Liquidity and asset prices: An empirical investigation of the Finnish stock market

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Abstract

This paper presents a simplified single period asset-pricing model that adjusts for illiquidity and tests for the Finnish stock market. The empirical testing for a small yet developed market is motivated by the increased relevance of the illiquidity effect for illiquid assets/markets vastly reported in the literature. Our results support our hypothesis. The results show that expected returns on illiquidity portfolios are cross-sectionally linked with illiquidity risks more so than the market risk, whereas the comparable U.S. evidence reports otherwise. The illiquidity premium maintains its persistence even if we exclude illiquidity prone periods from the sample, although it generates a lower share of the total model risk premium than the full period. The remaining evidence highlights variations in the types of illiquidity risks depending upon proxy measure used, time variations in illiquidity premia, and the superior performance of liquidity-adjusted model compared to the simple CAPM to explain variations in returns across assets and periods.

Keywords: Asset-pricing model, illiquidity effect, risk, illiquidity premium, CAPM

JEL Classifications: G10, G12, G15**.**

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1. Introduction

Studies connecting liquidity to asset pricing have evolved over time and are currently based on a twofold proposition such that the level of illiquidity and illiquidity risk are priced and both are mutually reinforcing. This proposition means that assets having high levels of illiquidity are the ones that are also vulnerable to illiquidity risk. Both effects result in a demand for higher returns for holding such assets. A level of illiquidity can then be defined as a high transaction cost involved in trading the asset, which even under normal market conditions is higher than liquid assets. Liquidity risk arises when the illiquidity of the market suddenly increases, making the prospect of transacting an illiquid asset difficult, thus raising the transaction cost even more.

Amihud and Mendelson (1986) first studied the relationship between expected returns and the level of illiquidity. Their empirics predicted that returns increase and are a concave function of the level of illiquidity. Several studies on this topic have been conducted since Amihud and Mendelson. The initial studies focus on illiquidity as an asset-specific characteristic. Pastor and Stambaugh (2003) documented and tested the systematic dimension of illiquidity, termed illiquidity risk. Furthermore, Amihud (2002) investigated the systematic illiquidity risk and proposed that expected market illiquidity is priced positively while shocks to market illiquidity lower contemporaneous returns.[1] Amihud (2002) tested the propositions with ten size portfolios for the U.S. market and reported consistent empirical evidence.

Bakaert et al. (2007) further tested these hypotheses for emerging markets, and their results confirm their propositions. Chordia et al. (2002) and Hasbrouck and Seppi (2001), among others, suggested another systematic dimension of liquidity risk by proposing that the liquidity risk arises because the market's illiquidity and the asset's illiquidity commonly vary over time. Illiquid assets are a major contributor to market illiquidity; hence, the higher covariation with market illiquidity results in a demand for higher expected returns. Finally, Acharya and Pedersen (2005) summed up all earlier dimensions of liquidity risk in their proposed model. Their model provides the literature with another illiquidity-related risk of overall depressed wealth effect on asset's illiquidity.

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[1] These propositions fulfill each other. A positive shock to asset illiquidity raises the prospect of higher (future) expected illiquidity and thus higher (future) expected returns. Therefore, the illiquidity shock lowers contemporaneous prices and contemporaneous returns while maintaining the return-illiquidity concave relationship.

We simplify the model by Acharya and Pedersen (2005) to make the liquidity adjustment in a single period model rather than an overlapping generation model (OLG). The model proposes that a market index, spanned from a mean-variance efficient asset space net of asset-specific liquidity costs, is a better candidate to reduce the reported mispricing by the empirical estimation of the mean-variance CAPM specification. The generalization of the model allows for the determination of asset prices inside the model and accounts for the total cost of trade rather than exogenously determined prices and model agents confronting the cost of selling, as in Acharya and Pederson (2005) respectively.[2] This limited effect of illiquidity handicaps the utility of their model for any measure of illiquidity constructed not using high frequency data. Illiquidity is typically measured using daily data instead of high frequency trade level data, which allows inexpensive long horizon asset pricing tests.

Therefore, these noted shortcomings require that illiquidity-adjusted CAPM are proposed under more generalized assumptions, in which assets returns could be priced subject to the overall effect of illiquidity. We solve the simple pricing equation in which investors discount the net return on any stock by aggregate market net returns, whereas net returns are excess returns adjusted for illiquidity. The solution to this pricing equation extends the applicability of the Acharya and Pedersen (2005) model for any measure of illiquidity and maintains a similar effect of level of illiquidity and (unconditional) separation among model risks. The separation among model risks enables the determination of the relative impact of a particular risk on expected returns.

As generally acknowledged, illiquidity effect matter the most for illiquid assets/markets. However, with few exceptions, most liquidity-related studies are conducted for the U.S. market. Arguably, the U.S. is the most liquid equity market (Bakaert et al., 2007) and therefore may not be as suitable for empirical testing as other illiquid markets. Illiquidity risk may not be prevalent in the world's most liquid markets. The corresponding liquidity premium is reportedly diminishing over time (Ben-Rephael et al., 2010). Therefore, we test the proposed model for evidence in the Finnish market. We argue that the testing of liquidity-related theories are more appropriate for markets that are illiquid enough to diagnose the level

[2] Selling costs can be deduced only when data for each trade, which allows for buy and sell orders to be distinguished, is available, but this method requires a lot of microstructure data. However, the distinction between buy orders and sell orders even is mingled at times in low frequency data. Thus no exact procedure exists to approximate the cost of selling from any illiquidity measure.

and strength of bearing such risks in comparison to other pertinent risks, such as market risk. The Finnish stock market is a small, developed market that, over the course of a decade, transformed from an illiquid to a liquid market; yet, the prospect of retrieving illiquidity remains a possibility due to the peculiar setting in which the market operates.[3]

To test the proposed model for the Finnish stock market, we construct 15 illiquidity-based and 10 non-illiquidity related test portfolios for the sample period from January 1994 through May 2009. Moreover, a larger cross-section of 25 test portfolios based on five different stock characteristics tests the real strength of the proposed model, as suggested in Lewellen et al. (2010). Furthermore, we purposefully calculate the measure of illiquidity for the stocks listed in the Finnish market in two distinct ways. The illiquidity measures used in our study were proposed by Lesmond et al. (1999) and Amihud (2002). Both of these illiquidity measures are highly correlated with finer spread and price impact proxies estimated from low frequency data, as reported by Goyenko et al. (2009).

Lesmond et al. (1999) argues that the stocks with more zero return days are more illiquid than others, such that the marginal return in transacting the asset is less than the transaction cost and the later proxy for the Kyle (1985) price impact measure. The primary purpose of measuring illiquidity in different ways is to report which illiquidity proxy better captures the unobserved illiquidity effect that explains the cross-sectional return differences. Finally, we also check for time variation in illiquidity and test all the models, excluding the periods with high illiquidity, for the reduced sample.

The results show that the illiquidity portfolios returns are more related to the systematic illiquidity risks than the systematic market risk. The impact of this relationship is substantial such that the percentage of the illiquidity premium in the total model risk compensation is approximately 92 percent, given model assumptions. In comparison, only 17 percent of the total risk premium is attributed to the illiquidity risks for the U.S. stock returns, as calculated

[3] The empirical literature on the Finnish market studying the relationship between stock returns and different illiquidity proxies is extensive. For instance, Swan and Westerholm (2002) found that the level of illiquidity has a positive and strong effect on the cross-section of stock returns from 1993–1998. Vaihekoski (2009) tested for market specific and asset specific liquidity risks for the cross-section of six size portfolios and found that asset specific risk is not priced, whereas the portfolio risk sensitivities show a flat relationship across the size of the portfolios. In the latter study, the illiquidity risk was captured by one factor that accounts for only Amihud’s (2002) flight to liquidity notion. As noted earlier, other illiquidity risks, such as commonality effect and depressed wealth effect on asset’s illiquidity, exist; therefore, the results contribute supplemental empirical evidence for other risk types affecting the Finnish stock return variations.

from Acharya and Pederson (2005). The remainder of the risk premium is attributed to CAPM risk in both markets. The larger association of model-predicted risk premia with liquidity risks remains intact even during calmer periods – that is, 60 percent of the aggregate model premium is the reward for bearing illiquidity risks. The main empirical finding confirms our motivation that the liquidity effects are more pronounced for illiquid assets/markets. Therefore, the evidence suggests liquidity related theories should give priority to illiquid markets than/along with the usual testing for U.S. market.

