u_{i,t-1}^2$ is the squared innovation and $h_{i,t-1}$ the conditional variance, both of the previous period. The restrictions of $\alpha_{i1}, \beta_i \geq 0$ for non-negativity of variances and $\alpha_{i1} + \beta_i < 1$ for stationarity apply (Bollerslev, 1986).

In Equation (20), R_t is an $n \times n$ conditional correlation matrix of standardized residuals. As H_t must be positive definite, R_t must also be positive definite to ensure this. Consequently, R_t is decomposed into

$$R_t = diag\{Q_t\}^{-\frac{1}{2}} Q_t \{Q_t\}^{-\frac{1}{2}}, \tag{22}$$

where the dynamic correlation structure of Q_t is

$$Q_t = (1 - \alpha - \beta)\bar{Q} + \alpha \varepsilon_{t-1} \varepsilon_{t-1}' + \beta Q_{t-1}. \tag{23}$$

In Equations (22)–(23), Q_t is the conditional covariance matrix of standardized residuals ε_t, and $diag\{Q_t\}$ refers to a diagonal matrix containing the square roots of the diagonal elements of Q_t. $\overline{Q}$ is the unconditional covariance matrix of the standardized residuals ε_t. Equation (23) is again subject to the restrictions $\alpha_{i1}, \beta_i > 0$ for non-negativity of variances and $\alpha_{i1} + \beta_i < 1$ for stationarity.

To ensure that R_t is positive definite, it is required to ensure that Q_t is positive definite. Q_t is positive definite for all t, as it is a weighted average of positive definite and positive semidefinite matrices. The specification in Equation (22) ensures that all elements of R_t are between the interval -1 and 1 (Engle, 2002).

The parameters of the model are estimated in two steps using quasi-maximum likelihood, similar to Engle (2002). First, each variable is modeled separately as a univariate GARCH(1,1) process. Subsequently, the parameters of the dynamic correlation process are estimated using the standardized residuals. Under the assumption of conditional normality, the joint log-likelihood function to estimate the parameters is

$$\ln L(\theta, \alpha, \beta) = -0.5 \sum_{t=1}^{T} (n \ln(2\pi) + ln|H_t| + \varepsilon_t' H_t^{-1} \varepsilon_t). \tag{24}$$

Above, n refers to the number of cross-sectional dimensions, which in this study is 4. T is the number of time periods, in this case 167, and θ, α, and β are unknown parameters to be estimated (Saad and Samet, 2015, p.132).

The quadvariate DCC-GARCH(1,1) estimator estimates four conditional covariances, $cov_t(r_t^i, r_t^M)$, $cov_t(c_t^i, c_t^M)$, $cov_t(r_t^i, c_t^M)$, and $cov_t(c_t^i, r_t^M)$, for all 60 portfolios. The covariances correspond to the market risk adjusted for liquidity, commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The conditional variances of market returns adjusted for liquidity, using *AdjILLIQ* and *PQS* alternatively, are modeled with an EGARCH(1,1).[12] Finally, the time-varying conditional illiquidity betas are computed for all

[12] Both series exhibit ARCH effects with the ARCH test of Engle (1982) and leverage effects with the sign bias test of Engle and Ng (1993). Negative shocks appear to have a higher impact on next-period volatility. Both AIC and BIC indicate that (1,1) is the ideal order.

portfolios as per Equations (12)–(14), using the conditional covariances and variances, and assigned to each portfolio constituent.

The time-varying conditional market risk factor (β^1) is not assigned from the portfolios to their constituents. Instead, the market risk factor is estimated at the stock level as per Equation (11) using a 5-year window that rolls over monthly, similar to the pre-ranking betas computed in Section 3.2.2, albeit at a higher frequency. To ensure that all stock-months which receive a conditional illiquidity beta also receive a market beta, the constraint of a minimum 36 observations within the 5-year window is dropped, but the data is balanced to only include contemporaneous observations of β^1 and the illiquidity betas. As the market risk of a stock may differ from its liquidity risk, this avoids potentially spurious results from forming portfolios based on liquidity risk and assigning the market risk of the portfolio to its constituents.

3.2.4 *Time trend in liquidity risk*

Liquidity risk and associated premia have been shown to vary substantially over time (Hagströmer, Hansson, and Nilsson, 2013; Saad and Samet, 2015) and between up and down markets (Vu, Chai, and Do, 2015). This study also finds substantial time-variation in liquidity risk. Moreover, Hagströmer, Hansson, and Nilsson (2013) find no evidence of a decreasing trend in liquidity risk premia in the US market, and Saad and Samet (2015) reach a similar conclusion on liquidity risk in their study of 83 countries.[13] Although the latter include Germany in their country-level analysis, this study also tests the sample for a time trend in liquidity risks, as both the timeframe and sample differ. Following Saad and Samet (2015), time trends are investigated using the trend tests of Vogelsang (1998) and Bunzel and Vogelsang (2005). Both tests examine a simple linear trend of the form

$$y_t = \beta_1 + \beta_2 t + \varepsilon_t, \tag{25}$$

where y_t is the conditional liquidity risk, β_1 a constant term, β_2 a time trend coefficient, and ε_t an error term.

[13] The only notable trend is a decrease in flight to liquidity and the depressed wealth effect in the UK.

The PS1 test of Vogelsang (1998) is designed to test for deterministic trend functions in univariate time series. The test requires no knowledge of the form of autocorrelation in the series and is asymptotically valid in the presence of general forms of autocorrelation or a unit root in the errors (Vogelsang, 1998, p.134). The DAN test of Bunzel and Vogelsang (2005) is a further development of the PS1 test. The general principle is similar, but the Daniell kernel is used to non-parametrically estimate the error variance required to compute the test statistic. The exact specification used in this study is the DAN-J test, which includes a scaling correction to the test statistic. Both the PS1 and DAN-J test use this scaling correction to mitigate strong autocorrelation and consequent inflated size of the test (Bunzel and Vogelsang, 2005, pp. 383-384). The DAN test is a natural choice for an additional test, as it performs equally well as the PS1 test in terms of size but shows greater power both asymptotically and in finite samples. Moreover, DAN-J is the specification recommended for practical use by the authors (Bunzel and Vogelsang, 2005, p. 387-391).

The test statistics follow a symmetric distribution, and therefore test statistics for a two-tailed test are simple to derive (Vogelsang, 1998, p. 135). As the liquidity risks in the sample vary substantially over time and no clear trend is visible, a two-tailed test is conducted. This allows the trend coefficient to be either positive or negative, indicating either an increase or decrease in liquidity risks. The null hypothesis is therefore of no linear trend against the alternative of a linear trend of any kind.

3.2.5 Pricing of time-varying liquidity risk

A fixed effects panel regression is used to estimate the pricing of liquidity risk instead of the conventional Fama-MacBeth (1973) regressions, similar to Vu, Chai, and Do (2015). This approach is taken because Petersen (2009, pp. 446-450) shows that the standard errors of the Fama-MacBeth method are biased downward in presence of a firm effect. Moreover, the bias is most likely when both the dependent and independent variables exhibit autocorrelation. Even after adjusting for autocorrelation with Newey-West (1987) standard errors, the estimates may remain biased (Petersen, 2009).

Acharya and Pedersen (2005) note that collinearity among the illiquidity betas poses a difficulty in distinguishing their separate effects in a joint test. The problem is that multicollinearity tends to inflate standard errors of the parameter estimates, widening the confidence intervals, and consequently increasing the chance of a Type II error. Moreover, even large changes in coefficient values between specifications are possible (Brooks, 2014, p. 218). To mitigate the issue of multicollinearity and to allow for separate estimation of market risk, liquidity risk, and the liquidity level, Acharya and Pedersen (2005) define an aggregate illiquidity beta as

$$\beta^{5i} \coloneqq \beta^{2i} - \beta^{3i} - \beta^{4i}. \tag{26}$$

Similarly, net systematic risk is defined as

$$\beta^{6i} \coloneqq \beta^{1i} + \beta^{2i} - \beta^{3i} - \beta^{4i}, \tag{27}$$

which enforces the model-implied constraint of equal risk premia (Acharya and Pedersen, 2005, p. 392). Similar to Vu, Chai, and Do (2015), the LCAPM is estimated in seven different specifications to first estimate each liquidity risk separately and then jointly. The seven different specifications are as listed below.

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{28}$$

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \lambda^2 \beta_t^{2i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{29}$$

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \lambda^3 \beta_t^{3i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{30}$$

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \lambda^4 \beta_t^{4i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{31}$$

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \lambda^5 \beta_t^{5i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{32}$$

$$E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^6 \beta_t^{6i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \tag{33}$$

$$\begin{aligned} E\left(r_t^i - r_t^f\right) = \alpha_t + \kappa E\left(c_t^i\right) + \lambda^1 \beta_t^{1i} + \lambda^2 \beta_t^{2i} + \lambda^3 \beta_t^{3i} + \lambda^4 \beta_t^{4i} \\ + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i \end{aligned} \tag{34}$$

The dependent variable in each specification is the monthly excess return of a given stock. The risk-free rate, r_t^f, is proxied by lagged values of the 12-month Euribor rate reported at the end of each month, converted into a monthly rate. Lagged values are used to avoid a look-ahead bias; the rate used for January is the rate reported at the end of December and so forth. The expected illiquidity cost, $E(c_t^i)$, is modeled as the illiquidity ratio of the previous month. The market risk adjusted for liquidity is β_t^{1i}, β_t^{2i} through β_t^{4i} are the conditional liquidity risks, and β_t^{5i} and β_t^{6i} are the aggregate liquidity risk and net systematic risk defined in Equations (26) and (27), respectively. *BM* and *Size* refer to the natural logarithms of the book-to-market ratio and market capitalization, respectively. Logarithms are taken to account for extreme values. *FF* refers to the free float ratio, which is introduced as a control variable due to its potentially confounding effect. Free float directly affects liquidity by limiting the amounts of shares available for trading, and a lower proportion of free float shares may increase information asymmetry which may further drive illiquidity (Kyle, 1985). Ding, Ni, and Zhong (2016) find a linkage between free float, liquidity, and liquidity risk, and suggest that free float may affect the expected returns of a stock through liquidity risk in markets where liquidity risk is priced. Controlling for free float allows for the examination of the systematic component of the liquidity risks.

The LCAPM assumes the expected illiquidity cost $E(c_t^i)$ to be incurred once per model period, whereby κ is a free parameter in the estimation. As the model-implied one-month holding period is likely to differ from the typical holding period of an investor, Acharya and Pedersen (2005) alternatively calibrate κ to correspond to an approximate average holding period. This is done empirically by setting κ to be the average monthly turnover (rate) of the sampled stocks. In the sample of this study, the average monthly turnover rate is 1.93 percent, which corresponds to a holding period of $1/0.0193 \approx 52$ months. To determine whether the results hold in a more general setting, the panel regressions are repeated with the calibrated value of κ. When the estimation period is κ times the model-implied one-month holding period, the expected returns and illiquidity betas are scaled by κ. This is because κ-period returns or illiquidity innovations are approximately the sum of κ one-period returns or illiquidity innovations, and both exhibit a small degree of autocorrelation. The expected illiquidity cost, however, does not scale with time because it is an average of daily illiquidities instead of a sum. Therefore, the term $\kappa E(c_t^i)$ is substituted to the left-hand side, and the dependent variable in the regressions is $E(r_t^i - r_t^f) - \kappa E(c_t^i)$ (Acharya and Pedersen, 2005, p. 393).

The use of fixed effects is validated with the following specification tests conducted for each regression model as per Equations (28)–(34), using each of the three portfolio sorts and both illiquidity measures. Firstly, the Breusch-Pagan LM test is used to determine whether a panel regression is more suitable than pooled OLS. The null hypothesis that error variance across panels is zero is rejected in all specifications, indicating that a panel regression is more suitable. The Hausman specification test compares the estimates of fixed and random effects models with the null hypothesis that the difference in coefficients is not systematic (Brooks, 2014, pp. 543-547). The null hypothesis is rejected in all specifications, indicating that fixed effects are present in the data. Lastly, the presence of time fixed effects is tested by adding dummy variables for time to the fixed effects model and using a Wald test to determine whether the dummy variables are jointly equal to zero (Brooks, 2014, pp. 529-532). The null hypothesis is rejected in all specifications, indicating that time fixed effects are present. The results for the model specification tests are found in Appendix 5.

Due to the results of the specification tests, the panel regressions are estimated with a two-way error component model which includes both firm and time fixed effects. The error term ε_t^i in Equations (28)–(34) decomposes into

$$\varepsilon_t^i = \mu_i + \lambda_t + v_{it}, \tag{35}$$

where μ_i is a time-invariant and individual-specific effect, λ_t is an individual-invariant and time-specific effect, and v_{it} is a remaining disturbance that varies over time and across individuals (Brooks, 2014, pp. 529-532). The time fixed effects account for market-wide heterogeneity in time and the firm fixed effects account for firm-level heterogeneity. Robust standard errors asymptotically equivalent to Arellano (1987) are used to account for autocorrelation at the firm level.

4 EMPIRICAL RESULTS

4.1 Innovations in illiquidity

As detailed in Section 3.2.1, liquidity is persistent and therefore predictable. Consequently, innovations are used to examine the unanticipated movements in illiquidity. Moreover, the use of innovations in the analyses mitigates the issue of autocorrelation widely documented in prior studies (Acharya and Pedersen, 2005; Lee, 2011; Saad and Samet, 2015). The illiquidity series are initially tested for first and second order autocorrelation using the Breusch-Godfrey LM test. First order autocorrelation is present in approximately 96 percent of the sample, and second order in approximately 69 percent of the sample. After obtaining innovations for both market illiquidity series and all stock-level illiquidity series with the procedure detailed in Section 3.2.1, the innovation series are again tested for autocorrelation. Autocorrelation is sufficiently removed from the sample.[14] The results of the Breusch-Godfrey LM test for both market illiquidity series as well as their innovations are found in Appendix 1. Market illiquidity measured by *PQS* exhibits first order autocorrelation, whereas both first and second order are found in the *AdjILLIQ* series. The innovations appear free of autocorrelation.

Figure 1 plots the innovations in market illiquidity using both proxies. As the figure plots the unanticipated movements in illiquidity, the upward spikes are associated with unexpected liquidity dry-ups. Moreover, the periods of higher volatility generally coincide with times of higher overall illiquidity, perhaps partly because the measure is bounded from below by zero. Both series show similar dynamics, albeit at different magnitudes.

[14] 3.50 percent of the *AdjILLIQ* innovations and 2.78 percent of the *PQS* innovations test positive for autocorrelation. As both figures are below the 5 percent change of Type I error, the conclusion is that autocorrelation is sufficiently removed from the sample.

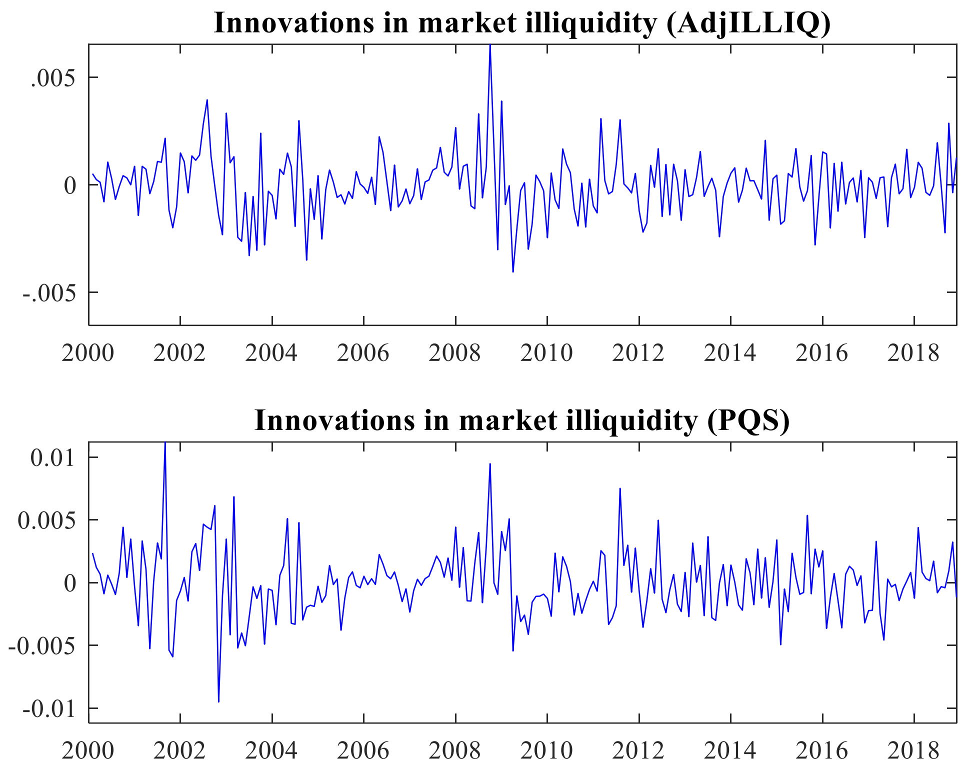

Figure 1. Innovations in market illiquidity.

The periods of most pronounced instability can be anecdotally linked to developments in the German economy. More specifically, as Brunnermeier and Pedersen (2009, p. 2206) note, sudden liquidity dry-ups tend to occur more frequently in declining markets. The period between 2000 and 2005 indicates increased uncertainty about market liquidity, which is especially pronounced in the *PQS* series, and coincides with a slumping economy. The financial crisis which affected Germany most severely in 2008 and 2009 is also a period of high volatility. The period between 2011 and 2013 also appears volatile and coincides with an economic decline. The relatively calm periods of 2005-2008, 2009-2011, and 2013 onwards appear to coincide with overall economic growth in the country.

4.2 Illiquidity portfolios

The decile portfolios are sorted on pre-ranking betas computed as per Section 3.2.2. Full-sample post-ranking betas are then computed to examine the efficacy of portfolio formation. Table 3 presents the post ranking betas for each portfolio. The leftmost column lists the decile, and β^n refers to both the relevant sorting criterion and the post-ranking beta. For example, β^2 under *AdjILLIQ* refers to the post-ranking β^2 of portfolios sorted on β^2 using *AdjILLIQ*, and so forth. Under β^2, portfolios are sorted from lowest to highest risk from decile 1 through 10, whereas the order is the opposite under β^3 and β^4.