The remaining evidence in the study can be summarized in three ways. First, the two measures of illiquidity perform equally well in reducing cross-sectional mispricing. However, the overall model effect may be vindicated by a different model risk (dimension) altogether. Second, the illiquidity effect is time varying. The Amihud (2002) price impact measure is more responsive in capturing these (time) variations to the extent that the model estimations using proxy price impact measure are more stable under the model assumptions. Third, the liquidity-adjusted model performs well in comparison to simple CAPM, even when the asset space of test portfolios includes non-illiquidity portfolios in the model estimations. For illiquidity test portfolios, this improvement is substantial in the full sample rather than in the calmer period.

This paper is organized as follows. Section 2 describes the methodology used in this paper. Section 3 discusses the data, in part which the portfolio and different measures of illiquidity are constructed and elaborated. Section 4 provides empirical analysis, and Section 5 concludes the study.

2. Methodology

The presence of the law of one price (LOP) provides a stochastic discount factor, M_t, such that all the assets are correctly priced:

$$E_t(M_{t+1}X_{t+1}) = P_t \qquad (1).$$

Equation (1) could also manifest the gross returns representation if we divide the equality by the non-zero stock price P_t, such that $E_t(M_{t+1}R^i_{t+1}) = 1$. The R^i_{t+1} is the period return on asset i, and if R^i_{t+1} is the excess period return over the risk free rate, then the relation can also be $E_t(M_{t+1}R^i_{t+1}) = 0$. All the subsequent equations from herein will represent R^i_{t+1} as the excess return for expositional convenience. If the discount factor is a function of the mean-variance efficient market factor return (R^m_{t+1}) equation (1) converges to the standard CAPM. One shortcoming of CAPM includes the model implication for stocks with similar expected cash flows that differ only in the ability to trade or transact quickly (Pastor & Stambaugh, 2003; Sadka, 2006). The model implies theoretically equal prices for such stocks; however, we observe violations to the model implications and LOP in the real world.

From here, we derive a simple pricing equation adjusted for liquidity related costs following the mean-variance optimizations discussed in Lo et al. (2004), assuming that investors observe the net asset returns of the transaction costs accrued in the inherent asset specific illiquidity constraints.[4] We use a proportional transaction cost measure such that $E(I^i) = \upsilon^i E(C^i)$. In the equality, $E(I^i)$ represents expected illiquidity, υ^i is a constant of proportionality that should be positive, and $E(C^i)$ is expected relative transaction cost. Similarly, we can represent the relationship between market illiquidity and transaction cost to hold for all the assets in the market as $E(I^m) = \upsilon^m E(C^m)$. The expected illiquidity is a function of the actual transaction costs. The expected asset illiquidity and expected market illiquidity are equal to the counterpart in transaction cost for $\upsilon = 1$, such that theoretical costs are exactly identified empirically. The subsequent model equations drop the term υ^i and υ^m for clarity.

Therefore, an asset-pricing model adjusting for the liquidity effect can be derived in expected excess net returns on stocks such that the pricing kernel is a function of net excess market return[5]:

$$E_t(M_{t+1}(R^m_{t+1} - C^m_{t+1})R^i_{t+1} - C^i_{t+1}) = 0 \qquad (2).$$

[4] TC^i_{t+1} is the total cost of the trade in our model, but when we convert the pricing relation, as in equation (4), in terms of net returns, the part $\frac{TC^i_{t+1}}{P^i_t}$ represents the relative cost of trade for stock *i*, such that $C^i_{t+1} = \frac{TC^i_{t+1}}{P^i_t}$ and similarly follows for total market portfolios, such that $C^M_{t+1} = \frac{TC^M_{t+1}}{P^M_t}$.

[5] The terms liquidity and illiquidity are used interchangeably throughout the paper – for example: liquidity effect, risks, or betas and illiquidity effect, risks, or betas.

Equation (2) accounts for the expected level of stock illiquidity, which for an illiquid asset is higher than the level of illiquidity of a liquid asset, such that $C^{ILLIQ} > C^{LIQ}$. Furthermore, the exposure of market illiquidity C^m on illiquid assets' pay-off is also higher. Therefore, even if the expected gross returns on both illiquid assets and liquid assets are identical, the observed price of the illiquid asset is lower, such that $P_t^{ILLIQ} < P_t^{LIQ}$ for bearing additional illiquidity exposure. This follows from the simple risk-return relationship that if two assets have equal excess return but one is (liquidity-adjusted) riskier, then the illiquid stock price is set to be lower than the liquid stock because investors want extra compensation for bearing higher risk. Consequently, pricing equation (2) can gauge a nexus between expected returns and aggregate risks, for any proxy measure of liquidity, catering to the wholesome systematic dimensions of illiquidity risks.

We argue that agents hypothetically assign equilibrium prices to all the stocks while having homogenous expectations for conditional expected net returns.[6] Therefore, in any period, agents choose consumption and portfolios to maximize the expected utility. In consideration of exogenously determined illiquidity related costs, net returns are identified in each period given that all agents are price takers and short selling is not allowed. The agents identifying net returns determine the new feasible set and the efficient asset combinations to hold in equilibrium. The net return adjustment will re-establish the capital market line tangent, given the poor empirical performance of the standard CAPM, to the efficient frontier at the position of net market (risk, return) tradeoff point in the reduced mean-variance space. The agents will take long positions in the net market portfolio, similar to the imagined CAPM economy. Moreover, the net return on the market portfolio may not be the imagined CAPM economy optimal solution because our proposed model adjusts for the observed mispricing.[7]

Heuristically, the model may prove capable for the justification of LOP and explain why, in the first instance, the prices for illiquid assets are set lower in lieu of the observed gross returns. The violation of LOP, under the empirical estimation of CAPM, occurs because the model ignores the liquidity effect, which results in model predictions that are not on par with market equilibrium prices. The proposed model views liquidity risk as including the total cost of trade, and thus is more liberalized than Acharya and Pederson's (2005) liquidity-adjusted

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[6] We assume expected net returns are jointly normally distributed.
[7] The non-conformability follows if one asset exists that is given positive weights under the imagined CAPM economy; such inclusion drives the optimal solution under the CAPM sub-optimal in the reduced net return investment set, owing to greater trading cost.

model, even though it generates a similar model in terms of model risks.[8] The proposed generalization of the Acharya and Pederson (2005) liquidity-adjusted CAPM, following Lo et al. (2004), can provide better real world predictions when pricing assets in lieu of a net mean-variance portfolio. Furthermore, similar to CAPM theory, the expected (net) rate of return on the stocks is systematically related to the return on a well-diversified market portfolio. The testable cross-sectional restriction on the assets will imply a single beta representation such that:

$$E_t(R^i_{t+1} - C^i_{t+1}) = \lambda_t \beta^{net}_i \quad (3)$$

where $\lambda_t = E_t(R^m_{t+1} - C^m_{t+1})$ and $\beta^{net}_i = \dfrac{Cov_t(R^i_{t+1} - C^i_{t+1}, R^m_{t+1} - C^m_{t+1})}{Var_t(R^m - C^m)}$.

The proposed model will converge to CAPM: (i) for no illiquidity related costs (ii) if the rank of an imagined CAPM opportunity space given constraints is equal to the proposed model rank; and (iii) if the reduced investment set is an efficient subset of the imagined CAPM economy and shares the same solution space. The simplified one-period model improves the Acharya and Pederson (2005) OLG model for the endogenous determination of asset prices and the accounting of total trade cost. The proposed model should be considered an abridgment of CAPM theory for the amelioration of its travails while allowing for liquidity-related costs (risks). Equivalently, we can spread out β^{net}_i into CAPM beta and three illiquidity related betas such that the unconditional representation of equation (3) expands to:

$$E(R^i) = E(C^i) + \lambda\left(\frac{Cov(R^m, R^i)}{Var(R^m - C^m)} + \frac{Cov(C^m, C^i)}{Var(R^m - C^m)} - \frac{Cov(R^i, C^m)}{Var(R^m - C^m)} - \frac{Cov(C^i, R^m)}{Var(R^m - C^m)}\right) \quad (4)$$

Equation (4) shows that expected excess returns are sensitive to the expected level of liquidity market risk and three liquidity-related beta risks. We can also write equation (4) as:

$$E(R^i) = E(C^i) + \lambda^1\beta^{i1} + \lambda^2\beta^{i2} - \lambda^3\beta^{i3} - \lambda^4\beta^{i4} \quad (5).$$

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[8] However, the feasible solution in their model is also applicable to the imagined CAPM economy, provided prices are exogenously determined. The other notable assumption in their OLG model is that the illiquidity discount incurred by the terminal period agents is revealed in the cost of selling. They described that agents can buy at P^i_t but must sell at $P^i_t - C^i_t$ (page 379), where C^i_t is the cost of selling an asset.

The purport of equation (5) is to adjust β^{i1}, the market beta, with other illiquidity-related betas $-\beta^{i2}$, β^{i3}, and β^{i4} – such that the excess return on liquid and illiquid assets are in harmony with what we observe in the market. Arguably, the illiquidity-related betas increase (or decrease) the exposure of expected returns on illiquid assets (or liquid assets) while accounting for the systematic risk of liquidity. The empirical estimation of the model is executed assuming all that investors have a one-month trading horizon.[9] The model risk premium, for using proportional illiquidity costs, is not exactly the excess net market return, as in Acharya and Pederson (2005), but rather is a proportional measure yielding relative risk premia. The model risks can be estimated with the constrained price of risk as implied in equations (4) and (5) under restriction, such that $\lambda^1 = \lambda^2 = -\lambda^3 = -\lambda^4$. The success of the proposed model, in reducing the equilibrium mispricing, is estimated with the specification testing as under:

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda\beta^{i1} + \lambda\beta^{i2} - \lambda\beta^{i3} - \lambda\beta^{i4} \qquad (6).$$

In equation (6), β^{i1} is a CAPM related beta, whereas the other three betas are liquidity related. All of these betas signify liquidity risks that have been studied extensively in the literature. The unconstrained estimation of equation (6) enables us to analyze all the liquidity risks along with the liquidity level under a simple model. We refer to Acharya and Pederson (2005) for a detailed discussion of the economic intuition of the three different liquidity betas. First, liquidity beta β^{i2} is associated with the commonality in assets and aggregate market illiquidities. The initial studies arguing for the effects of commonality in illiquidity are from Chordia et al. (2002) and Hasbrouck and Seppi (2001), among others. Second, liquidity beta β^{i3} is studied extensively, for example, by Amihud (2002) and Pastor and Stambaugh (2003) for the U.S. market. This beta captures the notion of flight to liquidity.[10]

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[9] Otherwise, in the real world, the holding period is preference dependent where usually the illiquid stocks for higher associated transaction costs are traded less frequently, and long positions are maintained relative to the liquid counterparts.

[10] The flight to liquidity, as noted by Amihud (2002), or shock to expected market illiquidity raises the prospect of higher future expected illiquidity, which should be compensated with higher expected future returns. Acharya and Pederson (2005), in addition to the above explanation, suggested that the negative premium for β^{i3} is also consistent for stocks that hedge for bad times. They further explained that the stocks whose returns are higher when market illiquidity is higher provide consumption in times when it is highly desired. Investors settle for lower returns on such stocks under liquid market equilibrium states and they also assign negative risk prices to poor timer stocks along with good timer stocks for bearing this covariance risk. For the U.S. market, β^{i3} is

The last liquidity beta β^{i4} is related to covariance between asset illiquidity and market returns. If an asset's illiquidity decreases when aggregate market returns decrease, such that the stock provides ease at transacting when overall wealth is depressed, then investors settle for lower expected returns on them in equilibrium for hedging needs. This illiquidity beta was first tested by Acharya and Pederson (2005) for the U.S. market and reportedly has the most pronounced impact compared to other illiquidity risks. These illiquidity betas are estimated by considering the liquidity risk arising from the overall cost for transaction:

$$\beta^{i1} = \frac{Cov(R_t^i, R_t^m - E_{t-1}(R^m))}{Var(R_t^m - E_{t-1}(R_t^m) - \left[C_t^m - E_{t-1}(C_t^m)\right])} \tag{7}$$

$$\beta^{i2} = \frac{Cov(C_t^i - E_{t-1}(C_t^t), C_t^m - E_{t-1}(C^m))}{Var(R_t^m - E_{t-1}(R_t^m) - \left[C_t^m - E_{t-1}(C_t^m)\right])} \tag{8}$$

$$\beta^{i3} = \frac{Cov(R_t^i, C_t^m - E_{t-1}(C^m))}{Var(R_t^m - E_{t-1}(R_t^m) - \left[C_t^m - E_{t-1}(C_t^m)\right])} \tag{9}$$

$$\beta^{i4} = \frac{Cov(C_t^i - E_{t-1}(C_t^t), R_t^m - E_{t-1}(R^m))}{Var(R_t^m - E_{t-1}(R_t^m) - \left[C_t^m - E_{t-1}(C_t^m)\right])} \tag{10}$$

We rely on the constancy of beta (or covariance) risks estimated directly from the data using equations (7) to (10). Generally, asset-pricing models use the beta risks estimated from the first-stage time series regressions that are subsequently required to explain the cross-sectional return variations in the second stage regression to command significant risk compensation. However, betas given in equation (6) with the imposed theoretical structure are not estimable through the first stage time series regression, the otherwise standard method. Nevertheless, directly estimating liquidity-related betas keeps intact the intuitive appeal in which betas are generally calculated and captures the illiquidity-related risks present through different channels.

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priced risk as reported by Pastor and Stambaugh (2003); it explains a significant proportion of higher realized return on the most illiquid portfolio, which is left unexplained by the three factor models of Fama and French (1993).Vaihekoski (2009) also reported β^{i3} is significantly priced for the Finnish market while using value-weighted, spread-based transaction cost measure.

3. Data

Numerous studies suggest that illiquidity risk is present for the assets whose returns are a function of illiquidity and use illiquidity-based characteristic test portfolios (Amihud, 2002; Acharya & Pederson, 2005; Pastor & Stambaugh, 2003). Acharya and Pederson (2005) reported that the results from illiquidity-adjusted CAPM do not corroborate evidence of liquidity risk being priced using non-illiquidity based (size-BM) portfolios. However, Lesmond et al. (2004) and Sadka (2006) indicated that illiquidity is a systematic risk and remains persistent even for momentum and post-earning-announcement (non-illiquidity) based characteristic portfolios.