The signs of the betas are as expected and consistent with those reported by Acharya and Pedersen (2005, p. 391). The only exception is decile 9 of β^4 portfolios using *PQS*, where the sign is positive. Largest magnitudes are generally seen in β^4, which corresponds to the depressed wealth effect. Moreover, the risk appears to be the most pronounced in terms of the dispersion between deciles. The magnitudes of β^3, which corresponds to the risk of flight to liquidity, are generally similar to those of β^4, aside from the extreme values. Consequently, the betas are less dispersed than β^4, indicating a more even distribution of risk between the deciles. While the risky deciles of β^3 have smaller values than β^4, the opposite is generally the case in the less risky deciles. Lastly, β^2, which corresponds to commonality in liquidity, uniformly has the smallest magnitude of betas.

All betas appear to be generally monotonic with a gradual increase in risk when moving from the least to most risky decile. Deviations from monotonicity tend to occur in the least risky deciles, most notably in decile 1 of β^2-sorted portfolios and decile 10 of β^4-sorted portfolios. In the β^2-sorted portfolios of both illiquidity proxies, decile 1 receives a notably high post-ranking beta, which is exceeded only by deciles 8-10 under *AdjILLIQ* and only decile 10 under *PQS*. A similar occurrence is found in β^4-sorted portfolios using *PQS* where the risk of decile 10 is only exceeded by deciles 1 and 2. These aberrations are strikingly similar to those reported by Kim and Lee (2014, p. 122) in portfolios using the Amihud (2002) proxy of illiquidity. As the portfolios are sorted annually, it is possible that the risks of portfolio constituents, and consequently of the portfolios, vary over time, which would naturally affect deciles 1 and 10 the most as they are bounded from one direction. The change in timeframe of estimation between pre- and post-ranking betas may also produce differing results.

Table 3. Post-ranking betas.

This table lists the post-ranking betas for liquidity risk sorted portfolios. The post-ranking betas are computed using data for the period spanning from 01/2005 to 12/2018. Post-ranking β^2 under *AdjILLIQ* refers to the portfolio that was sorted on β^2 using *AdjILLIQ*, and so forth. Under β^2, portfolio 1 comprises of stocks with lowest liquidity risk and 10 the highest, whereas under β^3 and β^4 the order is the opposite. HML refers to the difference between the high-risk and low-risk portfolios.

	AdjILLIQ			*PQS*		
Portfolio	β^2	β^3	β^4	β^2	β^3	β^4
1	0.0005	-0.0164	-0.0219	0.0015	-0.0213	-0.0433
2	0.0001	-0.0136	-0.0227	0.0004	-0.0196	-0.0304
3	0.0001	-0.0135	-0.0181	0.0002	-0.0197	-0.0164
4	0.0002	-0.0137	-0.0114	0.0006	-0.0165	-0.0198
5	0.0002	-0.0127	-0.0086	0.0004	-0.0182	-0.0125
6	0.0005	-0.0118	-0.0112	0.0008	-0.0158	-0.0093
7	0.0004	-0.0104	-0.0024	0.0011	-0.0168	-0.0062
8	0.0006	-0.0091	-0.0025	0.0009	-0.0132	-0.0081
9	0.0014	-0.0089	-0.0044	0.0014	-0.0110	0.0125
10	0.0012	-0.0093	-0.0104	0.0053	-0.0124	-0.0271
HML	**0.0007**	**-0.0071**	**-0.0115**	**0.0038**	**-0.0089**	**-0.0162**

Portfolio characteristics are also computed for additional insight. The characteristics of interest are averages and standard deviations in returns and illiquidity, as well as the average monthly market capitalization. Table 4 presents the above characteristics for the three sets of decile portfolios sorted using *AdjILLIQ*.

In Panel A, average returns tend to gradually increase with liquidity risk, aside from notable deviations in deciles 1 and 7. Decile 1 has the highest returns despite being designed to contain the lowest risk. Bearing in mind the post-ranking betas, the relationship between risk and average returns is more evident. Panels B and especially C, however, find little relationship between liquidity risk and average returns. Standard deviations of returns show mixed results. In all panels, the differences between deciles 1 and 10 are as expected. The riskiest portfolio has a higher standard deviation than the least risky portfolio, consistent with Acharya and Pedersen (2005, p.391). However, with the exception of Panel B, it requires a degree of optimism to find any clear pattern.

Average illiquidity is higher in the high-risk portfolios in Panels A and C, which is an intuitive result. Moreover, bearing in mind the post-ranking betas, the relationship is again more explicit. Panel B is an exception in this regard with no clear relationship. Standard deviations in illiquidity appear to have a similar relationship. In all panels, the high-risk decile has a higher standard deviation than the low-risk decile. Again, a monotonic relationship is more pronounced in Panels A and C, closely following the post-ranking betas. Average sizes of the portfolios also show a relatively monotonic trend in Panels A and C, indicating that larger stocks have, on average, a lower ex ante liquidity risk. Decile 1 in Panel A and deciles 9 and 10 in Panel C are exceptions, but in general it is apparent that larger stocks tend to have a lower liquidity risk.

Table 4. Characteristics of portfolios sorted using *AdjILLIQ*.

This table reports characteristics of liquidity risk sorted portfolios using *AdjILLIQ*. All figures are based on the sample spanning from 01/2005 to 12/2018. Mean portfolio returns and illiquidity, $\mu(r^p)$ and $\mu(c^p)$, respectively, as well as standard deviations of both, $\sigma(r^p)$ and $\sigma(c^p)$, are reported in percentages. Size refers to the time series average of the market capitalization (in millions) of each portfolio.

Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios										
$\mu(r^p)$	0.83	0.36	0.55	0.52	0.47	0.59	0.37	0.66	0.65	0.80
$\sigma(r^p)$	4.50	4.87	5.03	4.70	4.61	4.23	4.32	4.41	4.96	4.67
$\mu(c^p)$	1.22	0.13	0.13	0.22	0.35	0.56	0.72	1.15	1.67	2.24
$\sigma(c^p)$	0.70	0.16	0.11	0.14	0.25	0.41	0.44	0.75	0.92	0.80
Size	5252	10881	5742	1959	1367	605	233	151	73	45
Panel B: β^3 (flight to liquidity) sorted portfolios										
$\mu(r^p)$	0.53	0.46	0.61	0.88	0.89	0.57	0.58	0.50	0.45	0.38
$\sigma(r^p)$	6.14	5.30	4.92	4.94	4.67	4.05	4.08	3.70	3.50	3.99
$\mu(c^p)$	1.07	0.85	0.75	0.76	0.71	0.75	0.79	0.81	0.84	1.14
$\sigma(c^p)$	0.66	0.62	0.53	0.44	0.36	0.45	0.55	0.46	0.44	0.40
Size	748	2802	4694	3231	3247	2389	2417	3055	2216	1553
Panel C: β^4 (depressed wealth effect) sorted portfolios										
$\mu(r^p)$	0.69	0.48	0.75	0.63	0.20	0.75	0.63	0.29	0.69	0.70
$\sigma(r^p)$	5.00	4.69	4.40	4.27	4.56	4.82	4.79	4.89	4.48	4.39
$\mu(c^p)$	2.14	1.38	1.02	0.68	0.49	0.32	0.15	0.10	0.41	1.69
$\sigma(c^p)$	0.99	0.81	0.55	0.50	0.34	0.27	0.13	0.09	0.32	0.67
Size	50	80	155	401	919	1365	3304	13668	6224	297

Table 5 presents the same set of characteristics for portfolios sorted using *PQS* as the proxy of illiquidity. All panels indicate that the decile of highest risk has higher average returns than the decile of lowest risk. However, the variance between deciles indicates little consistent trend. Standard deviations of returns appear to exhibit a more consistent trend. In all panels, standard deviations increase with liquidity risk, consistent with Acharya and Pedersen (2005, p.391). Moreover, Panel B exhibits the most consistent gradual increase with liquidity risk.

Average illiquidity tends to increase between the least and most risky deciles in all panels. In Panels A and C, the increase is generally gradual with the exception of the least risky deciles, which seem to be an aberration in many ways. Standard deviations in illiquidity mostly follow a similar pattern; the riskiest deciles have higher standard deviations than the least risky deciles in all panels, and Panels A and C indicate a somewhat gradual increase with the exception of the two least risky deciles. Similar to the *AdjILLIQ* portfolios, average portfolio size appears to be linked with liquidity risk in Panels A and C. With the exception of the least risky deciles, the relationship between average market capitalization and liquidity risk appears to be monotonic. Again, Panel B indicates that the risk of flight to liquidity is not strongly linked to size, but commonality and the depressed wealth effect appear to be.

Table 5. Characteristics of portfolios sorted using *PQS*.

This table reports characteristics of liquidity risk sorted portfolios using *PQS*. All figures are based on the sample spanning from 01/2005 to 12/2018. Mean portfolio returns and illiquidity, $\mu(r^p)$ and $\mu(c^p)$, respectively, as well as standard deviations of both, $\sigma(r^p)$ and $\sigma(c^p)$, are reported in percentages. Size refers to the time series average of the market capitalization (in millions) of each portfolio.

Portfolio	1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios										
$\mu(r^p)$	0.57	0.66	0.38	0.53	0.54	0.75	0.50	0.58	0.55	0.87
$\sigma(r^p)$	3.51	4.45	4.24	4.77	4.47	3.99	4.55	4.44	4.15	4.75
$\mu(c^p)$	3.94	1.92	1.57	2.02	2.38	2.82	3.20	3.58	4.44	8.27
$\sigma(c^p)$	1.35	0.92	0.43	0.73	0.67	0.83	1.01	0.73	1.20	2.73
Size	1790	7420	5364	4157	2008	1190	548	432	113	93
Panel B: β^3 (flight to liquidity) sorted portfolios										
$\mu(r^p)$	0.63	1.01	0.55	0.27	0.87	0.60	0.52	0.51	0.67	0.35
$\sigma(r^p)$	5.85	5.25	4.96	4.51	4.23	3.94	4.12	3.36	3.41	3.65
$\mu(c^p)$	4.95	3.10	2.97	2.93	3.08	3.00	3.05	3.29	3.35	4.59
$\sigma(c^p)$	2.20	0.91	1.05	0.87	0.87	1.00	1.02	1.33	1.12	0.98
Size	899	1756	3227	3085	2440	2737	3188	2556	1975	1203
Panel C: β^4 (depressed wealth effect) sorted portfolios										
$\mu(r^p)$	0.66	0.76	0.55	0.48	0.58	0.54	0.64	0.65	0.58	0.52
$\sigma(r^p)$	4.52	4.55	4.19	4.70	4.18	4.63	4.28	4.26	3.85	3.92
$\mu(c^p)$	7.14	4.12	3.60	3.16	2.70	2.27	1.64	1.68	2.50	5.35
$\sigma(c^p)$	2.37	1.28	0.96	0.76	0.74	0.70	0.52	0.50	1.19	1.81
Size	122	146	231	531	1036	2269	5888	6713	5570	635

4.3 *Time-varying liquidity risk*

Time-varying conditional illiquidity betas are computed as per Equations (11)–(14) as discussed in Section 2.4, using the method described in Section 3.2.3. The conditional covariances for the betas are estimated using the DCC-GARCH(1,1) estimator, and the conditional variance of market returns is estimated with an EGARCH(1,1). Figure 2 plots the betas for decile portfolios 1 and 10, representing the lowest and highest liquidity risks. The betas plotted are the betas for portfolios sorted on the corresponding beta. For example, the commonality betas are those of portfolios sorted on the commonality beta, and so forth. The portfolio with the lower risk – decile 1 for commonality, elsewhere decile 10 – is plotted in blue, and the portfolio with the higher risk in red.

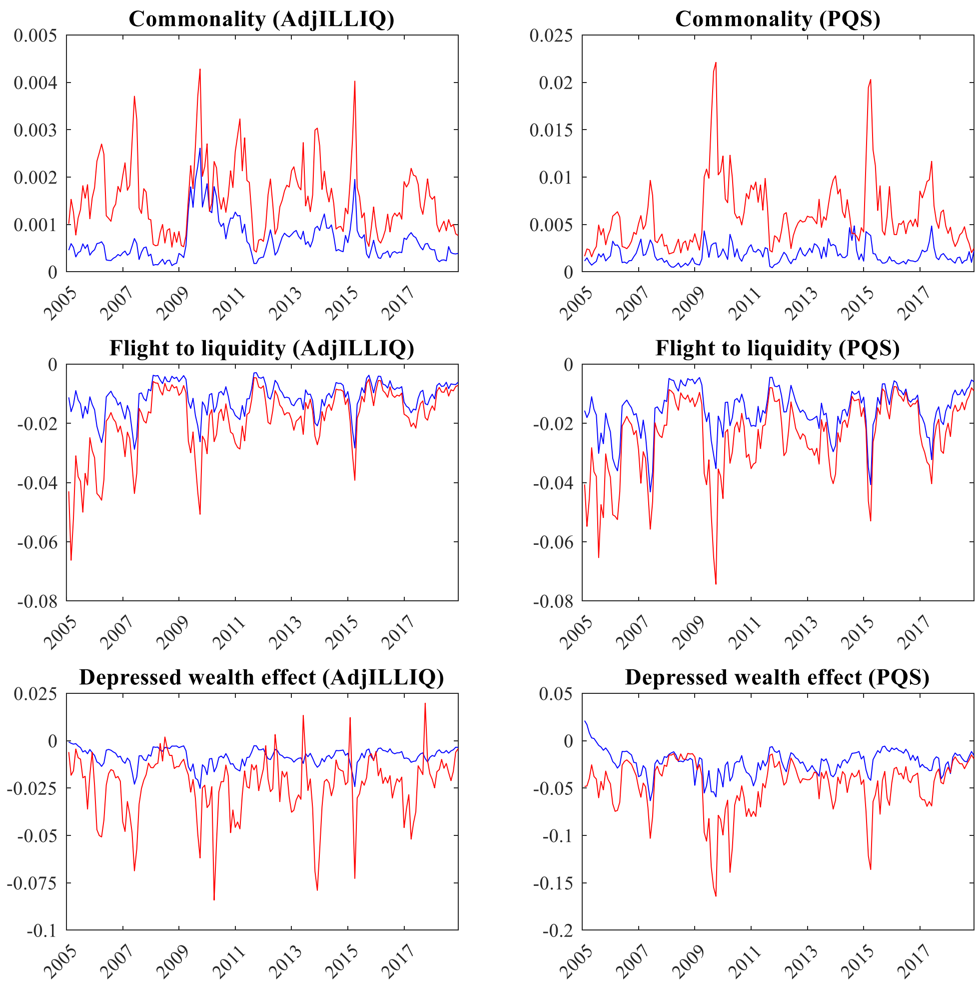

Figure 2. Time-varying conditional liquidity risks.

All betas vary substantially over time, consistent with prior findings (Hagströmer, Hansson, and Nilsson, 2013; Saad and Samet, 2015). The effects of the global financial crisis are evident in all series; the betas are generally at their lowest prior to the effects of the crisis becoming apparent, and subsequently reach their highest levels. As could be expected, the high-risk portfolios tend to react more strongly to market developments. The low-risk portfolios also show notable reactions, especially in terms of commonality and flight to liquidity, and to a lesser extent in the depressed wealth effect.

In all figures, the illiquidity betas tend to be higher for the high-risk portfolios, as expected. There are temporary exceptions, most notably in the depressed wealth effect using *AdjILLIQ*, where the portfolios cross over, and the high-risk portfolio takes on positive values. In terms of absolute magnitudes, the depressed wealth effect has the largest magnitudes and commonality in liquidity the smallest, similar to the post-ranking betas discussed in the previous section. Moreover, standard deviations indicate that the high-risk portfolios have greater variance in their risk. In all series, the high-risk portfolio has a greater standard deviation than the low-risk portfolio. In the *AdjILLIQ* series, these are 0.0004 and 0.0007, 0.0053 and 0.0112, and 0.0044 and 0.0163 for the pairs of low and high-risk portfolios in commonality, flight to liquidity, and the depressed wealth effect. In the *PQS* series, the same figures are 0.0009 and 0.0036, 0.0078 and 0.0131, and 0.0131 and 0.0277, respectively.

Visually, the spreads in risk between low and high-risk portfolios appear to be the smallest in flight to liquidity; the series seem to closely follow each other with a constantly narrow spread. In absolute terms, however, the smallest differences in means – 0.0009 for *AdjILLIQ* and 0.0041 for *PQS* – are found in the commonality betas, which tend to converge and diverge intermittently. The largest differences in means are found in the depressed wealth effect portfolios, with 0.0153 for *AdjILLIQ* and 0.0249 for *PQS*, and flight to liquidity stands in the middle with 0.0075 and 0.0090 for *AdjILLIQ* and *PQS*, respectively. Regarding the spreads, it is to be noted that not all 8 middle portfolios lie within the spread. The conditional betas follow a somewhat similar dispersion to the post-ranking betas. Therefore, on numerous occasions the low-risk portfolio has a higher conditional beta than neighboring deciles. This highlights the notion that an ex ante beta may not be a failsafe predictor of future risk.

4.3.1 Time trend in liquidity risk

The only series that exhibits a semblance of a trend in Figure 2 is the portfolio of highest risk in flight to liquidity when using *AdjILLIQ* as a proxy of illiquidity. Regardless, all series plotted in Figure 2 are tested for a linear trend using the PS1 test of Vogelsang (1998) and the DAN-J test of Bunzel and Vogelsang (2005). The results for both tests are reported in Table 6. The test is two-tailed, whereby the linear trend may be either positive or a negative. As positive values of β^2 indicate greater risk, a positive trend coefficient would indicate an increasing trend. Conversely, β^3 and β^4 take on negative values, and a larger negative value indicates greater risk. Therefore, a positive trend coefficient would indicate a decreasing trend.

Table 6. Tests for time trend in conditional liquidity risks.