The first problem with testing the illiquidity effect for the Finnish market concerns the small number of listed stocks in comparison to other developed markets. This limitation constrains the study to a large cross-section of portfolios with respect to a particular stock characteristic. Therefore, based on prior period sorting criteria, each month we divide the available stocks, into five quintile portfolios using five different stock characteristics. The asset characteristics related to illiquidity are zero measure (Lesmond et al., 1999), size, and price inverse (PI) ratio. The rest are generated using prior year momentum returns and book-to-market (BM) ratios. First, the availability of 25 characteristic portfolios enables the study to report the relative role of illiquidity for pricing illiquidity and non-illiquidity testing portfolios. Second, it provides an adequate number of testing portfolios for the statistical power of cross-sectional tests.

The construction of test portfolios is preceded with data retrieval from DATASTREAM from January 1994 through May 2009.[11] We prefer monthly sorting information criteria for ranking the characteristic stock returns. This method increases the information content (Vaihekoski, 2004) with monthly partitioning of the data for illiquidity related and other available sorting criteria, such as momentum returns.[12] Only the BM-ratio portfolios are

[11] Before 1994, the number of stocks was too few and the Finnish market suffered from a severe recession. Therefore, the constructed portfolios using data before 1994 may have assigned too much importance to the returns of only a few stocks with a stock-like variability during the recession (initial) period of the sample. For this reason, the models are estimated from January 1994 onwards to avoid substantial stock specific patterns in the testing portfolios and, subsequently, in the overall analysis.

[12] However, using yearly sorting may not change the overall depiction of results because illiquidity is a persistent characteristic and an illiquid asset is likely to be illiquid at monthly or yearly frequencies. Brennan and Subramanyam (1996) assumed one-year illiquidity estimates to be constant for upcoming three years in their study.

ranked on the year-end information. The retrieved stock prices are adjusted for dividends, splits, and other cash payouts.

The first five portfolios are sorted on the basis of the previous month's incidences of zero returns (zero measure onwards) for all available firms and for each month in the sample. The quintile portfolio increases in the zero measure; that is, L-1 is the portfolio containing the 20 percent of the partitioned stocks with the lowest number for percentage zero return days. Subsequently, L-2, L-3, L-4, and L-5 are increasing in the relative illiquidities respective to L-1 with higher zero incidences. In a similar fashion, the size and the stock's PI ratio-based quintile portfolios are generated based on the prior month's firm capitalizations and PI ratios respectively.[13] The chronological order for the size quintiles is such that S-1 represents the smallest capitalized firms, and S-5 contains the largest capitalization firms in the data. The price inverse portfolios are such that PI-1 contains the highest priced 20 percent of the total stocks, and PI-5 represents the lowest priced 20 percent of all the stocks.

Subsequently, we construct the 10 non-illiquidity-based portfolios. The five momentum portfolios are constructed while adopting the standard practice in the literature. The previous eleven-month rolling average returns (excluding the most recent monthly return) are estimated each month across all stocks and are then used to create five momentum partitions, iteratively. The generated portfolios indicate that each succeeding quintile contains the firms whose previous eleven month rolling average returns are higher than the preceding quintile; that is, M-1 are the loser stock portfolios, and M-5 are the winner stock portfolios. For the construction of BM portfolios, we rank the next year's stock returns into five portfolios, which are increasing in the BM ratios; that is, BM-1 represents growth (overpriced) stocks, and BM-5 are value (underpriced) stocks.

We use equal weighting for portfolio returns and portfolio-specific illiquidity measures for the Finnish market. Numerous liquidity-related studies have followed the equal weighting scheme for the test portfolio. The selection of equally-weighted portfolios is even more relevant for the Finnish market (Butt & Virk, 2012), such that the capitalized portfolios severely suffer in the presence of few large firms. Therefore, the empirical testing with the

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[13] The size and PI ratio based testing portfolios has been extensively used in the literature to proxy for illiquidity related characteristics. Amihud (2002) use size portfolios to test illiquidity premium. Whereas, price inverse ratio is suggested by Brennan and Subrahmanyam (1996) for the fact illiquid stocks generally have lower prices in comparison to liquid stocks.

value-weighted portfolios may miss the liquidity effect altogether, which is usually pronounced for small firms.

3.1. The (il)liquidity measures for the Finnish market

Generally, a proxy measure of transaction cost is deduced either by using daily return alone or by using daily return in conjunction with daily volume. The illiquidity measure thus constructed from the daily observable data falls under two categories; either the measure is a proxy of effective spread or a proxy of price impact.

The first measure of illiquidity used in the study is zero measure, which was proposed by Lesmond et al. (1999). They report the measure proxies for the bid-ask spread such that the firms for which relative frequency of zero return days is higher usually also have subsequently higher bid-ask spreads. Therefore, a premise of zero measure is that higher incidences of zero return days for any firm proxy for higher illiquidity. This is because investors holding an asset may trade only when anticipated profit from trading surpasses associated transaction costs. Thus, higher transaction costs relative to marginal gains lead to zero return days and reflects inherent illiquidity in the stock. The construction of zero measure, to proxy associated transaction costs, is initiated with recording the frequency of the zero return days in a month across all stocks. Then, for each stock we take a simple ratio of the zero return days in a given month over total number of trade days in that month:

Zero Measure = Number of days with zero return / Total number of days to trade

The underlying simplicity of the proposed measure enables us to construct the longest possible illiquidity series for the Finnish market.[14] The zero measure accommodates all the assets in the sample, which might have been omitted with some other proxy of illiquidity measure for additional requirement of data, such as traded volume and type of trade.

The second measure of illiquidity is volume related and measures a response of absolute return to unit traded euro volume for a particular stock, as proposed by Amihud (2002). The proposed measure caters to Kyle's (1985) concept of illiquidity, which appears due to

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[14] Bakaert et al. (2007) estimated the turnover for all emerging markets to see its relationship with zero measure; they reported that zero measure is negatively related to turnover. Therefore, we also estimate the turnover for all the stocks, which is the ratio between the shares traded to the number of shares outstanding.

Table 1 Relation of Size with other Factors

The results are based on monthly measures of different (il)-liquidity measures, price inverse ratio, BM ratio and momentum factor estimated in correspondence with five size related quintiles. Each size quintile increases in order, with each succeeding one having 20% of firms with higher capitalization than preceding percentile, making first percentile comprised of the lowest 20% capitalized firms and fifth quintile as composed of top 20% capitalized firms . Zero measure is proportion of zero returns over total available tradable days in any month for the firms falling into particular size quintile. Amihud is the ratio of absolute return of any firm over traded volume in Euro, which gives an impact of one Euro traded on the stock's daily absolute return, this measure is then averaged for any given month for the firms falling into particular quintile. Turnover is a monthly sum of daily ratio of equity value traded and number of shares outstanding for all firms falling into particular quintile. Similarly PI is price inverse ratio, BM is book to market ratio and Momentum is monthly momentum factor which is an average of last 11 monthly returns, all of these measures are monthly and calculated for the particular size quintile.

Size Percentile	Zero Measure (%)	Price Impact (%)	Turnover (%)	PI Ratio (%)	Momentum (%)	BM Ratio
1	57.40	7.26	2.41	185.86	0.70	1.91
2	42.00	1.17	2.57	51.93	1.4	1.51
3	31.07	0.52	2.71	27.61	1.3	1.54
4	22.68	0.09	3.68	19.30	1.3	1.48
5	11.13	0.03	6.21	12.44	1.7	1.73

asymmetrical information between market makers and market participants, and is usually higher for illiquid stocks. Underlying intuition suggests that the volume sensitivity measure captures the impact of traded order size on returns that actually occur at high frequency data, for instance, at five-minute intervals of trading.

The construction of the measure is started given the availability of traded volume for a particular stock. Consequently, the absolute return $|R_{imd}|$ on stock *i* on day *d* of the month *m* is divided by the traded volume (in euros) for the corresponding day $VOLD_{imd}$ in the same month such that $|R_{imd}|/VOLD_{imd}$. The daily traded volume in euros is the number of shares traded for stock *i* multiplied by the end of the day stock price. The measure gives absolute return change per euro traded, or the daily price impact. If a stock is illiquid, then it would have lesser depth and resilience and will be highly affected by per Euro traded volume in comparison to liquid stock. Therefore, for illiquid stock, the estimate monthly $ILLIQ$ should be higher than liquid stock. We estimate the monthly measure such that:

$$ILLIQ_{im} = 1/D_{im} \sum_{t=1}^{Dim} |R_{imd}|/VOLD_{imd} \quad (11)$$

where D_{im} is the number of trading days for stock *i* in any month *m*.

The calculated average monthly illiquidity $AILLIQ_m$ is the average price impact of the traded volume sensitivities across Finnish stocks:

$$AILLIQ_m = 1/N_m \sum_{t=1}^{N_m} ILLIQ_{im} \tag{12}$$

where N_m is the number of stocks in a month. Amihud (2002) placed few restrictions on the construction of price impact measure. For instance, illiquidity is calculated for stocks that are traded for at least 15 days in a month. Imposing, similar construction constraints as Amihud (2002), this measure remained available for only 40 percent of the stocks in the Finnish market. In order to increase the number of assets for which we could estimate price impact based illiquidity, the restrictions are waived.

We also estimate monthly market illiquidity while imposing all the restrictions as in Amihud (2002) and find that in comparison to the unrestricted measure, the restricted measure approximates only for the (relative) liquid stocks in the Finnish market. Furthermore, we assume that the non-availability of traded volume for more than 15 days may not change the stock illiquidities too overtly as measured with the available volume, even if the (non-reported) volume was available. The non-trading of the stock for a considerable number of days is still suggestive of higher illiquidity (Lesmond et al., 1999) and is candidate for inclusion in the Amihud (2002) price impact measure.

Moreover, Bakaert et al. (2007) also measured illiquidity by the relative frequency of the length of non-trading days compared to trading days in a month. However, stocks trading both infrequently or after long intervals show inherent stock illiquidity, although the latter displays a severe form of illiquidity. Hence, by waiving the restrictions in Amihud (2002), the unrestricted price impact measure still measures the illiquidity for an asset by accommodating Lesmond et al. (1999) and Bakaert et al. (2007). Therefore, the waiver of restrictions may help capturing additional illiquidity-related information in the price impact measure.

Whether the above measures of illiquidities are related to the transaction costs associated with trading of assets has yet to be determined. An indirect test suggested in the literature argues transaction cost is inversely related to the size of the firm. The empirical evidence establishing this relationship is fostered by Demsetz (1968), Benston and Hagerman (1974),

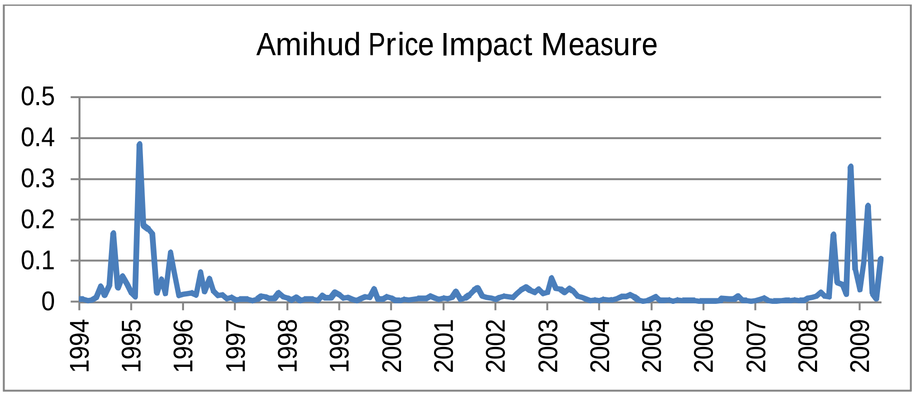

Figure 1. Amihud measure of illiquidity for the Finnish market 1994-2009

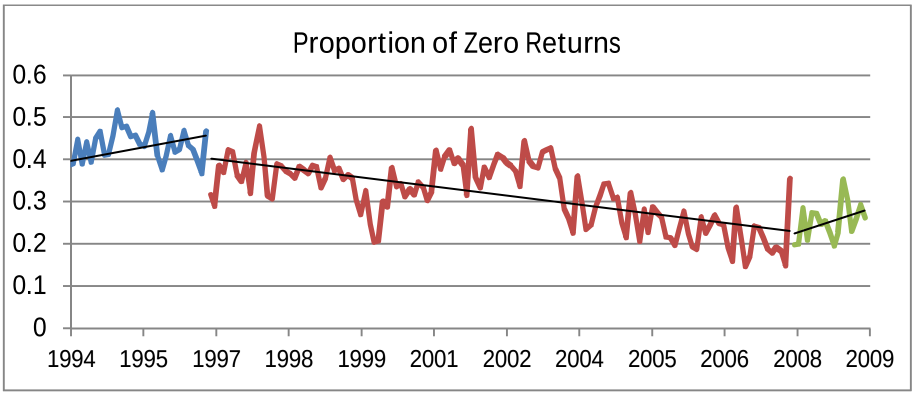

Figure 2. Zero measure of illiquidity for the Finnish market 1994-2009

Copeland and Galai (1983), and Roll (1984).

Accordingly, Lesmond et al. (1999) used firm size inverse as a measure of transaction cost and reported decreasing proportions of zero return days of the firms in the increasing size deciles. Similarly, high turnover is related to stocks with higher liquidity. If the illiquidity measures are appropriate proxies for transaction costs, then the candidate proxy may also decrease in relation to size and vice versa. In order to confirm this hypothesis, we partition all the stock returns into five size quintile portfolios. Subsequently, we calculate the respective illiquidity measures and other associated features for all the available stocks in the partitioned portfolios. We also estimate the momentum returns and BM ratios for the size portfolios. The associated characteristics for the five size portfolios are calculated on a monthly basis and the illiquidity-based features are the averages from the daily values in a month across the sample. The relationship is demonstrated with the noted key statistics (equally weighted) in Table 1.

The results suggest that the findings support the relevant literature on illiquidity for the Finnish stock market. The measures of illiquidity, that is, zero measure and price impact measure, decrease monotonically across size quintiles. Furthermore, turnover increases in size as expected, such that lesser transaction costs are associated with bigger firms. We also see that the price inverse ratio of stocks decreases in size, such that big firms also have high stock prices. The noted features are an indirect hint of the higher transaction cost of the illiquidity portfolios, which consist of higher zero return, higher price impact, higher PI ratio, and low turnover stocks; the inverse is true as well.

We do not see any explicit increase or decrease in either momentum returns for the size portfolios or in the BM ratios. This finding suggests that momentum returns and BM ratios for the size portfolios are not directly related to proxy transaction cost attributes, as shown in Table 1. Importantly, the statistics in Table 1 establish that zero measure and price impact measure are factually related to transaction cost. Moreover, the table also shows that the 15 test portfolios on zero measure, price impact, and price inverse ratios are candidates for illiquidity portfolios, whereas momentum and BM ratio portfolios could be regarded as non-illiquidity portfolios.

3.2. Illiquidity of the Finnish market

Because illiquidity is a main characteristic of any small market, understanding how illiquidity evolves over time in Finland is important. Figure 1 plots the series of price impact measures during 1994–2009. Periods of illiquidity and liquidity are evident in the Finnish market. The periods spanning 1994–1996 and 2008–2009 describe the obvious patterns for higher illiquidity such that the absolute return impact of one euro traded is exaggeratedly higher than the remaining (calm) period in the sample. Otherwise, the market is quite liquid during 1996–2007, when the market (absolute) return shows an impact of only 0.012 € for one euro traded, on average, whereas the price impact estimate increases to 0.070 € in the full sample, which is almost six times stronger than the estimate for the calm period. The difference bestows an impression of higher illiquidity for the total sample period.