The leftmost column lists the portfolio tested; β^2 *low risk* refers to the conditional β^2 series of the decile with lowest risk when sorted on β^2, and so forth. The test is two tailed, testing for either a positive or a negative trend. The table lists the time trend coefficient and the two tailed test statistic at the 5% significance level below in parentheses. Two tailed critical values at 5% significance are 2.152 for the PS1 test and 2.052 for the DAN-J test.

	AdjILLIQ		*PQS*	
	DAN-J	*PS1*	*DAN-J*	*PS1*
β^2 *low risk*	0.0000	0.0000	0.0000	0.0000
	(-0.067)	(0.185)	(0.019)	(0.615)
β^2 *high risk*	-0.0000	0.0000	0.0000	0.0000
	(-1.477)	(-1.062)	(0.815)	(0.992)
β^3 *low risk*	0.0000	0.0000	0.0000	0.0000
	(1.595)	(1.421)	(0.948)	(0.429)
β^3 *high risk*	0.0001*	0.0001	0.0001	0.0000
	(2.505)	(1.794)	(1.520)	(0.870)
β^4 *low risk*	0.0000	0.0000	-0.0001	-0.0001
	(1.032)	(0.409)	(-0.556)	(-0.533)
β^4 *high risk*	0.0000	0.0000	0.0001	0.0001
	(0.657)	(-0.035)	(1.056)	(0.576)

H0: No linear time trend. * indicates significance at the 5% level.

The results largely confirm the hypothesis of no trend in the risks, conforming to the results of prior studies (Hagströmer, Hansson, and Nilsson 2013; Saad and Samet, 2015). The co-efficients are minimal across the board, and only one coefficient is statistically significant at the 5 percent level. The significant coefficient corresponds to the high-risk portfolio sorted on flight to liquidity, using *AdjILLIQ* as the proxy of illiquidity. Judging by Figure 2, there appears to be a trend of a decreasing risk within the sample period. However, it could be argued that a longer timeframe is required to determine whether the result is generalizable or simply driven by the sample period. As is evident from Figure 2, the betas tend to peak shortly after a liquidity event such as the financial crisis, the brunt of which occurred during 2008. Bearing in mind that the sample period of the trend test covers the years 2005 through 2018, and that the innovations in market illiquidity plotted in Figure 1 indicate a period of increased uncertainty about market liquidity from 2000 until 2005, it is possible that the starting values of large magnitude are a product of the preceding period omitted from the trend test. Consequently, there is little evidence of a general trend in the liquidity risks, and hypothesis 6 of no trend in liquidity risks cannot be rejected.

4.4 Pricing of time-varying liquidity risk

As Acharya and Pedersen (2005) note multicollinearity among the betas, their pairwise correlations are examined in Table 7. The table lists the pairwise correlations among the illiquidity betas for each portfolio sorting and confirms collinearity in the sample. For brevity, only the betas which are regressed together with another beta are included. Although omitted from the table, it is noted that the net systematic risk (β^6) is largely defined by the market risk factor (β^1) due to its large magnitude compared to the illiquidity betas. Consequently, the correlation between the two is approximately 0.999.

The market risk factor (β^1) has negligible correlations with the illiquidity betas and the aggregate liquidity risk (β^5). The negative correlation between commonality in liquidity (β^2) and flight to liquidity (β^3) ranges from weak to moderate, with highest values in Panel B. Flight to liquidity (β^3) is positively correlated with the depressed wealth effect (β^4), but the coefficients again range from weak to moderate. Most notably, commonality (β^2) has a strong negative correlation with the depressed wealth effect (β^4) in all panels, with coefficients ranging from -0.756 to -0.860. This may cause difficulty in estimating coefficients and their statistical significance when the betas are regressed jointly.

Table 7. Pairwise correlations of conditional betas.

The table lists the Spearman correlation coefficients for the illiquidity betas. All values are significant at the 1 percent level.

	AdjILLIQ						*PQS*				
	Panel A: β^2 (commonality) sorted portfolios										
	β^1	β^2	β^3	β^4	β^5		β^1	β^2	β^3	β^4	β^5
β^1	1.000					β^1	1.000				
β^2	-0.097	1.000				β^2	-0.088	1.000			
β^3	-0.059	-0.437	1.000			β^3	-0.089	-0.350	1.000		
β^4	0.088	-0.850	0.421	1.000		β^4	0.048	-0.860	0.421	1.000	
β^5	-0.039	0.825	-0.749	-0.916	1.000	β^5	-0.005	0.816	-0.722	-0.930	1.000
	Panel B: β^3 (flight to liquidity) sorted portfolios										
	β^1	β^2	β^3	β^4	β^5		β^1	β^2	β^3	β^4	β^5
β^1	1.000					β^1	1.000				
β^2	0.130	1.000				β^2	0.105	1.000			
β^3	-0.257	-0.682	1.000			β^3	-0.226	-0.536	1.000		
β^4	-0.087	-0.756	0.453	1.000		β^4	-0.205	-0.762	0.536	1.000	
β^5	0.191	0.854	-0.821	-0.881	1.000	β^5	0.236	0.786	-0.794	-0.938	1.000
	Panel C: β^4 (depressed wealth effect) sorted portfolios										
	β^1	β^2	β^3	β^4	β^5		β^1	β^2	β^3	β^4	β^5
β^1	1.000					β^1	1.000				
β^2	-0.102	1.000				β^2	-0.089	1.000			
β^3	-0.059	-0.498	1.000			β^3	-0.064	-0.327	1.000		
β^4	0.069	-0.846	0.477	1.000		β^4	0.026	-0.814	0.338	1.000	
β^5	-0.029	0.837	-0.764	-0.931	1.000	β^5	-0.002	0.803	-0.642	-0.938	1.000

To mitigate the issue of multicollinearity, the LCAPM is estimated in seven different specifications as per Equations (28)–(34). This allows for the liquidity risks to be estimated both separately and jointly. A fixed effects panel regression described in Section 3.2.3 is used for the estimation. A two-way error component model is used to account for both firm and time fixed effects which are present in the data. Moreover, robust standard errors are used to account for autocorrelation in the regressors. The use of the model is justified with the following diagnostic tests conducted for each model specification. Firstly, the Breusch-Pagan LM test indicates that panel effects are present in the data and that a pooled OLS is not the most suitable model. Secondly, the Hausman test indicates the presence of a firm effect in the data. Lastly, a Wald test indicates that the coefficients differ between time periods, confirming the presence of a time fixed effect. The results of the diagnostic tests are found in Appendix 5.

The timeframe for the regressions spans from 2000 to 2018, as the first 5 years of data are used to obtain pre-ranking betas. Moreover, the illiquidity innovation of 01/2000 is lost due to differencing before estimating the AR model to obtain innovations, and consequently, there are no conditional betas for 01/2000. Therefore, the data in the regressions contains 167 time periods. In the *AdjILLIQ* regressions, 699 individual stocks are used as test assets. On average, the data contains 91.6 observations per stock, and the total number of observations is 63999. In the *PQS* regressions, 770 individual stocks with an average of 96.6 observations per stock combine for a total of 74415 observations.

Tables 8 and 9 report the results of the panel regressions using *AdjILLIQ* and *PQS*, alternatively, as the proxies for illiquidity. The numbering in the leftmost column refers to the LCAPM specification corresponding to Equations (28)–(34), and the top row lists the parameters estimated. In the first specification, the pricing of market risk adjusted for liquidity is estimated separately. Subsequently, the pricing of each liquidity risk, and finally the aggregate liquidity risk, are estimated jointly with the market risk. Specification 6 estimates the pricing of the net systematic risk, and finally, specification 7 estimates the pricing of the conditional liquidity risks jointly. All regressions consider the expected illiquidity level $E(c)$, which is hypothesized to be priced in the market. The natural logarithms of market capitalization and the book-to-market ratio are used to control for the size and value effects, and the free float ratio is included to control for its idiosyncratic effect on illiquidity.

When *AdjILLIQ* is used to proxy illiquidity, its expected level is not significantly related to stock returns at conventional levels in any of the regressions. In a bivariate regression, illiquidity has a positive and significant relationship with stock returns. Noting the negative and significant coefficient for size in all regressions and bearing in mind the size effect noted in Table 2, whereby small stocks tend to be less liquid, it is possible that the illiquidity premium is subsumed by a size effect. Another culprit may be a noted value effect whereby returns increase with the book-to-market ratio.[15]

Another consistent result across panels is that market risk (β^1) is priced negatively with a coefficient of -0.004, significant at the 10 percent level. Although counter-intuitive, the result is plausible when compared to the cross-sectional regressions of Brückner, Lehmann, and Stehle (2012). Unreported but worth noting is that sorting stocks on β^1 and estimating a conditional β^1 at the portfolio level would produce a similar result. As a consequence of the

[15] The book-to-market ratio has an indirect size implication. The natural logarithms of market capitalization and book-to-market ratio have a pairwise correlation of -0.235.

pricing of β^1, net systematic risk (β^6) is also priced with a coefficient of -0.004, significant at the 10 percent level.

Panel A contains the results for portfolios sorted on commonality in liquidity. Commonality (β^2) is positively related to returns with a coefficient of 2.665, significant at the 5 percent level. The signs of flight to liquidity (β^3) and the depressed wealth effect (β^4) are negative as hypothesized, but neither are significant at conventional levels. When regressed jointly in line 7, none of the liquidity risks have significant relationships with returns. Moreover, the coefficient for β^4 changes sign, which is possibly due to collinearity with β^2. As commonality in liquidity is priced, aggregate liquidity risk (β^5) is also priced with a coefficient of 0.103, albeit at the 10 percent significance level.

Panel B contains the results for portfolios sorted on flight to liquidity. The signs for the liquidity risks are all as hypothesized and remain so in joint estimation. However, only flight to liquidity (β^3) is priced with a coefficient of -0.455, significant at the 5 percent level. Moreover, β^3 remains priced in the joint estimation with a coefficient of -0.442, again significant at the 5 percent level. As a consequence of the pricing of β^3, aggregate liquidity risk (β^5) is priced with a coefficient of 0.132, significant at the 5 percent level.

Lastly, panel C contains the results for portfolios sorted on the depressed wealth effect. When estimated separately, none of the liquidity risks are priced at conventional significance levels. Moreover, the coefficient for the depressed wealth effect (β^4) is positive, contrary to expectations. In joint estimation, β^2 and β^4 gain significance; the coefficients are 3.832 and 0.193, respectively, both significant at the 10 percent level. Aggregate liquidity risk (β^5) is not priced at conventional significance levels.

Table 8. Panel regressions with fixed effects using *AdjILLIQ*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The intercept is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. $Ln(Sz)$, $ln(BM)$, and FF control for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding t-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel A: β^2 (commonality) sorted portfolios											
1	0.037***	-0.048	-0.004*						-0.005***	0.019***	-0.001
	(3.49)	(-0.98)	(-1.70)						(-2.72)	(8.64)	(-0.36)
2	0.034***	-0.046	-0.004*	2.665**					-0.005**	0.019***	-0.001
	(3.17)	(-0.93)	(-1.68)	(2.09)					(-2.55)	(8.67)	(-0.31)
3	0.035***	-0.047	-0.004*		-0.111				-0.005***	0.019***	-0.001
	(3.18)	(-0.94)	(-1.71)		(-0.54)				(-2.70)	(8.64)	(-0.36)
4	0.036***	-0.048	-0.004*			-0.102			-0.005***	0.019***	-0.001
	(3.35)	(-0.97)	(-1.68)			(-1.62)			(-2.64)	(8.65)	(-0.33)
5	0.034***	-0.046	-0.004*				0.103*		-0.005***	0.019***	-0.001
	(3.12)	(-0.93)	(-1.69)				(1.71)		(-2.61)	(8.65)	(-0.33)
6	0.037***	-0.048						-0.004*	-0.005***	0.019***	-0.001
	(3.49)	(-0.98)						(-1.66)	(-2.72)	(8.64)	(-0.36)
7	0.033***	-0.045	-0.004*	2.878	-0.089	0.017			-0.005**	0.019***	-0.001
	(2.91)	(-0.90)	(-1.69)	(1.29)	(-0.43)	(0.15)			(-2.53)	(8.68)	(-0.31)

Table 8 continued.

	α	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*ln(Sz)*	*ln(BM)*	*FF*
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	0.037***	-0.048	-0.004*						-0.005***	0.019***	-0.001
	(3.49)	(-0.98)	(-1.70)						(-2.72)	(8.64)	(-0.36)
2	0.036***	-0.048	-0.004*	2.933					-0.005***	0.019***	-0.001
	(3.34)	(-0.98)	(-1.82)	(1.22)					(-2.73)	(8.63)	(-0.37)
3	0.031***	-0.046	-0.005**		-0.455**				-0.005***	0.019***	-0.001
	(2.77)	(-0.93)	(-2.31)		(-2.28)				(-2.72)	(8.63)	(-0.38)
4	0.037***	-0.049	-0.004*			-0.058			-0.005***	0.019***	-0.001
	(3.48)	(-0.99)	(-1.74)			(-0.79)			(-2.73)	(8.64)	(-0.36)
5	0.035***	-0.049	-0.005**				0.132**		-0.005***	0.019***	-0.001
	(3.27)	(-0.99)	(-1.99)				(2.00)		(-2.74)	(8.63)	(-0.39)
6	0.037***	-0.048						-0.004*	-0.005***	0.019***	-0.001
	(3.49)	(-0.98)						(-1.66)	(-2.72)	(8.64)	(-0.36)
7	0.030***	-0.046	-0.006**	1.358	-0.442**	-0.039			-0.005***	0.019***	-0.001
	(2.72)	(-0.94)	(-2.37)	(0.48)	(-2.29)	(-0.44)			(-2.73)	(8.62)	(-0.39)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	0.037***	-0.048	-0.004*						-0.005***	0.019***	-0.001
	(3.49)	(-0.98)	(-1.70)						(-2.72)	(8.64)	(-0.36)
2	0.036***	-0.047	-0.004*	0.976					-0.005***	0.019***	-0.001
	(3.33)	(-0.95)	(-1.69)	(0.71)					(-2.65)	(8.63)	(-0.34)
3	0.031***	-0.042	-0.004*		-0.354				-0.005***	0.019***	-0.001
	(2.73)	(-0.85)	(-1.74)		(-1.53)				(-2.66)	(8.65)	(-0.32)
4	0.038***	-0.050	-0.004*			0.055			-0.005***	0.019***	-0.001
	(3.51)	(-1.01)	(-1.70)			(0.85)			(-2.74)	(8.66)	(-0.37)
5	0.038***	-0.049	-0.004*				-0.017		-0.005***	0.019***	-0.001
	(3.43)	(-1.00)	(-1.70)				(-0.29)		(-2.71)	(8.65)	(-0.36)
6	0.037***	-0.049						-0.004*	-0.005***	0.019***	-0.001
	(3.50)	(-0.99)						(-1.71)	(-2.72)	(8.64)	(-0.36)
7	0.029**	-0.041	-0.004*	3.832*	-0.363	0.193*			-0.005**	0.019***	-0.001
	(2.56)	(-0.82)	(-1.74)	(1.84)	(-1.55)	(1.96)			(-2.58)	(8.69)	(-0.32)

Alternatively, *PQS* is used to proxy illiquidity in Table 9. The method of analysis and layout of the table are identical to Table 8. Similar to the *AdjILLIQ* regressions, any illiquidity premium appears to be subsumed by other factors, such as the size or value effect. Moreover, the coefficient for market risk (β^1) remains negative but is not significant at conventional levels. Consequently, net systematic risk (β^6) has a negative coefficient which is neither significant at conventional levels.

Panel A again contains the results for portfolios sorted on commonality in liquidity. Commonality (β^2) is positively related to returns with a coefficient of 0.860, significant at the 5 percent level. The sign of the flight to liquidity (β^3) is as hypothesized, but the coefficient is not significant at conventional levels. The depressed wealth effect (β^4) is priced with a coefficient of -0.117, significant at the 1 percent level. In joint estimation, neither β^2 nor β^4 retain significance. Moreover, the sign of β^2 becomes negative, which is possibly due to collinearity with β^4. Due to the pricing of β^2 and β^4, aggregate liquidity risk (β^5) is also priced with a coefficient of 0.105, significant at the 1 percent level.

Panel B contains the results for portfolios sorted on flight to liquidity. When estimated separately, only flight to liquidity (β^3) is priced with a coefficient of -0.259, significant at the 5 percent level. Moreover, β^3 remains significantly priced in the joint estimation with a coefficient of -0.293, again significant at the 5 percent level. Although β^3 is priced, aggregate liquidity risk (β^5) is not priced at conventional significance levels.

Finally, panel C contains the results for portfolios sorted on the depressed wealth effect. The signs for the liquidity risks are all as hypothesized and remain so in joint estimation. However, only commonality (β^2) is priced with a coefficient of 0.813, significant at the 10 percent level. When regressed jointly, none of the liquidity risks have significant relationships with returns. As a consequence of the pricing of β^2, aggregate liquidity risk (β^5) is priced with a coefficient of 0.048, also significant at the 10 percent level.

Table 9. Panel regressions with fixed effects using *PQS*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The intercept is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. $Ln(Sz)$, $ln(BM)$, and FF control for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding t-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel A: β^2 (commonality) sorted portfolios											
1	0.032***	0.018	-0.003						-0.005**	0.017***	-0.000
	(2.79)	(0.23)	(-1.29)						(-2.37)	(8.52)	(-0.00)
2	0.030***	0.017	-0.003	0.860**					-0.005**	0.017***	0.000
	(2.63)	(0.22)	(-1.35)	(2.00)					(-2.29)	(8.50)	(0.04)
3	0.027**	0.019	-0.003		-0.211				-0.005**	0.017***	-0.000
	(2.29)	(0.24)	(-1.38)		(-1.42)				(-2.39)	(8.53)	(-0.02)
4	0.031***	0.017	-0.003			-0.117***			-0.005**	0.017***	-0.000
	(2.74)	(0.21)	(-1.39)			(-2.70)			(-2.33)	(8.53)	(-0.00)
5	0.029**	0.017	-0.003				0.105***		-0.005**	0.017***	-0.000
	(2.53)	(0.22)	(-1.43)				(2.74)		(-2.33)	(8.51)	(-0.01)
6	0.031***	0.018						-0.003	-0.005**	0.017***	-0.000
	(2.78)	(0.23)						(-1.16)	(-2.37)	(8.51)	(-0.02)
7	0.028**	0.017	-0.003	-0.011	-0.147	-0.111			-0.005**	0.017***	-0.000
	(2.31)	(0.22)	(-1.44)	(-0.01)	(-1.00)	(-1.47)			(-2.33)	(8.53)	(-0.02)

Table 9 continued.

	α	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*ln(Sz)*	*ln(BM)*	*FF*
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	0.032***	0.018	-0.003						-0.005**	0.017***	-0.000
	(2.79)	(0.23)	(-1.29)						(-2.37)	(8.52)	(-0.00)
2	0.032***	0.018	-0.003	-0.051					-0.005**	0.017***	-0.000
	(2.79)	(0.23)	(-1.29)	(-0.09)					(-2.37)	(8.50)	(-0.00)
3	0.026**	0.019	-0.004*		-0.259**				-0.005**	0.017***	-0.000
	(2.26)	(0.24)	(-1.66)		(-2.05)				(-2.32)	(8.49)	(-0.03)
4	0.032***	0.018	-0.003			-0.007			-0.005**	0.017***	-0.000
	(2.79)	(0.23)	(-1.31)			(-0.18)			(-2.37)	(8.51)	(-0.00)
5	0.031***	0.018	-0.003				0.021		-0.005**	0.017***	-0.000
	(2.75)	(0.23)	(-1.39)				(0.65)		(-2.36)	(8.51)	(-0.01)
6	0.032***	0.018						-0.003	-0.005**	0.017***	-0.000
	(2.79)	(0.23)						(-1.25)	(-2.37)	(8.52)	(-0.00)
7	0.026**	0.019	-0.004	-0.047	-0.293**	0.025			-0.005**	0.017***	-0.000
	(2.17)	(0.24)	(-1.63)	(-0.06)	(-2.33)	(0.50)			(-2.33)	(8.49)	(-0.03)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	0.032***	0.018	-0.003						-0.005**	0.017***	-0.000
	(2.79)	(0.23)	(-1.29)						(-2.37)	(8.52)	(-0.00)
2	0.030***	0.017	-0.003	0.813*					-0.005**	0.017***	0.000
	(2.65)	(0.22)	(-1.33)	(1.92)					(-2.28)	(8.54)	(0.02)
3	0.031**	0.018	-0.003		-0.048				-0.005**	0.017***	-0.000
	(2.59)	(0.23)	(-1.30)		(-0.32)				(-2.37)	(8.51)	(-0.01)
4	0.031***	0.018	-0.003			-0.050			-0.005**	0.017***	-0.000
	(2.74)	(0.23)	(-1.37)			(-1.65)			(-2.32)	(8.53)	(-0.01)
5	0.030***	0.018	-0.003				0.048*		-0.005**	0.017***	-0.000
	(2.64)	(0.23)	(-1.38)				(1.73)		(-2.31)	(8.53)	(-0.01)
6	0.032***	0.018						-0.003	-0.005**	0.017***	-0.000
	(2.79)	(0.23)						(-1.21)	(-2.38)	(8.51)	(-0.01)
7	0.029**	0.018	-0.003	0.799	-0.074	-0.003			-0.005**	0.017***	0.000
	(2.38)	(0.23)	(-1.35)	(1.39)	(-0.49)	(-0.08)			(-2.28)	(8.54)	(0.01)

The following briefly summarizes the findings related to hypotheses 1-5 and considers differences between the illiquidity proxies. Hypothesis 1, which states that the level of expected illiquidity has a positive and significant relationship with stock returns receives no support. None of the regressions of either illiquidity proxy find a positive and significant relationship. As already noted, a positive and significant relationship exists in bivariate regressions, but the illiquidity premium appears to be subsumed by other factors.

Hypothesis 2 states that commonality in liquidity is positively and significantly related to stock returns. When estimated separately from the other conditional betas, both illiquidity proxies find a positive and significant relationship at the 5 percent level in portfolios sorted on commonality. When estimated jointly with other conditional betas, both estimates lose significance most likely due to multicollinearity, but a lack of empirical relevance remains a possibility. Additionally, commonality is priced in panel C with both proxies: when estimated separately using *PQS* and in joint estimation using *AdjILLIQ*. The estimated coefficients are generally substantially larger in magnitude when using *AdjILLIQ*.

Hypothesis 3, which states that flight to liquidity has a negative and significant relationship with stock returns, receives stronger support. Both illiquidity proxies find a negative and significant relationship in portfolios sorted on flight to liquidity. Moreover, the estimates remain significant in joint estimation. All significant relationships are at the 5 percent level. The estimated coefficients are again substantially larger in magnitude when using *AdjILLIQ*.

Hypothesis 4 states that the depressed wealth effect has a negative and significant relationship with stock returns. The *AdjILLIQ* regressions find no evidence of a negative and significant relationship. When using *PQS*, a negative and significant relationship is found at the 1 percent level in portfolios sorted on commonality in liquidity. The estimate loses its significance in joint estimation most likely due to multicollinearity, but again a lack of empirical relevance remains a possibility. Although the result is plausible as the stocks are sorted on commonality in liquidity and β^4 considers stock illiquidity as a variable, a lack of pricing in portfolios sorted on β^4 casts doubt on the meaningfulness of the result.

Lastly, hypothesis 5 states that the aggregate liquidity risk has a positive and significant relationship with stock returns. Aggregate liquidity risk is priced in panels A and B using

AdjILLIQ, and panels A and C using *PQS*. Arguably the most reliable estimates are at the 5 percent level in panel B using *AdjILLIQ* and at the 1 percent level in panel A using *PQS*.

In light of the results, hypothesis 1 is rejected. Illiquidity does appear to be generally linked with higher returns, but the relationship seems to be subsumed by other factors. Despite difficulty caused by multicollinearity, hypothesis 2 cannot be rejected. Hypothesis 3 receives stronger support and can neither be rejected. Hypothesis 4 receives no support using *AdjILLIQ* and evidence is weak at best using *PQS*, but the hypothesis should be examined further rather than outright rejected. Lastly, hypothesis 5 cannot be rejected. Aside from hypothesis 4, the results are fairly similar between the proxies, which could be considered a validation of the assumption that *AdjILLIQ* is a valid proxy for illiquidity.

4.4.1 Pricing with an endogenous holding period

When modeling illiquidity costs and associated premia, it is important to consider how often the illiquidity cost is incurred (Acharya and Pedersen, 2005; Hagströmer, Hansson, and Nilsson, 2013). The regressions in the previous section assume a one-month holding period, which is likely to differ from the typical holding period of an investor. Similar to Acharya and Pedersen (2005), the average holding period is determined empirically from the sample as the period during which all the stocks are turned over once. Using end-of-month market capitalization of free-floating stocks and total monthly trading volume in Euros based on the end-of-month price, the average turnover rate across all stocks over the entire sample period is determined to be 1.93 percent. This corresponds to an average holding period of $1/0.0193 \approx 52$ months.[16]

For sake of brevity, the results of the regressions are presented in Tables 29 and 30 of Appendix 6. The regressions remain similar to the ones in the previous section. The expected illiquidity cost scaled by the holding period is substituted to the left-hand side of the equation, as in Acharya and Pedersen (2005).

[16] It is noted that the average holding period is likely to vary over time, making this a crude proxy (Atkins and Dyl, 1997; Hagströmer, Hansson, and Nilsson, 2013). Nevertheless, it shows whether the results hold in a more general setting.

In terms of *AdjILLIQ*, the results largely gain significance. In panel A, β^2 retains its positive relationship with returns but the significance increases to the 1 percent level. Additionally, the coefficients for β^3 and β^4 are negative and significant at the 5 and 10 percent levels, respectively. Consequently, the coefficient for β^5 is positive and significant at the 1 percent level. When estimated jointly, β^2 and β^3 retain significance at the 5 percent level. In panel B, only β^3 is priced negatively and significant at the 5 percent level, both separately and jointly, and β^5 loses its significance. In panel C, the coefficient for β^2 is positive and significant at the 1 percent level, both separately and jointly. Moreover, the coefficient for β^3 is negative and significant at the 1 percent level, both separately and jointly. β^4 is not priced on its own but is negative and significant at the 5 percent level in joint estimation. As the liquidity risks are priced, the coefficient for β^5 is also positive and significant at the 10 percent level. All coefficients are substantially larger in magnitude when accounting for the holding period.

To the contrary, the results largely lose significance in terms of *PQS*. Only the coefficient for β^3 remains negative and significant in all panels when estimated both separately and jointly. All coefficients are significant at the 5 percent level, aside from the joint estimation in panel B which is at the 1 percent level. All coefficients are again substantially larger in magnitude when accounting for the holding period.

4.5 Robustness tests

The results of this study are tested for robustness to both alternative methods and subsamples. Firstly, the same sample is analyzed with the Fama-MacBeth (1973) regressions to determine whether the results hold in cross-sectional estimation. Secondly, the sample is split into size groups to determine whether a certain size group is driving the results. The following subsections explain the motivation and method in more detail.

4.5.1 Fama-MacBeth regressions

Petersen (2009) highlights drastic differences in the estimation of standard errors, and consequently, rejection rates for test statistics using alternative methods. This raises the notion that the chosen methodology may drive the results. Moreover, the study of Saad and Samet (2015) indicates considerable differences between estimation methods when the sample and timeframe are held constant. The Fama-MacBeth (1973) method is forgone in estimating the main results of this study due to potentially biased estimates, as highlighted by Petersen (2009). However, the method is included as a robustness test as it is widely used in related literature (Acharya and Pedersen, 2005; Lee, 2011; Saad and Samet, 2015). In addition to determining whether the results differ between the methods, it is an additional curiosity to examine whether the method is more prone to find significant coefficients, as the potentially downward-biased estimates of standard errors would imply (Petersen, 2009, pp. 446-450).

The general method of the Fama-MacBeth (1973) regressions contains two steps. In the first step, cross-sectional regressions are estimated at each point in time. In the second step, the final parameter estimates are obtained as time series averages of the estimates of the first step. The test statistics are computed from the time series averages. Similar to Acharya and Pedersen (2005), the standard errors are adjusted with the method of Newey and West (1987) using two lags to account for autocorrelation in the time series of coefficients.[17]

Table 10 presents the results of the Fama-MacBeth regressions using *AdjILLIQ* as the proxy for illiquidity. The relationship between the expected level of illiquidity and returns remains insignificantly different from zero at conventional levels. Curiously, the size effect evident in the panel regressions is not found, either. Therefore, the illiquidity premium may be subsumed by a value effect.

In panel A, the results of the panel regressions hold and gain significance. The coefficient for β^2 remains positive and gains significance at the 1 percent level. Moreover, β^3 and β^4, which were not priced in the panel regressions are priced negatively and are significant at the 1 percent level. In the joint estimation, only β^3 retains its significance, possibly due to collinearity between β^2 and β^4. As the liquidity risks are priced, the coefficient for β^5 is positive and significant at the 1 percent level. The estimated coefficients are substantially larger in magnitude in the Fama-MacBeth regressions. In panel B, none of the liquidity risks are priced at conventional significance levels. This is contrary to the panel regressions, which find β^3 and β^5 to be priced factors. Similarly, in panel C, none of the liquidity risks are priced at conventional significance levels. This result is in line with the panel regressions.

[17] The lag order is set due to autocorrelation in the underlying data. It is noted that the adjustment is made to autocorrelation in the time series of coefficients rather than the underlying data.

Table 10. Fama-MacBeth regressions using *AdjILLIQ*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The constant term is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. *Ln*(*Sz*), *ln*(*BM*), and *FF* are control variables for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding *t*-statistic below in parentheses. The test statistics are computed using standard errors adjusted with the Newey and West (1987) method with two lags. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel A: β^2 (commonality) sorted portfolios											
1	0.006*	0.010	0.000						0.000	0.004***	-0.004*
	(1.69)	(0.14)	(0.08)						(1.15)	(2.86)	(-1.85)
2	0.001	-0.007	0.000	5.073***					0.001**	0.004***	-0.003*
	(0.18)	(-0.10)	(0.14)	(3.76)					(2.11)	(2.94)	(-1.69)
3	-0.011	0.003	0.000		-2.206***				0.001	0.004***	-0.003*
	(-1.65)	(0.05)	(0.09)		(-3.07)				(1.62)	(2.89)	(-1.70)
4	-0.000	0.001	0.000			-0.367***			0.001**	0.004***	-0.003
	(-0.02)	(0.01)	(0.12)			(-3.82)			(2.17)	(2.97)	(-1.62)
5	-0.003	0.003	0.000				0.329***		0.001**	0.004***	-0.003
	(-0.80)	(0.04)	(0.12)				(3.89)		(2.25)	(2.98)	(-1.59)
6	0.006*	0.010						0.000	0.000	0.004***	-0.003*
	(1.70)	(0.14)						(0.11)	(1.14)	(2.85)	(-1.86)
7	-0.016**	-0.008	0.000	0.359	-2.405***	-0.370			0.001**	0.004***	-0.003
	(-2.03)	(-0.10)	(0.11)	(0.09)	(-2.89)	(-1.49)			(2.43)	(3.06)	(-1.54)

Table 10 continued.

	α	E(c)	β^1	β^2	β^3	β^4	β^5	β^6	ln(Sz)	ln(BM)	FF
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	0.006*	0.010	0.000						0.000	0.004***	-0.004*
	(1.69)	(0.14)	(0.08)						(1.15)	(2.86)	(-1.85)
2	0.007*	0.013	0.000	-1.645					0.000	0.004***	-0.003*
	(1.91)	(0.17)	(0.16)	(-0.66)					(1.08)	(2.88)	(-1.73)
3	0.005	0.012	-0.000		-0.065				0.000	0.004***	-0.003*
	(1.59)	(0.17)	(-0.12)		(-0.18)				(1.12)	(2.87)	(-1.81)
4	0.006*	0.012	0.000			0.056			0.000	0.004***	-0.003*
	(1.77)	(0.16)	(0.11)			(0.70)			(1.10)	(2.85)	(-1.81)
5	0.007**	0.012	0.000				-0.072		0.000	0.004***	-0.003*
	(2.02)	(0.16)	(0.09)				(-0.87)		(1.09)	(2.87)	(-1.76)
6	0.006*	0.010						0.000	0.000	0.004***	-0.004*
	(1.70)	(0.14)						(0.08)	(1.14)	(2.85)	(-1.85)
7	0.004	0.015	-0.000	-0.566	-0.164	-0.110			0.000	0.004***	-0.003*
	(1.10)	(0.21)	(-0.16)	(-0.14)	(-0.38)	(-0.81)			(1.06)	(2.92)	(-1.72)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	0.006*	0.010	0.000						0.000	0.004***	-0.004*
	(1.69)	(0.14)	(0.08)						(1.15)	(2.86)	(-1.85)
2	0.003	0.009	0.000	1.305					0.001	0.004***	-0.003*
	(0.77)	(0.12)	(0.11)	(0.64)					(1.44)	(2.90)	(-1.72)
3	0.001	0.014	0.000		-0.309				0.001	0.004***	-0.003*
	(0.14)	(0.19)	(0.06)		(-0.81)				(1.38)	(2.85)	(-1.69)
4	0.005	0.015	0.000			-0.005			0.001	0.004***	-0.003*
	(1.24)	(0.21)	(0.10)			(-0.06)			(1.10)	(2.86)	(-1.79)
5	0.004	0.015	0.000				0.044		0.001	0.004***	-0.003*
	(0.96)	(0.20)	(0.10)				(0.55)		(1.14)	(2.85)	(-1.78)
6	0.006*	0.010						0.000	0.000	0.004***	-0.004*
	(1.71)	(0.14)						(0.08)	(1.15)	(2.86)	(-1.85)
7	0.001	0.005	0.000	5.389	-0.156	0.229			0.001*	0.004***	-0.003
	(0.18)	(0.06)	(0.13)	(1.51)	(-0.33)	(1.24)			(1.66)	(2.93)	(-1.50)

Table 11 presents the results of the Fama-MacBeth regressions using *PQS* as the proxy for illiquidity. Again, the relationship between the expected level of illiquidity and returns remains insignificantly different from zero at conventional levels. Again, the size effect evident in the panel regressions is absent, which indicates that the illiquidity premium may be subsumed by the value effect.

In panel A, the results of the panel regressions largely hold but lose some of their significance. The coefficient for β^2 remains positive but is significant at the 10 percent level. Similarly, the coefficient for β^4 remains negative but is significant at the 5 percent level. As β^2 and β^4 are priced, the coefficient for β^5 is positive and significant at the 10 percent level.

Panel B is a slight departure from the panel regressions. Contrary to the panel regressions, β^3 is not priced. However, β^5, which is not priced in the panel regression, receives a positive coefficient which is significant at the 10 percent level.

Panel C is also a departure from the panel regressions. β^2 is not priced, contrary to the panel regression. However, the coefficient for β^4 is negative and significant at the 5 percent level. The coefficient for β^5 remains positive and gains significance at the 1 percent level. Again, the estimated coefficients are consistently larger in magnitude in the Fama-MacBeth regressions.