When the market is most liquid, we find that, especially for Nokia, the return impact to one euro traded is as low as 2.1×10^{-7}. Vaihekoski (2009) also reported that the bid-ask spread for Nokia was 0.2 percent during his studied sample. The use of zero measure highlights similar patterns in illiquidity across samples but in a less vigorous manner than the Amihud measure. We divide the zero measure illiquidity series into three subsamples along the impression suggested in Figure 1 by the Amihud (2002) price impact measure. We report increasing incidences of zero return days during 1994–1996 and 2008–2009, as indicated by the steepness of the respective trend line. The increased incidences of zero return days are a sign of increasing illiquidity.

Generally, turnover, or the volume, also increases when the market faces illiquidity shock as few investors are bound to hit their liquidity constraints, thus they sell at lower prices. The traded prices may result in reduced zero returns. If these conditions are left unconsidered, then the impact of such volume over prices, in approximating illiquidity as is with zero measure, may generate a false sense of liquidity when illiquidity occurs. However, this conjecture cannot account for the actual activity, such as how many investors under such illiquidity shocks hit their liquidity constraints and how many investors can hold on to their asset holdings. Therefore, we presume that the Amihud measure is robust to capture the greater impact of illiquidity under the dynamic market conditions for which the zero measure of illiquidity is not as engrossing.

Furthermore, to illustrate the point that the Finnish market is more illiquid then many large capitalized (developed) markets, we rely upon the illiquidity estimates from the studies on the U.S. market. The reported price impact measure for the U.S. stock returns in Amihud (2002) is 3.37×10^{-7} with a standard deviation of 5.12×10^{-7}.[15] Under similar criteria for the Finnish market, which stipulate that a stock is traded at least for 200 days in a year and are priced at more than five euro, result in an annual mean price impact of 3.79×10^{-4} of all firms with a standard deviation of 5.69×10^{-4}. The comparable sample (1993–2005) price impact measure for the U.S. market is 6.31×10^{-6} with a standard deviation of 9.12×10^{-7}, as provided in Goyenko et al. (2009).[16] The comparable estimates show that the Amihud (2002) measure for the U.S. markets is significantly lower than the corresponding Finnish market estimates.

Goyenko et al. (2009) also calculated the average zero measure for the U.S., which is 14.3 percent with a standard deviation of 14.7 percent, whereas the corresponding zero measure

[15] See Table 1 in Amihud (2002) for the U.S. market price impact measure descriptive statistics during 1963–1999.

[16] Table 1 panel A and panel D in Goyenko et al. (2008) provided detailed descriptive statistics for the price impact measure and percentage zero measure of the U.S. market for 1993–2005 respectively. For the Finnish market, the corresponding estimates for price impact measure and zero measure, in a similar period used by Goyenko et al. (2008), are 3.84×10^{-4} with a standard deviation of 6.36×10^{-4} and 36 percent with a standard deviation of 4.31 percent respectively.

Table 2 Properties of portfolios with liquidity betas calculated by zero measure

This Table reports presents properties of 25 equally weighted portfolios formed monthly for the period from 1994 to 2009 on the basis of different characteristics. First five portfolios are based on measure of illiquidity constructed by number of zero returns in a month for a given firm. Each succeeding portfolio consists of 20% of firms with higher number of zero returns. This construction of portfolio for illiquidity also guides formation of other portfolios with different characteristics which in the order of Table are as, L represents illiquidity, S represents Size, P represents price inverse ratio, M represents momentum and lastly BM represents book to market ratio portfolios. β^{i1} is usual market beta whereas, β^{i2} , β^{i3} and β^{i4} illiquidity based betas, these betas are calculated using equation (7), (8),(9) and (10). $E(L^i)$, $E(A^i)$, $E(TO^i)$ are the expected illiquidity calculated from Lesmond zero measure of illiquidity, Amihud measure of price impact, and turnover. Size shows average market capitalization of each portfolio and $E(R^e)$ is average gross returns.

Portfolios	β^{i1} (.100)	β^{i2} (.100)	β^{i3} (.100)	β^{i4} (.100)	$E(L^i)$ (%)	$E(A^i)$ (,1000)	$E(TO^i)$ (%)	Size Ml.€	E (R)
L-1	60.13	26.76	-7.53	5.78	12.16	0.71	5.95	3703.92	1.009
	(6.83)	(5.70)	(-0.39)	(2.82)					
L-3	49.79	45.10	-11.02	-3.62	29.84	4.26	3.12	277.82	1.011
	(8.82)	(7.89)	(-2.01)	(0.18)					
L-5	66.71	29.81	-22.56	-7.59	67.10	85.29	1.54	39.26	1.022
	(4.36)	(6.14)	(-1.74)	(-0.52)					
S-1	68.85	35.10	-21.38	-7.54	57.40	72.61	2.41	13.07	1.020
	(7.13)	(7.10)	(-2.18)	(-0.97)					
S-3	52.69	38.18	-12.32	-4.81	31.07	5.21	2.71	139.67	1.014
	(7.82)	(6.60)	(-2.68)	(0.19)					
S-5	52.13	29.64	-3.50	6.20	11.13	0.27	6.21	5090.61	1.010
	(6.47)	(6.08)	(0.17)	(1.85)					
P-1	48.88	37.67	-5.11	-2.42	20.82	1.36	4.87	3668.69	1.004
	(6.94)	(6.97)	(-0.32)	(0.09)					
P-3	48.11	37.72	-10.79	-2.45	31.87	5.55	3.18	405.19	1.013
	(8.07)	(6.82)	(-1.44)	(0.22)					
P-5	83.33	33.74	-23.54	-7.54	46.99	76.52	2.96	93.15	1.026
	(8.01)	(6.63(	(-2.19)	(-1.10)					
M-1	65.96	34.28	-13.18	-0.97	35.55	25.80	3.76	891.13	1.008
	(6.59)	(6.68)	(-2.32)	(0.51)					
M-3	44.11	40.24	-9.83	-2.47	31.85	17.72	3.35	951.74	1.010
	(7.86)	(6.64)	(-1.65)	(0.23)					
M-5	61.94	37.24	-12.26	-1.70	32.12	34.36	4.16	2038.92	1.021
	(6.34)	(5.63)	(-1.53)	(0.06)					
BM-1	60.11	40.28	-13.26	-8.89	26.18	6.36	3.88	3336.37	1.003
	(7.81)	(8.63)	(-2.73)	(-0.75)					
BM-3	59.01	37.21	-13.74	-3.52	35.45	14.57	3.53	698.15	1.015
	(6.89)	(6.46)	(-1.14)	(0.23)					
BM-5	57.47	28.63	-10.41	6.48	35.26	72.44	2.88	619.05	1.018
	(5.97)	(5.43)	(-1.02)	(1.98)					

for the Finnish market is 33.15 percent with a standard deviation of 8.5 percent in the full period. The average zero measure for the Finnish market is comparable to the average zero measure of nineteen emerging markets, as reported in Bekaert et al. (2007). The reported zero measure for the emerging markets is 30.8 percent with a standard deviation of 13.5 percent for the time period ranging from 1987 to 2003. This result indicates that, on liquidity measures, the Finnish market is too illiquid in comparison to the U.S. market and much akin to emerging markets in terms of zero measure. The illiquidity characteristics and the hybrid nature of the Finnish market make the study more interesting and relevant for its empirical contribution.[17]

4. Estimation Procedure

In this section, we estimate the equally weighted monthly portfolio illiquidities through zero measure and price impact measure. We proceed in sections. First, in section 4.1, we discuss making the monthly innovation in the illiquidity series of the testing portfolios and the market portfolio. Additionally, we also retrieve the innovation series in the monthly market returns. The estimation of models as proposed in section 2 uses four betas. The beta risks are directly estimated from the innovations series in section 4.1 using equations (7), (8), (9), and (10). The calculated beta risks are subsequently used for the calculation of the liquidity-adjusted net beta series. We analyze the properties of the estimated betas in section 4.2, in nexus to the expected excess returns on the 25 testing portfolios.[18] In section 4.3, we estimate our model equations (3) and (6) and numerous nested specifications for the sample from 1994:01 to 2009:05. Then in section 4.4, we test all the specifications for only the illiquidity portfolios. Finally, in section 4.5, we check for the robustness of the illiquidity specification across the samples.