Table 11. Fama-MacBeth regressions using *PQS*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The constant term is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. *Ln*(*Sz*), *ln*(*BM*), and *FF* are control variables for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding *t*-statistic below in parentheses. The test statistics are computed using standard errors adjusted with the Newey and West (1987) method with two lags. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel A: β^2 (commonality) sorted portfolios											
1	0.002	0.034	-0.000						0.001**	0.004***	-0.003
	(0.40)	(0.86)	(-0.15)						(2.10)	(2.80)	(-1.47)
2	-0.001	0.026	-0.000	1.216*					0.001**	0.004***	-0.003
	(-0.18)	(0.65)	(-0.16)	(1.70)					(2.58)	(2.86)	(-1.39)
3	0.001	0.033	-0.001		0.043				0.001**	0.003***	-0.003
	(0.18)	(0.84)	(-0.22)		(0.15)				(2.17)	(2.78)	(-1.52)
4	-0.001	0.026	-0.000			-0.140**			0.001***	0.004***	-0.002
	(-0.27)	(0.65)	(-0.20)			(-2.10)			(2.65)	(2.90)	(-1.34)
5	-0.003	0.026	-0.001				0.110*		0.001***	0.004***	-0.003
	(-0.73)	(0.65)	(-0.22)				(1.85)		(2.70)	(2.90)	(-1.35)
6	0.002	0.033						-0.000	0.001**	0.004***	-0.003
	(0.39)	(0.85)						(-0.10)	(2.09)	(2.79)	(-1.50)
7	0.003	0.028	-0.000	0.289	0.245	-0.132			0.001**	0.004***	-0.003
	(0.47)	(0.71)	(-0.20)	(0.31)	(0.77)	(-1.34)			(2.51)	(2.80)	(-1.46)

Table 11 continued.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	0.002	0.034	-0.000						0.001**	0.004***	-0.003
	(0.40)	(0.86)	(-0.15)						(2.10)	(2.80)	(-1.47)
2	0.002	0.034	-0.000	0.193					0.001**	0.004***	-0.003
	(0.41)	(0.86)	(-0.11)	(0.21)					(2.06)	(2.79)	(-1.44)
3	-0.002	0.033	-0.002		-0.171				0.001**	0.003***	-0.003
	(-0.48)	(0.85)	(-0.77)		(-1.05)				(2.20)	(2.79)	(-1.35)
4	0.001	0.035	-0.001			-0.093			0.001**	0.004***	-0.003
	(0.16)	(0.89)	(-0.41)			(-1.61)			(2.18)	(2.81)	(-1.43)
5	-0.000	0.035	-0.001				0.079*		0.001**	0.004***	-0.003
	(-0.11)	(0.89)	(-0.59)				(1.68)		(2.20)	(2.82)	(-1.41)
6	0.002	0.034						-0.000	0.001**	0.004***	-0.003
	(0.40)	(0.86)						(-0.16)	(2.11)	(2.80)	(-1.48)
7	-0.001	0.034	-0.002	-0.597	-0.000	-0.165*			0.001**	0.003***	-0.002
	(-0.30)	(0.86)	(-0.85)	(-0.53)	(-0.00)	(-1.84)			(2.11)	(2.77)	(-1.32)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	0.002	0.034	-0.000						0.001**	0.004***	-0.003
	(0.40)	(0.86)	(-0.15)						(2.10)	(2.80)	(-1.47)
2	0.000	0.034	-0.000	0.650					0.001**	0.004***	-0.003
	(0.02)	(0.85)	(-0.17)	(1.15)					(2.42)	(2.82)	(-1.43)
3	0.001	0.032	-0.000		-0.001				0.001**	0.004***	-0.003
	(0.28)	(0.83)	(-0.17)		(-0.01)				(2.26)	(2.84)	(-1.55)
4	-0.000	0.033	-0.001			-0.100**			0.001**	0.004***	-0.003
	(-0.11)	(0.84)	(-0.22)			(-2.55)			(2.59)	(2.85)	(-1.38)
5	-0.002	0.033	-0.001				0.093***		0.001**	0.004***	-0.003
	(-0.41)	(0.83)	(-0.22)				(2.63)		(2.61)	(2.85)	(-1.39)
6	0.002	0.033						-0.000	0.001**	0.004***	-0.003
	(0.39)	(0.85)						(-0.12)	(2.11)	(2.80)	(-1.48)
7	-0.002	0.035	-0.000	-0.068	-0.146	-0.083			0.001**	0.004***	-0.003
	(-0.30)	(0.87)	(-0.18)	(-0.05)	(-0.39)	(-0.89)			(2.61)	(2.84)	(-1.52)

The following briefly summarizes the results of the Fama-MacBeth regressions and relates them to both the panel regressions and the hypotheses. Hypothesis 1, which states that the expected level of illiquidity is positively and significantly related to stock returns, is robust to the method. The expected level of illiquidity is not priced in any of the regressions using either illiquidity proxy.

In terms of *AdjILLIQ*, the methods are somewhat consistent. The results concerning hypothesis 2 are consistent between the methods, as β^2 is a priced factor in commonality-sorted portfolios. The results concerning hypothesis 3 are mixed, as β^3 is not priced in the flight to liquidity-sorted portfolios with the Fama-MacBeth method. On the contrary, it is a priced factor under commonality sorting. Hypothesis 4 is supported as β^4 is a priced factor under commonality sorting, contrary to the panel regressions. Lastly, hypothesis 5 is supported by both methods as β^5 is a priced factor under commonality sorting with both methods. However, it is not priced in flight to liquidity-sorted portfolios, contrary to the panel regressions.

When *PQS* is used to proxy illiquidity, the two methods show more discrepancy in results. Hypothesis 2 is supported by both methods as β^2 is a priced factor in commonality-sorted portfolios. It is not, however, priced in the depressed wealth effect portfolios, contrary to the panel regressions. Hypothesis 3 receives no support as β^3 is never priced, again contrary to the panel regressions. Hypothesis 4 is supported as β^4 is a priced factor under commonality sorting. Moreover, it is also priced in β^4-sorted portfolios. Lastly, hypothesis 5 is supported by both methods, as β^5 is priced in all portfolios.

4.5.2 Panel regressions using size groups

Section 3.1.1 notes a size effect in illiquidity within the sample. Moreover, size effects of various kinds are reported in related literature. When examining commonality in liquidity in the US market, Chordia, Roll, and Subrahmanyam (2000) note that commonality is more pronounced in large stocks, and Fabre and Frino (2004) make a similar finding in Australian stocks. When estimating the LCAPM on Australian stocks within a panel regression framework, Vu, Chai, and Do (2015) note considerable differences in the pricing of liquidity risks between size groups. Therefore, the sample of this study is split into size groups to determine whether the results are driven by a size effect. This also gives further insight into where the liquidity risks are priced.

Following Vu, Chai, and Do (2015), the sample is split into three size groups. At the beginning of year *y*, the stocks are sorted on their market capitalization at the end of year *y*-1 and split into three groups with a 30/40/30 split. The panel regressions from Section 4.4 are then repeated using only the individual size groups. Aside from the split into subsamples, the data remains unaltered. Perhaps of most interest are the portfolios sorted on commonality in liquidity, as they present the broadest evidence for the pricing of liquidity risks. Tables 12 and 13 present the results for panel regressions using each size group and the commonality sorting.

Table 12 presents the results using *AdjILLIQ* to measure illiquidity. The small group has observations for 336 separate stocks with an average of 49.2 observations per stock. The medium-sized group comprises of observations for 410 stocks with an average of 64.8 observations each. The large group has 238 separate stocks with an average of 87.8 observations per stock.

Table 12. Fixed effects panel regressions of size groups using *AdjILLIQ*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The intercept is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. $Ln(Sz)$, $ln(BM)$, and FF control for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding t-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel A: Small stocks											
1	0.026	-0.025	-0.007						-0.012**	0.020***	0.005
	(1.26)	(-0.46)	(-1.42)						(-2.34)	(5.99)	(0.58)
2	0.026	-0.025	-0.007	0.322					-0.012**	0.020***	0.005
	(1.25)	(-0.45)	(-1.41)	(0.11)					(-2.33)	(5.99)	(0.58)
3	0.041*	-0.027	-0.008		0.606				-0.012**	0.020***	0.005
	(1.81)	(-0.48)	(-1.44)		(1.18)				(-2.38)	(5.98)	(0.58)
4	0.026	-0.025	-0.007			-0.071			-0.012**	0.020***	0.005
	(1.20)	(-0.45)	(-1.39)			(-0.43)			(-2.32)	(5.99)	(0.60)
5	0.027	-0.025	-0.007				-0.018		-0.012**	0.020***	0.005
	(1.24)	(-0.46)	(-1.41)				(-0.12)		(-2.34)	(5.99)	(0.57)
6	0.027	-0.025						-0.007	-0.012**	0.020***	0.005
	(1.27)	(-0.46)						(-1.41)	(-2.34)	(5.99)	(0.58)
7	0.040*	-0.026	-0.007	0.119	0.628	-0.087			-0.012**	0.020***	0.005
	(1.77)	(-0.48)	(-1.41)	(0.03)	(1.21)	(-0.34)			(-2.37)	(5.97)	(0.60)

Table 12 continued.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel B: Medium-sized stocks											
1	0.051***	-0.352**	-0.003						-0.006*	0.025***	-0.005
	(2.88)	(-2.01)	(-0.68)						(-1.71)	(6.93)	(-0.98)
2	0.047**	-0.343*	-0.003	4.374**					-0.005	0.026***	-0.005
	(2.59)	(-1.97)	(-0.71)	(2.28)					(-1.51)	(7.00)	(-0.96)
3	0.045**	-0.347**	-0.003		-0.359				-0.005*	0.025***	-0.005
	(2.30)	(-1.98)	(-0.70)		(-1.11)				(-1.66)	(6.94)	(-0.99)
4	0.050***	-0.350**	-0.003			-0.116			-0.005*	0.025***	-0.005
	(2.81)	(-2.00)	(-0.69)			(-1.19)			(-1.65)	(6.95)	(-0.99)
5	0.047***	-0.347**	-0.003				0.133		-0.005	0.025***	-0.005
	(2.64)	(-1.99)	(-0.70)				(1.50)		(-1.62)	(6.96)	(-1.00)
6	0.051***	-0.352**						-0.002	-0.006*	0.025***	-0.005
	(2.87)	(-2.01)						(-0.65)	(-1.71)	(6.93)	(-0.98)
7	0.041**	-0.337*	-0.003	6.466**	-0.283	0.145			-0.005	0.026***	-0.005
	(2.07)	(-1.93)	(-0.72)	(2.16)	(-0.89)	(0.96)			(-1.46)	(7.02)	(-0.93)
Panel C: Large stocks											
1	0.058**	0.009	-0.000						-0.008**	0.019***	0.001
	(2.57)	(0.02)	(-0.08)						(-2.57)	(4.73)	(0.17)
2	0.061***	0.039	-0.000	-3.935					-0.008***	0.019***	0.001
	(2.66)	(0.09)	(-0.11)	(-1.59)					(-2.66)	(4.72)	(0.12)
3	0.056**	0.025	-0.000		-0.151				-0.008**	0.019***	0.001
	(2.36)	(0.06)	(-0.08)		(-0.45)				(-2.56)	(4.73)	(0.16)
4	0.057**	0.011	-0.000			-0.073			-0.007**	0.019***	0.001
	(2.51)	(0.02)	(-0.08)			(-0.65)			(-2.51)	(4.74)	(0.17)
5	0.056**	0.018	-0.000				0.071		-0.007**	0.019***	0.001
	(2.42)	(0.04)	(-0.08)				(0.66)		(-2.50)	(4.74)	(0.17)
6	0.058**	0.010						-0.000	-0.008**	0.019***	0.001
	(2.57)	(0.02)						(-0.07)	(-2.57)	(4.73)	(0.17)
7	0.060**	0.152	-0.001	-14.631***	-0.171	-0.591***			-0.008***	0.019***	0.000
	(2.51)	(0.33)	(-0.17)	(-3.75)	(-0.51)	(-3.38)			(-2.63)	(4.78)	(0.03)

As expected, the pricing of liquidity risks differs between size groups. The expected level of illiquidity, when measured in terms of price impact, is not significantly priced in the smallest or largest groups of stocks. Medium-sized stocks appear to exhibit an illiquidity discount, contrary to a hypothesized premium.

In the full-sample regression, only β^2 is priced. The split into size groups indicates that commonality in liquidity is only priced among the medium-sized stocks. Curiously, β^2 and β^4 both have negative coefficients which are significant at the 1 percent level in joint estimation among large stocks. In terms of β^2 this would represent a risk discount. This may simply be a result of the split in the sample, as the relationship becomes insignificant in quartiles and quintiles in an unreported test. Lastly, β^5, which is priced in the full sample, is not priced in any size group.

For the other two portfolio sorts, it is briefly worth noting the results of a similar analysis. In portfolios sorted on flight to liquidity, an illiquidity discount persists among medium-sized stocks. β^3, which is priced in the full sample, is only priced among medium-sized stocks. β^4, which is not priced in the full sample, is priced among large stocks. Lastly, β^5, which is priced in the full sample, is only priced among large stocks. Finally, in portfolios sorted on the depressed wealth effect, an illiquidity discount again persists among medium-sized stocks. Although none of the liquidity risks are priced in the full sample, pricing occurs among small and medium-sized stocks. β^2 receives a negative coefficient among small stocks, but a positive one among medium-sized stocks. Moreover, β^4 receives a positive coefficient among small stocks. As both β^2 and β^4 represent a risk discount among small stocks, β^5 consequently receives a negative coefficient among small stocks, again representing a risk discount.

Table 13 presents the results when *PQS* is used to measure illiquidity, alternatively. The small group comprises of observations for 366 stocks, with an average of 53.2 observations per stock. The medium-sized group contains observations for 463 stocks, with an average of 66.8 observations per stock. The 284 stocks in the large size group have an average of 84.5 observations each.

Table 13. Fixed effects panel regressions of size groups using *PQS*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The dependent variable in all regressions is the monthly excess return of a given stock. The top row lists the estimated parameters. The intercept is α, the expected illiquidity cost is $E(c)$, and the market risk adjusted for liquidity is β^1. β^2, β^3, and β^4 refer to commonality in liquidity, flight to liquidity, and the depressed wealth effect, respectively. The aggregate liquidity risk is β^5, and the net systematic risk is β^6. *Ln*(*Sz*), *ln*(*BM*), and *FF* control for size, book-to-market ratio, and the free float ratio, respectively. The table lists the parameter estimate and the corresponding robust *t*-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*ln(Sz)*	*ln(BM)*	*FF*
Panel A: Small stocks											
1	0.022	0.047	-0.003						-0.010*	0.016***	0.001
	(1.00)	(0.54)	(-0.59)						(-1.86)	(5.09)	(0.16)
2	0.021	0.047	-0.003	0.437					-0.010*	0.016***	0.002
	(0.97)	(0.54)	(-0.60)	(0.53)					(-1.85)	(5.08)	(0.18)
3	0.023	0.047	-0.003		0.056				-0.010*	0.016***	0.001
	(1.01)	(0.54)	(-0.58)		(0.16)				(-1.85)	(5.16)	(0.16)
4	0.020	0.046	-0.003			-0.114			-0.009*	0.016***	0.001
	(0.94)	(0.53)	(-0.61)			(-1.21)			(-1.84)	(5.09)	(0.17)
5	0.018	0.046	-0.003				0.083		-0.010*	0.016***	0.001
	(0.86)	(0.54)	(-0.62)				(1.02)		(-1.84)	(5.09)	(0.16)
6	0.022	0.047						-0.003	-0.010*	0.016***	0.001
	(0.99)	(0.55)						(-0.54)	(-1.86)	(5.09)	(0.16)
7	0.026	0.046	-0.003	-1.054	0.209	-0.231			-0.009*	0.016***	0.001
	(1.11)	(0.53)	(-0.56)	(-0.75)	(0.61)	(-1.43)			(-1.83)	(5.21)	(0.13)

Table 13 continued.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel B: Medium-sized stocks											
1	0.049***	-0.120	-0.003						-0.006*	0.025***	-0.001
	(2.73)	(-0.81)	(-0.87)						(-1.92)	(7.27)	(-0.12)
2	0.047***	-0.120	-0.004	1.285***					-0.006*	0.025***	-0.001
	(2.62)	(-0.81)	(-0.96)	(2.71)					(-1.86)	(7.31)	(-0.19)
3	0.042**	-0.120	-0.004		-0.342*				-0.006*	0.025***	-0.001
	(2.21)	(-0.81)	(-0.97)		(-1.67)				(-1.91)	(7.26)	(-0.17)
4	0.048***	-0.122	-0.004			-0.149***			-0.006*	0.025***	-0.001
	(2.70)	(-0.82)	(-0.96)			(-2.91)			(-1.89)	(7.32)	(-0.20)
5	0.045**	-0.122	-0.004				0.140***		-0.006*	0.025***	-0.001
	(2.53)	(-0.82)	(-1.01)				(3.07)		(-1.88)	(7.32)	(-0.22)
6	0.049***	-0.120						-0.003	-0.006*	0.025***	-0.001
	(2.71)	(-0.80)						(-0.74)	(-1.92)	(7.26)	(-0.14)
7	0.042**	-0.122	-0.004	0.379	-0.264	-0.102			-0.006*	0.025***	-0.001
	(2.25)	(-0.82)	(-1.04)	(0.43)	(-1.30)	(-1.10)			(-1.87)	(7.30)	(-0.24)
Panel C: Large stocks											
1	0.065***	0.019	-0.002						-0.009***	0.018***	-0.000
	(3.27)	(0.25)	(-0.57)						(-3.18)	(5.00)	(-0.08)
2	0.065***	0.017	-0.002	0.403					-0.009***	0.018***	-0.000
	(3.19)	(0.22)	(-0.56)	(0.63)					(-3.16)	(4.99)	(-0.04)
3	0.064***	0.018	-0.002		-0.102				-0.009***	0.018***	-0.000
	(3.06)	(0.23)	(-0.57)		(-0.50)				(-3.16)	(5.00)	(-0.09)
4	0.065***	0.016	-0.002			-0.035			-0.009***	0.018***	-0.000
	(3.26)	(0.21)	(-0.57)			(-0.52)			(-3.15)	(5.01)	(-0.05)
5	0.065***	0.015	-0.002				0.039		-0.009***	0.018***	-0.000
	(3.17)	(0.20)	(-0.58)				(0.66)		(-3.13)	(5.02)	(-0.05)
6	0.065***	0.019						-0.002	-0.009***	0.018***	-0.000
	(3.26)	(0.25)						(-0.55)	(-3.18)	(5.00)	(-0.08)
7	0.063***	0.015	-0.002	0.228	-0.105	-0.019			-0.009***	0.018***	-0.000
	(3.01)	(0.20)	(-0.57)	(0.29)	(-0.52)	(-0.21)			(-3.13)	(4.98)	(-0.05)

Again, differences occur between size groups. Contrary to the *AdjILLIQ* regressions, the expected level of illiquidity is not priced in any of the size groups. β^2, β^4, and β^5, which are priced in the full sample, are only priced among medium-sized stocks. Additionally, β^3, which is not priced in the full sample, receives a negative coefficient which is significant at the 10 percent level among medium-sized stocks.

It is again worth briefly noting the results concerning similar analyses for portfolios sorted on flight to liquidity and the depressed wealth effect, as they are quite different from the above. In the portfolios sorted on flight to liquidity, the expected level of illiquidity is not priced in any of the size groups. β^3, which is priced in the full sample, is only priced among large stocks. β^4, which is not priced in the full sample, receives a positive coefficient among small stocks, again representing a risk discount. Lastly, β^5, which is not priced in the full sample, receives a negative coefficient among small stocks, and a positive one among large stocks. Among small stocks, this appears to be a consequence of the coefficient for β^4. Finally, in portfolios sorted on the depressed wealth effect, the expected level of illiquidity is neither priced in any of the size groups. β^2, which is priced in the full sample, is only priced among medium-sized stocks. β^4, which is not priced in the full sample, is priced among medium-sized stocks. Lastly, β^5, which is priced in the full sample, is not priced in any of the size groups.

Overall, the results of Section 4.4 do not appear very robust to size groups with the 30/40/30 split. There are no instances where the liquidity risk priced in the full sample is priced in all size groups. However, the results generally support the findings of Section 4.4 and shed new light on where the liquidity risks are priced. In terms of both illiquidity proxies, the main results appear to be mainly driven by medium-sized stocks and, to a lesser extent, large stocks. It is noted that caution should be exercised in generalizations. The results appear quite sensitive to the split, and many instances of a risk discount in small or large stocks lose their significance when the split is altered, for example to quartiles or quintiles.

5 DISCUSSION

This section discusses the economic implications of the liquidity risks and relates the results of this study to prior findings in the literature. Annual premia related to the liquidity risks are also computed to gain an understanding of the magnitude of the liquidity risks. Finally, limitations and generalizability of the study as well as further considerations are discussed separately.

Generally, this study finds no evidence that the level of illiquidity is priced in the Frankfurt Stock Exchange (FSE). In unreported bivariate regressions, both *AdjILLIQ* and *PQS* are positively and significantly related to stock returns, but this relationship appears to be subsumed by other factors found in the sample, such as the size and value effects. These results contradict prior findings of an illiquidity premium among German stocks (Hagemeister and Kempf, 2010; Koch, 2010). The contradiction to Koch (2010) is particularly noteworthy, as the study also controls for size and value factors and notes a reverse size effect, albeit over a different sample period. The differing sampling periods may explain the differing results, as the size effect among German stocks is not robust to time period (Artmann, Finter, and Kempf, 2012) and varies between market conditions (Amel-Zadeh, 2011).

Commonality in liquidity, measured by β^2 as the covariance between stock illiquidity and market illiquidity, describes a phenomenon where a stock becomes illiquid with the market. As described by Acharya and Pedersen (2005), when the market becomes illiquid, investors may choose to trade other assets with a lower degree of commonality, and therefore a lower cost of selling. Consequently, a return premium is required for holding an asset which becomes illiquid with the market. The results of this study indicate that such a return premium exists in the FSE. Moreover, the results are robust to the method in cross-sectional regressions, and in terms of *AdjILLIQ*, generalize to a longer holding period. The results extend the findings of commonality in liquidity in German stocks (Johann et al., 2019) with a pricing implication. They also conform to those of Saad and Samet (2015) who find commonality priced in developed markets where Germany is included as a constituent.

Flight to liquidity is measured by β^3 as the covariance between stock returns and market illiquidity. A negative covariance would indicate that as the market becomes illiquid, returns decrease, which is an undesirable trait for an asset. Consequently, investors accept lower returns from stocks which tend to yield higher returns during illiquid markets. The main results of this study give strong evidence for such a phenomenon in the FSE; β^3 is priced negatively, which indicates that expected returns increase with the risk. The results are not robust to cross-sectional regressions but generalize to a longer holding period. The results extend those of Lee (2011) and Saad and Samet (2015) where Germany is grouped together with other developed markets at the country level. In fact, the results mainly contrast both; β^3 is priced within developed markets only in Saad and Samet (2015), in a cross-sectional framework using nonlocal covariates.

The third liquidity risk, the depressed wealth effect, is measured by β^4 as the covariance between stock illiquidity and market returns. A negative covariance would indicate that the stock becomes illiquid during down markets, which is an undesirable trait as investors often seek to exit their positions in declining markets. Therefore, investors accept lower returns from stocks with lower illiquidity costs during market declines (Acharya and Pedersen, 2005). In terms of spread (*PQS*), the main results give tentative evidence that investors in FSE are willing to accept lower returns from stocks which remain liquid in down markets. Cross-sectional regressions confirm the finding, and also provide evidence of pricing in terms of price impact (*AdjILLIQ*). The results concerning *PQS* are not robust to holding period. Further examination of pricing within size groups indicates that the risk is priced mainly among medium-sized and, to a lesser extent, large stocks. The results again extend those of Lee (2011) and Saad and Samet (2015) with more detail. Saad and Samet (2015) find β^4 priced negatively in developed markets in a cross-sectional regression under partial integration, whereas Lee (2011) finds the risk only priced in developed countries with respect to US and global covariates.

Before discussing the annualized premia related to the above liquidity risks, it is worthwhile to note the nature of the illiquidity proxies. *PQS* is based on the bid-ask spread, and as such is more apt at describing the illiquidity cost of a single trade regardless of size. Private investors rarely engage in trades large enough to notably impact the price of a security and should therefore be more interested in results obtained using *PQS*. *AdjILLIQ*, on the other hand, is a proxy for cost per volume of transaction, and is therefore geared more towards the institutional investors engaging in large transactions which may actually impact the price.

The annualized premia related to the three liquidity risks are computed as the differences in annualized expected returns between the highest- and lowest-risk portfolios, attributable to the respective liquidity risks (Acharya and Pedersen, 2005). Similar to Saad and Samet (2015), the annualized risk premia are computed from the estimates for aggregate liquidity risk (λ^5), which assumes that the risk premium for market- and liquidity risk are different. For example, the difference in returns attributable to commonality in liquidity is $\lambda^5(\beta^{2,p10}-\beta^{2,p1})12$, and so forth. The values of λ^5 are taken from the panel regressions for flight to liquidity-sorted portfolios using *AdjILLIQ* and commonality-sorted portfolios using *PQS*. These two are chosen as they are the most reliable estimates; λ^5 is significant at the 5 and 1 percent levels for *AdjILLIQ* and *PQS*, respectively. The values for β are the post-ranking betas reported in Table 3.

When using *AdjILLIQ* and considering the model-implied one-month holding period, the annualized risk premia attributable to commonality in liquidity, flight to liquidity, and the depressed wealth effect are 0.11, 1.13, and 1.83 percent, respectively. The total annualized premium attributable to liquidity risk is therefore 3.07 percent. In terms of *PQS*, the figures tend to be slightly larger. The annualized premia for commonality in liquidity, flight to liquidity, and the depressed wealth effect are 0.48, 1.12, and 2.05 percent, respectively, and the total annualized premium attributable to liquidity risk is 3.66 percent.

Similar to Acharya and Pedersen (2005) and Saad and Samet (2015), the premium attributable to the depressed wealth effect consistently contributes the most to the total premium. Detailed comparison to prior studies is difficult, however, as the calculations tend to differ between studies. On one hand, Acharya and Pedersen (2005) assume equal risk premia for market- and liquidity risk and use the values of λ^6 to compute annualized premia. On the other hand, Saad and Samet (2015) use the values of λ^5 but compute differences in covariance terms rather than post-ranking betas, and Lee (2011) uses λ^2 through λ^4. Consequently, the estimated total annualized premia vary greatly. Acharya and Pedersen (2005) estimate a premium of 1.1 percent in the US market, whereas Saad and Samet (2015) estimate premia of 0.73 and 1.91 percent in developed and emerging markets respectively, and Lee (2011) estimates premia of 1.53 and 5.58 percent globally and in emerging markets, respectively. Although a comparison of the annualized premia is arguably not meaningful, the results nevertheless indicate that liquidity risk is priced in the FSE and should therefore be considered in portfolio diversification.

5.1 Generalizability, limitations, and further research

Regarding the generalizability of the findings, it should be borne in mind that the estimated premia are subject to the sample and method, and therefore may not generalize across time or to other specifications. The results of the size group regressions further indicate that the results may vary between size groups. It is noted that the split may affect the results, and therefore a more thorough examination is in order before drawing detailed conclusions on pricing of the risks within size groups. Nevertheless, the generic results in terms of finding premia for liquidity risks, aside from flight to liquidity (β^3), appear fairly robust to the method. Moreover, the results remain consistent with a longer holding period in terms of *AdjILLIQ*, which implies generalizability to a more general setting beyond the LCAPM.

Although the calibration for a longer holding period allows for a generalization beyond the LCAPM, it has a clear limitation. The empirically estimated holding period of 52 months is assumed to remain constant throughout the sample, which is a fairly strong assumption. The average holding period has been found to vary over time (Atkins and Dyl, 1997; Hagströmer, Hansson, and Nilsson, 2013) and ideally, the calibrated holding period would account for this. Another minor limitation worth noting is the possibility of a look-ahead bias in the estimation of innovations. The AR models are fitted using the entire time series, whereby innovations may be influenced by subsequent values of the time series. However, using one-step ahead predictions as a remedy are likely to produce noisy innovations and potentially make liquidity events less explicit (Kim and Lee, 2014). The most notable limitation, however, is posed by the multicollinearity among the conditional illiquidity betas. This causes difficulty in estimating the joint significance of the liquidity risks. In cases where highly correlated betas are found significant when estimated separately, and obvious signs of multicollinearity such as sign flipping are detected in joint estimation, it is presumable that the risk remains significant. Moreover, the use of alternative estimation methods may be considered to strengthen the evidence. However, it remains a possibility that the method drives the difference and that the risk is not empirically relevant in joint estimation.

In future studies on the same topic, the generalizability of the results could be enhanced by a more detailed estimation of the average holding period, similar to Hagströmer, Hansson, and Nilsson (2013). As another matter, prior studies note a common component in various illiquidity proxies (Korajczyk and Sadka, 2008; Kim and Lee, 2014). Employing a variety of proxies and estimating their common component, assuming a sufficiently large sample, could produce less noisy estimates of illiquidity with an acceptable level of information loss. Another simple and informative addition to the literature would be to estimate the pricing of the liquidity risks under different timeframes, for example in bull and bear markets. Baradarannia and Peat (2013) note differences in the pricing of liquidity risk under very long timeframes, whereas Vu, Chai, and Do (2015) directly examine differences between bull and bear markets. Using a timeframe long enough to cover multiple bull and bear markets would be ideal for examining whether generalizable differences between the market conditions exist.

Lastly, and partly heading into a different domain, as the time-variance of liquidity risk is evident, it would be worthwhile to consider its causes. There appears to be a budding literature on the topic. Of the papers cited in this study, Amihud et al. (2015) examine the influence of market openness and the adoption of the Euro on commonality in the illiquidity premium. Related to the liquidity risks, Karolyi, Lee, and van Dijk (2012) examine macroeconomic determinants of commonality, whereas Saad and Samet (2015) focus on macroeconomic determinants of the LCAPM liquidity risk premium. Insights from such studies should be relevant to both academics and practitioners.

6 CONCLUSIONS

This thesis examined the pricing of the level of expected illiquidity and systematic liquidity risk in the Frankfurt Stock Exchange (FSE) by considering a sample of all stocks quoted at the FSE between 1.1.2000 and 31.12.2018. Illiquidity was measured by two proxies, *AdjILLIQ* and *PQS*, which pertain to the price impact of a transaction and the bid-ask spread, respectively. Time-varying conditional liquidity risks were modeled at the portfolio level using a DCC-GARCH estimator, whereas their pricing was examined at the stock level by estimating a conditional version of the LCAPM using a fixed effects panel regression. Additionally, the time-varying liquidity risks were examined for a trend.

The results indicate that the relationship between the level of expected illiquidity and stock excess returns is not significant at conventional levels. The hypothesized illiquidity premium appears to be subsumed by other factors, such as the size and value effects. The three systematic liquidity risks considered in this study – commonality in liquidity, flight to liquidity, and the depressed wealth effect – are all significantly related to stock excess returns. The results concerning the latter are tentative and vary between the illiquidity proxies. Total annualized premia attributable to liquidity risk are 3.07 and 3.66 percent with *AdjILLIQ* and *PQS*, respectively. Conforming to prior results in the literature, the depressed wealth effect is found to be the largest contributor to the annualized risk premium, followed by flight to liquidity and commonality in liquidity. The results hold when controlling for size, the book-to-market ratio, and the free float ratio of a stock. Moreover, the results are fairly robust to an alternative estimation method in Fama-MacBeth (1973) regressions and generalize beyond the model-implied one-month holding period of the LCAPM in terms of *AdjILLIQ*. Regressions on subsamples of size groups indicate that the pricing of liquidity risk varies between small, medium-sized, and large stocks.

The generic results of this study are quite similar between the illiquidity proxies used. Whether measured by the bid-ask spread or price impact, the covariances of stock and market returns and stock and market illiquidity represent a significant systematic risk which should be considered in portfolio diversification. Moreover, liquidity risk appears to vary over time with no clear trend. The results are relevant to both private investors and large-scale institutional investors. The results obtained using *PQS*, which measures the illiquidity cost regardless of transaction size, are particularly relevant to private investors, while institutional investors, who are likely to engage in trades large enough to sway prices, should find additional insight from the results obtained using *AdjILLIQ*.

This thesis contributes to the literature in several ways. Firstly, to the knowledge of the author, this study is first in providing a country-level estimation of a conditional version of the LCAPM in the German market. Prior studies have mainly grouped Germany together with other developed markets. Moreover, prior findings of commonality in liquidity (Kempf and Mayston, 2008; Johann et al., 2019) are extended with a pricing implication. Lastly, this study controls for the free float ratio of a stock due to its idiosyncratic effect on liquidity, which has not been considered in prior literature.

The results could be refined by more detailed and time-varying estimates of the average holding period of the investor. Moreover, a lengthier sample period and estimation of the LCAPM using several periods of bull and bear markets could provide further insight into generalizable differences in the pricing of liquidity risk under different market conditions.

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APPENDICES

APPENDIX 1: AUTOCORRELATION TESTS FOR MARKET SERIES.

Table 14. Autocorrelation tests for market returns and illiquidity.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of market returns, illiquidity, and innovations in illiquidity. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

		CDAX	
Return			
	Lag 1	1.655	
		(0.099)	
	Lag 2	-0.629	
		(0.530)	
		PQS	*AdjILLIQ*
Illiquidity			
	Lag 1	13.984*	13.166*
		(0.000)	(0.000)
	Lag 2	1.018	1.798
		(0.310)	(0.074)
Innovations			
	Lag 1	0.001	-0.064
		(0.999)	(0.949)
	Lag 2	0.046	0.086
		(0.963)	(0.932)

H0: No autocorrelation. * indicates significance at the 5% level.

APPENDIX 2: AUTOCORRELATION TESTS FOR PORTFOLIO SERIES.

Table 15. Autocorrelation tests for portfolio illiquidity using *AdjILLIQ*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the illiquidity series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity											
	Lag 1	7.123*	9.010*	6.641*	10.263*	10.029*	9.119*	9.056*	10.392*	7.653*	8.710*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	7.072*	4.814*	6.134*	1.870	2.519*	3.388*	4.075*	2.275*	6.438*	4.564*
		(0.000)	(0.000)	(0.000)	(0.063)	(0.013)	(0.001)	(0.000)	(0.024)	(0.000)	(0.000)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity											
	Lag 1	8.944*	7.428*	8.465*	9.177*	8.576*	9.386*	8.387*	8.004*	8.064*	7.741*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	4.030*	6.864*	4.528*	3.534*	4.157*	3.457*	4.706*	4.968*	5.239*	6.079*
		(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity											
	Lag 1	7.990*	7.882*	7.835*	10.122*	9.926*	9.013*	10.679*	8.716*	10.039*	7.771*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	5.795*	5.840*	5.722*	2.281*	2.533*	3.461*	0.721	2.805*	2.134*	6.097*
		(0.000)	(0.000)	(0.000)	(0.024)	(0.012)	(0.001)	(0.472)	(0.006)	(0.034)	(0.000)

H0: No autocorrelation. * indicates significance at the 5% level.

Table 16. Autocorrelation tests for portfolio illiquidity using *PQS*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the illiquidity series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity											
	Lag 1	11.115*	9.442*	11.786*	14.577*	12.040*	13.192*	11.193*	9.532*	10.537*	10.198*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	1.942	3.851*	1.019	-1.729	0.702	-0.392	1.628	3.721*	2.392*	2.919*
		(0.054)	(0.000)	(0.310)	(0.086)	(0.484)	(0.696)	(0.105)	(0.000)	(0.018)	(0.004)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity											
	Lag 1	12.599*	12.812*	12.647*	11.830*	11.800*	10.890*	9.717*	12.227*	10.299*	10.874*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	0.038	-0.125	0.049	0.904	1.055	1.889	3.470*	0.487	2.668*	1.996*
		(0.970)	(0.900)	(0.961)	(0.367)	(0.293)	(0.061)	(0.001)	(0.627)	(0.008)	(0.048)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity											
	Lag 1	11.216*	11.675*	11.564*	13.429*	13.651*	10.081*	11.314*	11.431*	11.993*	12.590*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	1.675	1.131	1.233	-0.606	-1.001	2.990*	1.571	1.387	0.514	0.214
		(0.096)	(0.260)	(0.219)	(0.545)	(0.318)	(0.003)	(0.118)	(0.167)	(0.608)	(0.831)

H0: No autocorrelation. * indicates significance at the 5% level.