4.1. Testing portfolios and innovation in return and illiquidity series

We use innovations in our empirical analysis instead of original series because the literature indicates that liquidity is predictable; an illiquid portfolio is expected to be illiquid for a considerable length of time. Moreover, employing innovations also circumvents the stationarity issues, given high persistence in the levels of illiquidity series. The innovations in illiquidity are gathered by imposing ARMA structures of varying order in (p, q), where p is

[17] The Finnish stock market is a developed marketplace that is included in the MSCI global. Yet the Finnish market shares the illiquidity features of emerging markets.
[18] We use the monthly returns on the one-month EURIBOR rates from the beginning of January 1, 1999 and for the earlier period to match the sample in the study, which is completed with the one-month HELIBOR rate, available from the Bank of Finland.

Table 3 Properties of portfolios with liquidity betas calculated by price impact measure

This Table reports presents properties of 25 equally weighted portfolios formed monthly for the period from 1994 to 2009 on the basis of different characteristics. First five portfolios are based on measure of illiquidity constructed by number of zero returns in a month for a given firm. Each succeeding portfolio consists of 20% of firms with higher number of zero returns. This construction of portfolio for illiquidity also guides formation of other portfolios with different characteristics which is order of Table are as, L represents illiquidity, S represents Size, P represents price inverse ratio, M represents momentum and lastly BM represents book to market ratio portfolios. β^{i1} is usual market beta whereas, β^{i2} , β^{i3} and β^{i4} illiquidity based betas, these betas are calculated using equation (7), (8),(9) and (10). $E(L^i)$, $E(A^i)$, $E(TO^i)$ are the expected illiquidity calculated from Lesmond zero measure of illiquidity, Amihud measure of price impact, and turnover. Size shows average market capitalization of each portfolio and $E\ (R^e)$ is average gross returns.

Portfolios	β^{i1} (.100)	β^{i2} (.100)	β^{i3} (.100)	β^{i4} (.100)	$E(L^i)$ (%)	$E(A^i)$ (.1000)	$E(TO^i)$ (%)	Size Ml.€	E (R)
L-1	63.48	0.00	-9.08	0.05	12.16	0.71	5.95	3703.92	1.009
	(9.34)	(0.57)	(-4.58)	(0.59)					
L-3	52.56	0.19	-13.93	-0.92	29.84	4.26	3.12	277.82	1.011
	(9.48)	(1.18)	(-3.70)	(0.04)					
L-5	70.43	70.37	-10.05	-13.80	67.10	85.29	1.54	39.26	1.022
	(3.54)	(1.52)	(-4.19)	(-1.45)					
S-1	72.68	58.39	-9.93	-11.32	57.40	72.61	2.41	13.07	1.020
	(5.46)	(1.56)	(-3.20)	(-1.51)					
S-3	55.62	0.22	-12.26	-0.33	31.07	5.21	2.71	139.67	1.014
	(10.01)	(1.06)	(-3.39)	(0.01)					
S-5	55.03	0.02	-10.57	-0.01	11.13	0.27	6.21	5090.61	1.010
	(8.47)	(-0.07)	(-4.39)	(-0.75)					
P-1	51.59	0.08	-10.80	-0.24	20.82	1.36	4.87	3668.69	1.004
	(8.98)	(0.39)	(-4.03)	(-2.08)					
P-3	50.79	0.21	-11.37	-0.26	31.87	5.55	3.18	405.19	1.013
	(9.69)	(2.02)	(-4.19)	(0.01)					
P-5	87.97	63.00	-10.80	-10.47	46.99	76.52	2.96	93.15	1.026
	(6.24)	(1.47)	(-3.16)	(-0.64)					
M-1	69.63	13.27	-12.19	-3.87	35.55	25.80	3.76	891.13	1.008
	(7.74)	(1.44)	(-2.95)	(-0.26)					
M-3	46.56	43.32	-9.88	-7.24	31.85	17.72	3.35	951.74	1.010
	(8.28)	(1.05)	(-3.55)	(0.02)					
M-5	65.38	18.93	-11.56	9.20	32.12	34.36	4.16	2038.92	1.021
	(7.08)	(1.39)	(-3.78)	(1.08)					
BM-1	63.45	1.31	-11.30	-0.92	26.18	6.36	3.88	3336.37	1.003
	(8.13)	(2.61)	(-4.09)	(-1.13)					
BM-3	62.29	1.75	-11.11	-2.05	35.45	14.57	3.53	698.15	1.015
	(6.04)	(2.31)	(-4.56)	(0.07)					
BM-5	60.66	128.05	-11.64	-35.65	35.26	72.44	2.88	619.05	1.018
	(8.22)	(1.18)	(-5.43)	(-1.47)					

the lag length for the autoregressive term, and q is the lag length of the moving average term:

$$L_t^i = c + \sum_{i=1}^{p} \Phi_i L_{t-i}^i + \sum_{i=1}^{q} \Theta_i \varepsilon_{t-i}^i + \varepsilon_t^i \quad (13)$$

L_t^i is the expected level of illiquidity of each testing portfolio and market portfolio. The innovations in the asset-specific illiquidities are collected for both measures of illiquidity. We also collect innovations in the aggregate market illiquidity and market return series. In imposing the ARMA structure across all the illiquidity series, we ensure that no predictability is left in the respective innovation series. We retrieve innovation in the market return series while using an AR (1) model along with Fama and French (1993) factors, illiquidity measures, and volume as explanatory variables. Subsequently, the illiquidity related betas are calculated using innovations in portfolio and market illiquidity series.

4.2. Liquidity related betas over time

We present the descriptive statistics for the testing portfolios along with the key characteristics and estimated beta risks in Table 2 and Table 3 for initial analysis with zero and price impact measures, respectively.

First, in Table 2 the illiquidity-based testing portfolios provide adequate results in terms of sharing key illiquidity characteristics, similar to the size portfolios as discussed in Table 1. The expected portfolio illiquidities estimated with zero measure and price impact are given under the headlines $E(L^i)$ and $E(A^i)$ respectively. The estimated illiquidites are increasing in the odd numbered illiquidity and PI portfolios and show that illiquidity is persistent across the sample, whereas for size related portfolios both illiquidity measures are decreasing in the capitalization of size portfolios.[19] Moreover, the portfolio expected turnovers, $E(TO^i)$, decrease as the illiquidity of portfolios increases.

The average illiquid portfolios returns are higher than those of the liquid portfolios. Importantly, sorting the previous month's zero measure produces a wide spread in the returns of the extreme portfolios. The annual return differential between the most illiquid portfolio

[19] Results also hold for even numbered portfolios, but to conserve space the results are presented for only odd numbered portfolios.