Table 17. Autocorrelation tests for innovations in portfolio illiquidity using *AdjILLIQ*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the innovation series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	-0.080	-0.144	-0.565	-0.279	-0.420	-0.769	0.126	-0.200	0.476	-0.856
		(0.936)	(0.886)	(0.573)	(0.781)	(0.675)	(0.443)	(0.900)	(0.842)	(0.635)	(0.393)
	Lag 2	-0.421	-0.621	-1.031	-0.470	-0.346	-0.754	0.110	-0.392	0.835	-1.106
		(0.674)	(0.536)	(0.304)	(0.639)	(0.730)	(0.452)	(0.912)	(0.696)	(0.405)	(0.271)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	-0.173	0.093	-0.059	-0.131	-0.765	-0.135	-0.031	0.025	-0.837	-0.632
		(0.863)	(0.926)	(0.953)	(0.896)	(0.446)	(0.893)	(0.975)	(0.980)	(0.404)	(0.529)
	Lag 2	-0.700	-0.160	-0.044	-0.285	-1.414	-0.542	-0.227	-0.381	-1.670	-0.990
		(0.485)	(0.873)	(0.965)	(0.776)	(0.159)	(0.589)	(0.821)	(0.704)	(0.097)	(0.324)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	-0.172	0.289	-0.777	-0.017	-0.020	-0.018	-1.103	-0.020	-0.829	-0.645
		(0.863)	(0.773)	(0.438)	(0.986)	(0.984)	(0.986)	(0.271)	(0.984)	(0.409)	(0.520)
	Lag 2	-0.477	0.594	-1.442	-0.252	-0.511	-0.247	-1.017	-0.212	-0.593	-1.820
		(0.634)	(0.553)	(0.151)	(0.802)	(0.610)	(0.805)	(0.311)	(0.832)	(0.554)	(0.071)

H0: No autocorrelation. * indicates significance at the 5% level.

Table 18. Autocorrelation tests for innovations in portfolio illiquidity using *PQS*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the innovation series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	-0.232	-1.018	-0.115	0.007	-0.328	-0.084	-0.012	-0.193	-0.075	-0.032
		(0.817)	(0.310)	(0.908)	(0.995)	(0.743)	(0.933)	(0.991)	(0.847)	(0.940)	(0.975)
	Lag 2	-0.201	-0.583	-0.191	-0.050	-0.118	-0.008	0.064	-0.648	-0.654	0.108
		(0.841)	(0.560)	(0.849)	(0.960)	(0.906)	(0.993)	(0.949)	(0.518)	(0.514)	(0.914)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	0.009	0.054	-0.264	-0.111	-0.319	-0.013	-0.281	0.085	-0.120	-0.304
		(0.993)	(0.957)	(0.792)	(0.912)	(0.750)	(0.990)	(0.779)	(0.932)	(0.904)	(0.762)
	Lag 2	0.012	-0.224	0.061	-0.216	-0.224	0.019	-0.317	-0.150	-0.423	-0.700
		(0.990)	(0.823)	(0.952)	(0.829)	(0.823)	(0.985)	(0.752)	(0.881)	(0.673)	(0.485)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity (innovation)											
	Lag 1	0.003	-0.082	-0.019	-0.205	0.202	-0.133	0.036	-0.081	-0.072	-0.345
		(0.997)	(0.935)	(0.985)	(0.838)	(0.840)	(0.894)	(0.972)	(0.935)	(0.943)	(0.730)
	Lag 2	-0.027	-0.102	-0.115	0.332	-0.307	-0.084	-0.139	-0.214	-0.107	0.657
		(0.978)	(0.919)	(0.908)	(0.741)	(0.759)	(0.933)	(0.889)	(0.831)	(0.915)	(0.512)

H0: No autocorrelation. * indicates significance at the 5% level.

Table 19. Autocorrelation tests for returns of portfolios sorted using *AdjILLIQ*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the return series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity											
	Lag 1	3.330*	3.576*	2.761*	3.332*	3.568*	3.421*	3.998*	3.533*	4.045*	3.604*
		(0.001)	(0.000)	(0.006)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.000)
	Lag 2	0.885	-2.167*	-0.814	-0.902	-0.585	-0.049	-1.207	0.996	-0.834	1.080
		(0.378)	(0.032)	(0.417)	(0.369)	(0.559)	(0.961)	(0.229)	(0.321)	(0.406)	(0.282)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity											
	Lag 1	3.802*	3.976*	3.656*	4.235*	4.217*	3.592*	3.664*	3.181*	2.618*	2.827*
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.010)	(0.005)
	Lag 2	-1.224	-0.113	-0.138	0.264	-0.611	-0.407	-0.908	0.158	-0.653	1.011
		(0.223)	(0.910)	(0.890)	(0.792)	(0.542)	(0.685)	(0.365)	(0.874)	(0.515)	(0.314)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity											
	Lag 1	3.421*	3.671*	4.186*	4.190*	3.790*	3.317*	3.029*	3.500*	2.950*	2.515*
		(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.003)	(0.001)	(0.004)	(0.013)
	Lag 2	0.037	-0.293	-0.162	0.214	-0.552	-0.587	-1.737	-1.610	-0.100	1.441
		(0.971)	(0.770)	(0.871)	(0.831)	(0.582)	(0.558)	(0.084)	(0.109)	(0.920)	(0.152)

H0: No autocorrelation. * indicates significance at the 5% level.

Table 20. Autocorrelation tests for returns of portfolios sorted using *PQS*.

This table reports the results of the Breusch-Godfrey LM test for autocorrelation. The test was conducted for up to two lags of the return series of each portfolio. The table lists the *t*-statistic for each coefficient and the corresponding p-value below in parentheses.

Portfolio		1	2	3	4	5	6	7	8	9	10
Panel A: β^2 (commonality) sorted portfolios											
Illiquidity											
	Lag 1	3.184*	2.963*	3.567*	3.845*	3.664*	4.173*	4.344*	3.461*	4.290*	3.878*
		(0.002)	(0.004)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)
	Lag 2	0.630	-0.462	-0.921	-0.778	-1.408	-0.513	0.535	-0.661	0.638	-0.065
		(0.529)	(0.645)	(0.358)	(0.437)	(0.161)	(0.609)	(0.594)	(0.510)	(0.524)	(0.949)
Panel B: β^3 (flight to liquidity) sorted portfolios											
Illiquidity											
	Lag 1	3.959*	4.199*	3.083*	3.035*	3.709*	4.039*	4.058*	3.914*	3.597*	3.273*
		(0.000)	(0.000)	(0.002)	(0.003)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
	Lag 2	-1.364	-1.568	0.449	0.226	0.427	-0.636	-0.223	0.158	0.585	0.189
		(0.175)	(0.119)	(0.654)	(0.821)	(0.670)	(0.526)	(0.824)	(0.875)	(0.559)	(0.850)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
Illiquidity											
	Lag 1	3.334*	3.997*	4.560*	3.738*	3.108*	3.360*	3.564*	3.724*	4.787*	4.042*
		(0.001)	(0.000)	(0.000)	(0.000)	(0.002)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)
	Lag 2	0.539	0.392	-0.737	-0.786	-0.537	-0.782	-0.926	-0.893	0.320	0.448
		(0.591)	(0.696)	(0.462)	(0.433)	(0.592)	(0.436)	(0.356)	(0.373)	(0.749)	(0.655)

H0: No autocorrelation. * indicates significance at the 5% level.

APPENDIX 3: UNIT ROOT AND STATIONARITY TESTS FOR PORTFOLIO SERIES.

Table 21. Unit root and stationarity tests for innovations in portfolio illiquidity using *AdjILLIQ*.

This table reports the results of the ADF, PP, and KPSS tests for innovations in portfolio illiquidity. Both ADF and PP test for a unit root; AR refers to a test with an autoregressive null model, and ARD to a test with an autoregressive with drift null model. KPSS tests for stationarity. The table lists the test statistic for each portfolio and the corresponding critical value at the 5% level in the rightmost column.

Portfolio	1	2	3	4	5	6	7	8	9	10	Critical value
Panel A: β^2 (commonality) sorted portfolios											
ADF test (AR)	-3.781*	-0.876	-5.460*	-5.622*	-3.664*	-3.508*	-4.135*	-3.696*	-3.484*	-3.756*	-1.942
ADF test (ARD)	-3.769*	-0.696	-5.442*	-5.606*	-3.650*	-3.494*	-4.116*	-3.682*	-3.469*	-3.743*	-2.881
PP test (AR)	-12.955*	-12.813*	-14.545*	-15.431*	-13.559*	-13.955*	-12.806*	-13.085*	-12.366*	-14.627*	-1.942
PP test (ARD)	-12.910*	-12.771*	-14.487*	-15.360*	-13.510*	-13.904*	-12.761*	-13.043*	-12.326*	-14.568*	-2.880
KPSS test	0.039	0.142	0.052	0.051	0.046	0.056	0.068	0.043	0.067	0.069	0.146
Panel B: β^3 (flight to liquidity) sorted portfolios											
ADF test (AR)	-3.148*	-3.144*	-4.564*	-4.387*	-4.908*	-4.288*	-3.953*	-3.655*	-3.532*	-4.411*	-1.942
ADF test (ARD)	-3.135*	-3.134*	-4.548*	-4.372*	-4.891*	-4.269*	-3.942*	-3.633*	-3.519*	-4.392*	-2.881
PP test (AR)	-13.363*	-12.789*	-12.809*	-13.390*	-14.877*	-13.676*	-13.792*	-12.770*	-14.112*	-14.904*	-1.942
PP test (ARD)	-13.315*	-12.752*	-12.769*	-13.340*	-14.818*	-13.619*	-13.736*	-12.719*	-14.060*	-14.840*	-2.880
KPSS test	0.056	0.057	0.048	0.049	0.055	0.066	0.061	0.073	0.039	0.056	0.146
Panel C: β^4 (depressed wealth effect) sorted portfolios											
ADF test (AR)	-3.029*	-3.289*	-4.101*	-4.139*	-3.768*	-4.709*	-3.833*	-3.928*	-2.809*	-3.385*	-1.942
ADF test (ARD)	-3.021*	-3.276*	-4.083*	-4.124*	-3.746*	-4.692*	-3.819*	-3.894*	-2.789	-3.374*	-2.881
PP test (AR)	-13.125*	-12.531*	-14.210*	-13.433*	-14.157*	-14.069*	-16.678*	-13.878*	-13.641*	-13.936*	-1.942
PP test (ARD)	-13.082*	-12.492*	-14.155*	-13.381*	-14.094*	-14.009*	-16.605*	-13.816*	-13.596*	-13.883*	-2.880
KPSS test	0.056	0.062	0.062	0.039	0.087	0.050	0.048	0.063	0.067	0.068	0.146

ADF and PP H0: Unit root exists. KPSS H0: Stationary series. * indicates significance at the 5% level.

Table 22. Unit root and stationarity tests for innovations in portfolio illiquidity using *PQS*.

This table reports the results of the ADF, PP, and KPSS tests for innovations in portfolio illiquidity. Both ADF and PP test for a unit root; AR refers to a test with an autoregressive null model, and ARD to a test with an autoregressive with drift null model. KPSS tests for stationarity. The table lists the test statistic for each portfolio and the corresponding critical value at the 5% level in the rightmost column.

Portfolio	1	2	3	4	5	6	7	8	9	10	Critical value
Panel A: β^2 (commonality) sorted portfolios											
ADF test (AR)	-2.515*	-3.786*	-4.178*	-4.746*	-4.182*	-3.893*	-5.184*	-3.917*	-3.974*	-3.282*	-1.942
ADF test (ARD)	-2.419	-3.773*	-4.161*	-4.731*	-4.167*	-3.880*	-5.165*	-3.906*	-3.961*	-3.265*	-2.881
PP test (AR)	-13.161*	-14.220*	-13.575*	-13.225*	-14.959*	-13.064*	-13.101*	-13.202*	-13.336*	-12.950*	-1.942
PP test (ARD)	-13.115*	-14.171*	-13.522*	-13.174*	-14.911*	-13.021*	-13.053*	-13.155*	-13.286*	-12.913*	-2.880
KPSS test	0.076	0.043	0.079	0.063	0.061	0.039	0.041	0.047	0.038	0.046	0.146
Panel B: β^3 (flight to liquidity) sorted portfolios											
ADF test (AR)	-3.802*	-3.627*	-4.284*	-3.252*	-3.048*	-4.626*	-4.033*	-4.509*	-4.123*	-4.624*	-1.942
ADF test (ARD)	-3.787*	-3.616*	-4.251*	-3.241*	-3.035*	-4.610*	-4.020*	-4.493*	-4.110*	-4.598*	-2.881
PP test (AR)	-12.717*	-12.829*	-13.370*	-13.371*	-13.493*	-13.805*	-13.678*	-12.875*	-13.016*	-15.913*	-1.942
PP test (ARD)	-12.675*	-12.785*	-13.322*	-13.321*	-13.445*	-13.747*	-13.626*	-12.831*	-12.971*	-15.838*	-2.880
KPSS test	0.043	0.045	0.072	0.040	0.060	0.044	0.067	0.048	0.041	0.058	0.146
Panel C: β^4 (depressed wealth effect) sorted portfolios											
ADF test (AR)	-3.573*	-3.826*	-4.330*	-4.346*	-4.939*	-3.714*	-3.907*	-3.915*	-4.105*	-4.087*	-1.942
ADF test (ARD)	-3.556*	-3.813*	-4.313*	-4.333*	-4.920*	-3.700*	-3.886*	-3.903*	-4.091*	-4.060*	-2.881
PP test (AR)	-12.943*	-12.963*	-13.519*	-14.315*	-13.304*	-13.063*	-13.260*	-13.235*	-13.444*	-13.346*	-1.942
PP test (ARD)	-12.899*	-12.921*	-13.466*	-14.257*	-13.251*	-13.019*	-13.214*	-13.187*	-13.392*	-13.300*	-2.880
KPSS test	0.052	0.053	0.048	0.063	0.044	0.041	0.056	0.070	0.037	0.043	0.146

ADF and PP H0: Unit root exists. KPSS H0: Stationary series. * indicates significance at the 5% level.

Table 23. Unit root and stationarity tests for returns of portfolios sorted using *AdjILLIQ*.

This table reports the results of the ADF, PP, and KPSS tests for portfolio returns. Both ADF and PP test for a unit root; AR refers to a test with an autoregressive null model, and ARD to a test with an autoregressive with drift null model. KPSS tests for stationarity. The table lists the test statistic for each portfolio and the corresponding critical value at the 5% level in the rightmost column.

Portfolio	1	2	3	4	5	6	7	8	9	10	Critical value
Panel A: β^2 (commonality) sorted portfolios											
ADF test (AR)	-2.926*	-3.578*	-3.243*	-3.182*	-3.093*	-3.049*	-3.286*	-2.571*	-3.220*	-2.584*	-1.942
ADF test (ARD)	-3.105*	-3.561*	-3.205*	-3.159*	-3.012*	-3.075*	-3.235*	-2.602	-3.204*	-2.487	-2.881
PP test (AR)	-10.198*	-9.826*	-10.624*	-10.281*	-9.690*	-9.703*	-9.673*	-9.564*	-9.029*	-9.868*	-1.942
PP test (ARD)	-10.128*	-9.798*	-10.595*	-10.245*	-9.651*	-9.664*	-9.643*	-9.536*	-9.021*	-9.837*	-2.879
KPSS test	0.048	0.050	0.065	0.058	0.076	0.078	0.073	0.073	0.083	0.076	0.146
Panel B: β^3 (flight to liquidity) sorted portfolios											
ADF test (AR)	-2.819*	-3.234*	-3.001*	-2.980*	-2.993*	-3.307*	-3.139*	-3.318*	-3.014*	-2.199*	-1.942
ADF test (ARD)	-2.775	-3.180*	-2.930*	-3.056*	-3.086*	-3.380*	-3.118*	-3.372*	-3.001*	-2.083	-2.881
PP test (AR)	-9.670*	-9.331*	-9.732*	-8.978*	-9.721*	-9.838*	-9.804*	-10.035*	-10.416*	-10.430*	-1.942
PP test (ARD)	-9.648*	-9.294*	-9.700*	-8.941*	-9.689*	-9.794*	-9.774*	-9.994*	-10.407*	-10.384*	-2.879
KPSS test	0.067	0.072	0.064	0.060	0.067	0.052	0.077	0.064	0.091	0.077	0.146
Panel C: β^4 (depressed wealth effect) sorted portfolios											
ADF test (AR)	-2.698*	-2.976*	-2.932*	-2.714*	-2.710*	-3.223*	-3.206*	-3.585*	-2.911*	-2.475*	-1.942
ADF test (ARD)	-2.549	-2.981*	-2.949*	-2.705	-2.642	-3.335*	-3.263*	-3.525*	-2.919*	-2.487	-2.881
PP test (AR)	-9.601*	-9.640*	-9.303*	-9.161*	-9.785*	-10.128*	-10.372*	-9.940*	-10.347*	-10.773*	-1.942
PP test (ARD)	-9.583*	-9.610*	-9.290*	-9.119*	-9.754*	-10.081*	-10.332*	-9.906*	-10.328*	-10.748*	-2.879
KPSS test	0.089	0.062	0.057	0.081	0.069	0.049	0.057	0.061	0.079	0.078	0.146

ADF and PP H0: Unit root exists. KPSS H0: Stationary series. * indicates significance at the 5% level.

Table 24. Unit root and stationarity tests for returns of portfolios sorted using *PQS*.

This table reports the results of the ADF, PP, and KPSS tests for portfolio returns. Both ADF and PP test for a unit root; AR refers to a test with an autoregressive null model, and ARD to a test with an autoregressive with drift null model. KPSS tests for stationarity. The table lists the test statistic for each portfolio and the corresponding critical value at the 5% level in the rightmost column.

Portfolio	1	2	3	4	5	6	7	8	9	10	Critical value
Panel A: β^2 (commonality) sorted portfolios											
ADF test (AR)	-2.527*	-3.291*	-3.109*	-3.250*	-3.197*	-3.032*	-3.037*	-3.050*	-2.734*	-2.685*	-1.942
ADF test (ARD)	-2.555	-3.429*	-3.090*	-3.289*	-3.196*	-3.082*	-2.988*	-3.008*	-2.686	-2.653	-2.881
PP test (AR)	-10.173*	-10.507*	-9.990*	-9.438*	-9.718*	-9.397*	-8.872*	-9.942*	-9.095*	-9.720*	-1.942
PP test (ARD)	-10.135*	-10.473*	-9.949*	-9.390*	-9.661*	-9.376*	-8.838*	-9.931*	-9.064*	-9.754*	-2.879
KPSS test	0.086	0.055	0.060	0.048	0.061	0.059	0.063	0.080	0.084	0.081	0.146
Panel B: β^3 (flight to liquidity) sorted portfolios											
ADF test (AR)	-3.006*	-3.271*	-3.091*	-2.948*	-3.307*	-3.030*	-3.374*	-2.907*	-2.480*	-2.455*	-1.942
ADF test (ARD)	-2.934*	-3.501*	-3.101*	-2.883*	-3.518*	-3.034*	-3.416*	-2.867	-2.525	-2.361	-2.881
PP test (AR)	-9.724*	-9.704*	-10.131*	-9.920*	-9.805*	-9.504*	-9.436*	-9.684*	-9.820*	-9.987*	-1.942
PP test (ARD)	-9.705*	-9.703*	-10.098*	-9.883*	-9.800*	-9.477*	-9.404*	-9.663*	-9.769*	-9.949*	-2.879
KPSS test	0.068	0.064	0.046	0.060	0.071	0.080	0.056	0.069	0.076	0.091	0.146
Panel C: β^4 (depressed wealth effect) sorted portfolios											
ADF test (AR)	-2.974*	-3.079*	-3.240*	-3.305*	-2.891*	-2.926*	-3.378*	-3.260*	-2.858*	-2.653*	-1.942
ADF test (ARD)	-2.899*	-3.102*	-3.238*	-3.257*	-2.878	-2.874	-3.536*	-3.406*	-2.804	-2.670	-2.881
PP test (AR)	-9.381*	-9.395*	-8.973*	-9.735*	-10.382*	-10.191*	-9.916*	-9.796*	-8.795*	-9.208*	-1.942
PP test (ARD)	-9.389*	-9.398*	-8.940*	-9.702*	-10.339*	-10.152*	-9.875*	-9.755*	-8.766*	-9.153*	-2.879
KPSS test	0.089	0.062	0.057	0.081	0.069	0.049	0.057	0.061	0.079	0.078	0.146

ADF and PP H0: Unit root exists. KPSS H0: Stationary series. * indicates significance at the 5% level.

APPENDIX 4: UNIT ROOT AND STATIONARITY TESTS FOR MARKET SERIES.

Table 25. Unit root and stationarity tests for market series.

This table reports the results of the ADF, PP, and KPSS tests for market series. Both ADF and PP test for a unit root; AR refers to a test with an autoregressive null model, and ARD to a test with an autoregressive with drift null model. KPSS tests for stationarity. The table lists the test statistic for each series and the corresponding critical value at the 5% level below in parentheses.

	AdjILLIQ	PQS	CDAX Returns
ADF AR	-4.072*	-4.064*	-3.906*
	(-1.942)	(-1.942)	(-1.942)
ADF ARD	-4.060*	-4.059*	-4.017*
	(-2.875)	(-2.875)	(-2.875)
PP AR	-15.075*	-14.994*	-13.620*
	(-1.942)	(-1.942)	(-1.942)
PP ARD	-15.043*	-14.961*	-13.608*
	(-2.875)	(-2.875)	(-2.875)
KPSS	0.047	0.047	0.074
	(0.146)	(0.146)	(0.146)

ADF and PP H0: Unit root exists. KPSS H0: Stationary series. * indicates significance at the 5% level.

APPENDIX 5: MODEL SPECIFICATION TESTS FOR PANEL REGRESSIONS.

Table 26. Breusch-Pagan LM test for panel effects.

The Breusch-Pagan LM test determines whether the variance in error terms across panel variables is zero (i.e. no panel effect). The numbering corresponds to the regression specifications as per Equations (28)–(34), and the portfolio sorting is denoted by β^2, β^3, and β^4. The test statistic follows a Chi-bar-square distribution with 1 degree of freedom. The table lists the test statistic and corresponding p-value below in parentheses. * indicates significance at the 1% level.

	1	2	3	4	5	6	7
Panel A: AdjILLIQ portfolios							
β^2	51.49*	44.64*	53.87*	43.49*	46.99*	51.41*	43.94*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	51.49*	53.80*	55.76*	52.86*	55.14*	51.48*	54.41*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	51.49*	45.96*	54.17*	46.94*	49.14*	51.43*	47.66*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: PQS portfolios							
β^2	28.29*	31.06*	30.67*	29.35*	30.55*	28.25*	30.55*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	28.29*	28.23*	30.69*	28.29*	29.18*	28.24*	30.14*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	28.29*	30.57*	30.18*	28.52*	29.39*	28.25*	31.30*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

H0: Error variance across panel variables is zero.

Table 27. Hausman specification test.

The Hausman specification test compares fixed and random effects estimates to determine whether there is a systematic difference between fixed and random effects estimates (i.e. fixed effects). The numbering corresponds to the regression specifications as per Equations (28)–(34), and the portfolio sorting is denoted by β^2, β^3, and β^4. The table lists the Chi-square test statistic and corresponding p-value below in parentheses. * indicates significance at the 1% level.

	1	2	3	4	5	6	7
Panel A: AdjILLIQ portfolios							
β^2	376.98*	389.58*	394.37*	387.66*	378.40*	375.42*	414.79*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	376.98*	381.74*	405.22*	382.49*	385.97*	375.58*	405.06*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	376.98*	384.83*	397.69*	397.42*	378.72*	375.81*	410.27*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: PQS portfolios							
β^2	488.90*	498.50*	498.02*	506.41*	500.23*	487.39*	522.98*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	488.90*	495.67*	494.45*	497.35*	493.90*	487.55*	511.28*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	488.90*	505.06*	509.03*	507.73*	503.96*	487.45*	529.10*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

H0: Difference in coefficients is not systematic.

Table 28. Wald test for time fixed effects.

Factor variables for time periods are added to the fixed effects regression, and a Wald test is performed to determine whether the coefficients for the time periods are jointly different from 0 (i.e. time fixed effects). The numbering corresponds to the regression specifications as per Equations (28)–(34), and the portfolio sorting is denoted by β^2, β^3, and β^4. The table lists the *F*-statistic and corresponding p-value below in parentheses. * indicates significance at the 1% level.

	1	2	3	4	5	6	7
Panel A: AdjILLIQ portfolios							
β^2	55.68*	55.42*	55.43*	55.43*	55.35*	55.69*	55.34*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	55.68*	55.45*	55.43*	55.48*	55.38*	55.69*	55.40*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	55.68*	55.55*	55.46*	55.59*	55.49*	55.69*	55.49*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: PQS portfolios							
β^2	49.59*	49.44*	49.29*	49.46*	49.34*	49.59*	49.30*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^3	49.59*	49.41*	49.27*	49.49*	49.36*	49.59*	49.25*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
β^4	49.59*	49.41*	49.26*	49.50*	49.36*	49.59*	49.23*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)

H0: Coefficients for time periods are jointly 0.

APPENDIX 6: PANEL REGRESSIONS WITH AN ENDOGENOUS HOLDING PERIOD.

Table 29. Fixed effects panel regressions with an endogenous holding period using *AdjILLIQ*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The excess returns, expected illiquidity cost, and illiquidity betas are scaled by the empirically estimated holding period. Special cases of the relation $E\left(r_t^i - r_t^f\right) - \kappa E\left(c_t^p\right) = \alpha_t + \lambda^1\beta_t^{1i} + \lambda^2\beta_t^{2i} + \lambda^3\beta_t^{3i} + \lambda^4\beta_t^{4i} + \lambda^5\beta_t^{5i} + \lambda^6\beta_t^{6i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i$ are considered in each specification. *BM and Size* are natural logarithms of book-to-market ratio and market capitalization, respectively. *FF* is the free float ratio of a stock. The table lists the parameter estimate and the corresponding robust *t*-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	*E(c)*	β^1	β^2	β^3	β^4	β^5	β^6	*ln(Sz)*	*ln(BM)*	*FF*
Panel A: β^2 (commonality) sorted portfolios											
1	-0.000	0.019	-0.002						0.000^{*}	0.000^{***}	0.000
	(-0.92)	(−)	(-0.68)						(1.77)	(9.31)	(0.19)
2	-0.000	0.019	-0.002	4.333^{***}					0.000^{**}	0.000^{***}	0.000
	(-1.32)	(−)	(-0.64)	(3.03)					(1.98)	(9.38)	(0.25)
3	-0.000^{*}	0.019	-0.002		-0.561^{**}				0.000^{*}	0.000^{***}	0.000
	(-1.74)	(−)	(-0.73)		(-2.58)				(1.82)	(9.34)	(0.18)
4	-0.000	0.019	-0.002			-0.132^{*}			0.000^{*}	0.000^{***}	0.000
	(-1.05)	(−)	(-0.66)			(-1.96)			(1.84)	(9.32)	(0.22)
5	-0.000	0.019	-0.002				0.182^{***}		0.000^{*}	0.000^{***}	0.000
	(-1.37)	(−)	(-0.67)				(2.77)		(1.90)	(9.34)	(0.23)
6	-0.000	0.019						-0.002	0.000^{*}	0.000^{***}	0.000
	(-0.93)	(−)						(-0.62)	(1.77)	(9.30)	(0.19)
7	-0.000^{**}	0.019	-0.002	5.492^{**}	-0.516^{**}	0.095			0.000^{**}	0.000^{***}	0.000
	(-2.05)	(−)	(-0.69)	(2.16)	(-2.39)	(0.75)			(2.02)	(9.43)	(0.24)

Table 29 continued.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	-0.000	0.019	-0.002						0.000*	0.000***	0.000
	(-0.92)	(−)	(-0.68)						(1.77)	(9.31)	(0.19)
2	-0.000	0.019	-0.002	2.503					0.000*	0.000***	0.000
	(-1.01)	(−)	(-0.77)	(1.01)					(1.77)	(9.29)	(0.18)
3	-0.000	0.019	-0.003		-0.537**				0.000*	0.000***	0.000
	(-1.57)	(−)	(-1.37)		(-2.45)				(1.77)	(9.32)	(0.17)
4	-0.000	0.019	-0.002			-0.012			0.000*	0.000***	0.000
	(-0.92)	(−)	(-0.69)			(-0.15)			(1.77)	(9.30)	(0.19)
5	-0.000	0.019	-0.002				0.109		0.000*	0.000***	0.000
	(-1.09)	(−)	(-0.89)				(1.50)		(1.76)	(9.29)	(0.17)
6	-0.000	0.019						-0.002	0.000*	0.000***	0.000
	(-0.92)	(−)						(-0.65)	(1.77)	(9.30)	(0.19)
7	-0.000	0.019	-0.004	1.568	-0.519**	0.010			0.000*	0.000***	0.000
	(-1.59)	(−)	(-1.39)	(0.54)	(-2.44)	(0.11)			(1.76)	(9.31)	(0.16)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	-0.000	0.019	-0.002						0.000*	0.000***	0.000
	(-0.92)	(−)	(-0.68)						(1.77)	(9.31)	(0.19)
2	-0.000	0.019	-0.002	3.917***					0.000*	0.000***	0.000
	(-1.23)	(−)	(-0.67)	(2.68)					(1.91)	(9.28)	(0.25)
3	-0.001**	0.019	-0.002		-0.969***				0.000*	0.000***	0.000
	(-2.34)	(−)	(-0.81)		(-4.03)				(1.85)	(9.40)	(0.28)
4	-0.000	0.019	-0.002			-0.039			0.000*	0.000***	0.000
	(-0.95)	(−)	(-0.68)			(-0.58)			(1.79)	(9.29)	(0.20)
5	-0.000	0.019	-0.002				0.111*		0.000*	0.000***	0.000
	(-1.18)	(−)	(-0.69)				(1.86)		(1.84)	(9.29)	(0.24)
6	-0.000	0.019						-0.002	0.000*	0.000***	0.000
	(-0.92)	(−)						(-0.64)	(1.77)	(9.30)	(0.19)
7	-0.001***	0.019	-0.002	6.671***	-0.941***	0.212**			0.000**	0.000***	0.000
	(-2.61)	(−)	(-0.80)	(3.00)	(-3.88)	(2.08)			(1.98)	(9.41)	(0.31)

Table 30. Fixed effects panel regressions with an endogenous holding period using *PQS*.

The numbering in the leftmost column corresponds to the model specification as per Equations (28)–(34). The excess returns, expected illiquidity cost, and illiquidity betas are scaled by the empirically estimated holding period. Special cases of the relation $E\left(r_t^i - r_t^f\right) - \kappa E\left(c_t^p\right) = \alpha_t + \lambda^1\beta_t^{1i} + \lambda^2\beta_t^{2i} + \lambda^3\beta_t^{3i} + \lambda^4\beta_t^{4i} + \lambda^5\beta_t^{5i} + \lambda^6\beta_t^{6i} + \gamma^1 BM_t^i + \gamma^2 FF_t^i + \gamma^3 Size_t^i + \varepsilon_t^i$ are considered in each specification. *BM and Size* are natural logarithms of book-to-market ratio and market capitalization, respectively. *FF* is the free float ratio of a stock. The table lists the parameter estimate and the corresponding robust *t*-statistic below in parentheses. *, **, and *** indicate significance at 10%, 5%, and 1% levels, respectively.

	α	*E(c)*	*β¹*	*β²*	*β³*	*β⁴*	*β⁵*	*β⁶*	*ln(Sz)*	*ln(BM)*	*FF*
Panel A: β² (commonality) sorted portfolios											
1	-0.001***	0.019	0.001						0.000***	0.000***	0.000
	(-5.37)	(−)	(0.25)						(4.25)	(2.77)	(0.65)
2	-0.002***	0.019	0.001	0.603					0.000***	0.000***	0.000
	(-5.57)	(−)	(0.22)	(1.00)					(4.33)	(2.78)	(0.67)
3	-0.002***	0.019	0.000		-0.390**				0.000***	0.000***	0.000
	(-5.93)	(−)	(0.12)		(-2.39)				(4.23)	(2.74)	(0.62)
4	-0.002***	0.019	0.001			-0.078			0.000***	0.000***	0.000
	(-5.45)	(−)	(0.21)			(-1.30)			(4.30)	(2.78)	(0.65)
5	-0.002***	0.019	0.001				0.086		0.000***	0.000***	0.000
	(-5.68)	(−)	(0.17)				(1.65)		(4.30)	(2.78)	(0.64)
6	-0.001***	0.019						0.001	0.000***	0.000***	0.000
	(-5.39)	(−)						(0.33)	(4.25)	(2.77)	(0.64)
7	-0.002***	0.019	0.000	0.147	-0.357**	-0.047			0.000***	0.000***	0.000
	(-5.93)	(−)	(0.10)	(0.13)	(-2.24)	(-0.39)			(4.30)	(2.74)	(0.63)

Table 30 continued.

	α	$E(c)$	β^1	β^2	β^3	β^4	β^5	β^6	$ln(Sz)$	$ln(BM)$	FF
Panel B: β^3 (flight to liquidity) sorted portfolios											
1	-0.001***	0.019	0.001						0.000***	0.000***	0.000
	(-5.37)	(−)	(0.25)						(4.25)	(2.77)	(0.65)
2	-0.001***	0.019	0.001	-0.010					0.000***	0.000***	0.000
	(-5.44)	(−)	(0.25)	(-0.01)					(4.27)	(2.78)	(0.65)
3	-0.002***	0.019	-0.001		-0.348**				0.000***	0.000***	0.000
	(-5.88)	(−)	(-0.20)		(-2.30)				(4.29)	(2.77)	(0.63)
4	-0.001***	0.019	0.001			0.001			0.000***	0.000***	0.000
	(-5.37)	(−)	(0.25)			(0.01)			(4.26)	(2.77)	(0.65)
5	-0.002***	0.019	0.000				0.022		0.000***	0.000***	0.000
	(-5.45)	(−)	(0.16)				(0.52)		(4.27)	(2.77)	(0.64)
6	-0.001***	0.019						0.001	0.000***	0.000***	0.000
	(-5.38)	(−)						(0.28)	(4.25)	(2.77)	(0.65)
7	-0.002***	0.019	-0.000	0.242	-0.412***	0.059			0.000***	0.000***	0.000
	(-6.00)	(−)	(-0.15)	(0.28)	(-2.81)	(1.06)			(4.30)	(2.78)	(0.63)
Panel C: β^4 (depressed wealth effect) sorted portfolios											
1	-0.001***	0.019	0.001						0.000***	0.000***	0.000
	(-5.37)	(−)	(0.25)						(4.25)	(2.77)	(0.65)
2	-0.002***	0.019	0.001	0.442					0.000***	0.000***	0.000
	(-5.52)	(−)	(0.24)	(0.73)					(4.33)	(2.78)	(0.65)
3	-0.002***	0.019	0.001		-0.337**				0.000***	0.000***	0.000
	(-5.61)	(−)	(0.20)		(-2.01)				(4.25)	(2.76)	(0.62)
4	-0.002***	0.019	0.001			-0.046			0.000***	0.000***	0.000
	(-5.44)	(−)	(0.20)			(-1.12)			(4.31)	(2.79)	(0.64)
5	-0.002***	0.019	0.001				0.053		0.000***	0.000***	0.000
	(-5.57)	(−)	(0.18)				(1.47)		(4.31)	(2.79)	(0.64)
6	-0.001***	0.019						0.001	0.000***	0.000***	0.000
	(-5.38)	(−)						(0.31)	(4.25)	(2.77)	(0.64)
7	-0.002***	0.019	0.000	0.317	-0.339**	-0.022			0.000***	0.000***	0.000
	(-5.81)	(−)	(0.16)	(0.44)	(-2.02)	(-0.45)			(4.33)	(2.77)	(0.62)