(L-5) and liquid portfolio (L-1) is approximately 15.37 percent.[20] This result highlights the greater illiquidity effect in the Finnish market. A similar return differential for the odd numbered momentum portfolios is also present, and the annual return difference between winners (M-5) and losers (M-1) is approximately 15.6 percent, although the average illiquidity levels captured in columns $E(L^i)$, $E(A^i)$, and $E(TO^i)$ are not exactly co-correspondent. The varying illiquidity characteristics imply that the portfolios with approximately equal return differentials are not necessarily hoarding similar firms such that the proposed model is not estimated with redundant test portfolios.

Larger per annum gross return differentials are noted for PI (26 percent) and BM (18 percent) portfolios. The lowest return differential is observed for size portfolios (S-1 minus S-5), which still average a substantial 12 percent per annum, importantly with visibly different characteristic patterns than the others. This result reinforces our motivation for sorting portfolios based on five stock characteristics, given the limitations of the Finnish stock market, such that the Lewellen et al. (2010) criticism of the success of asset-pricing models is incorporated to settle numerous related issues. The reported statistics regarding the three illiquidity betas in Table 2 show that the beta risks are a function of the portfolio's illiquidity level and also increase in the portfolio illiquidity.

Furthermore, zero measure based illiquidity betas in Table 2 are monotonically linked with the mean returns of the illiquidity portfolios, with the exception of the commonality risk β^{i2}. Notably, the illiquidity portfolios show substantial monotonic sensitivity to β^{i3}. It may be construed that most important illiquidity risk, to explain cross-sectional variations in the test portfolios, is captured by flight to liquidity risk (Amihud, 2002) when quantified for the Finnish market. The most illiquid portfolio has beta sensitivity of -22.56 for β^{i3}, whereas for L-1 the beta sensitivity is -7.53. The negative sign shows the effect of flight to liquidity, for which the positive shocks to market illiquidity further depress the contemporaneous returns on the illiquid stocks; that is, the illiquidity risk is negatively correlated with the expected stock returns.

The non-responsiveness of the non-illiquidity portfolios to the liquidity risks is also exhibited in Table 2. The illiquidity-related betas for the momentum and BM portfolios do

[20] In Acharya and Pedersen (2005) in Table 1 column $E(r^{e,p})$, the yearly difference between the most illiquid and liquid portfolios is 7.44 percent, which is roughly half the size for the Finnish market. This result also hints that the liquidity compensation is large in respect to the severity of illiquidity in the market.

not have any monotonic sensitivity towards illiquidity beta risks. Because these return differentials are not a function of the level of illiquidity, the liquidity-related betas are also not increasing. We use the beta risks calculated from the whole sample for model estimations, whereas the reported significance t-ratios are from the estimated series of yearly betas across the sample years. In order to get the sampling distribution for the beta risks, we calculate fifteen yearly beta risks across test portfolios for each sample year (1994–2009). Subsequently, we estimate the sample standard errors for each beta risk using the formula $\sigma/\sqrt{T}$, where σ is the standard deviation of the yearly series of beta risks. Small differences are bound to emerge for the small sample at hand. However, the full sample beta values and yearly mean betas converge to similar levels. Furthermore, the means of yearly illiquidity related betas are also increasing across portfolios' illiquidities (results available upon request).

In Table 3, the analyses for model risks are reported with the price impact measure such that the only differences from Table 2 are in the four model beta risks. The reported beta risks show that β^{i3} is not prominently increasing with the mean returns of the illiquidity portfolios. On the other hand, β^{i2} and β^{i4}, in comparison to zero measure based corresponding liquidity betas, are increasing in the anticipated direction across the illiquidity portfolios. Another notable difference is the monotonic relationship between the price impact based illiquidity risks and BM portfolio average returns compared to what we reported in Table 2. The monotonic increases across illiquidity beta risks are such that value stocks show the largest price impact sensitivity compared to all other test portfolios. The price impact sensitivity for BM portfolios is also larger for BM-1, BM-3 compared to the corresponding values for illiquidity portfolios L-1, and L-3 reported under column $E(A^i)$ of Tables 2 and 3.

We also estimated the beta risks for the tranquil period, that is, for the sample period 1996–2007 to compare the performance of illiquidity-related betas and the market beta during different liquidity periods.[21] Moreover, model equation (6) imposes the restriction that the unconditional price of risk associated with all four beta risks remains identical. However, establishing the theoretical separation among the model risks in the empirical estimation of

[21] The estimated beta risks show that the price impact on returns is the least in the calm period. However, the smoothness does not devoid them of the reported monotonicity across portfolio mean returns in the full sample. The zero measure based liquidity is also downsized but not as smooth as observed for the Amihud measure. The calm period estimates for beta risks are not reported and are available upon request.

Table 4 Equally weighted portfolios using zero measure of illiquidity

This Table provides estimates for the illiquidity related betas and market beta using cross-sectional regression analysis for the period of 1994-2009. In panel A we estimate coefficients for all 25 test portfolios using different variants of following relation between excess returns and explanatory factors

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda^1 \beta^{i1} + \lambda^2 \beta^{i2} - \lambda^3 \beta^{i3} - \lambda^4 \beta^{i4} + \lambda \beta^{net,p}$$

where $\beta^{net,p} = \beta^{i1} + \beta^{i2} - \beta^{i3} - \beta^{i4}$, the total of nine models from above relation are estimated .In panel B the cross-section regressions are performed for equally weighted 15 portfolios which are ranked with some illiquidity related characteristics. The *t*-statistics is reported in parentheses and these are with corrected standard deviation using Newey and West (1987) method with two lags. R^2 is obtained for each of the estimated model and adjusted R^2 is reported in parentheses.

	Constant	$E(L^i)$	$\beta^{net,i}$	β^{i1}	β^{i2}	β^{i3}	β^{i4}	R^2
Panel A: equally weighted 25 portfolios:								
1	0.0002	0.0282						0.386
	(0.09)	(5.77)						(0.359)
2	-0.0130		0.0214					0.372
	(-2.29)		(3.91)					(0.345)
3	-0.0092	0.0175	0.0123					0.454
	(-1.08)	(1.69)	(1.19)					(0.404)
4	0.0120			0.0392				0.425
	(-3.93)			(6.56)				(0.400)
5	0.0198				-0.0283			0.047
	(2.12)				(-1.18)			(0.006)
6	0.0008					-0.0756		0.495
	(0.59)					(-7.44)		(0.473)
7	0.0087						-0.0282	0.046
	(7.67)						(-0.83)	(0.005)
8	-0.0047			0.0109	0.0002	-0.0782	0.0347	0.573
	(-0.61)			(0.92)	(0.01)	(-2.93)	(0.99)	(0.487)
9	-0.0230	0.0257		0.0308	0.0203	-0.0067	0.0465	0.620
	(-1.30)	(1.08)		(1.50)	(0.67)	(-0.11)	(1.01)	(0.520)
Panel B: equally weighted 15 illiquidity related portfolios.								
1	0.0008	0.0267						0.530
	(0.50)	(5.64)						(0.493)
2	-0.0206		0.0288					0.819
	(-8.24)		(12.31)					(0.805)
3	-0.0202	0.0009	0.0282					0.819
	(-6.96)	(0.17)	(7.21)					(0.789)
4	-0.0169			0.0482				0.751
	(-6.16)			(10.50)				(0.732)
5	0.0210				-0.0315			0.059
	(1.55)				(-0.91)			(-0.014)
6	0.0001					-0.0823		0.809
	(0.05)					(-7.78)		(0.795)
7	0.0078						-0.0771	0.379
	(9.12)						(-3.55)	(0.332)
8	-0.0131			0.0271	0.0061	-0.0485	-0.0019	0.897
	(-2.19)			(4.13)	(0.51)	(-2.47)	(-0.09)	(0.856)
9	-0.010	-0.0055		0.0228	0.0036	-0.0649	-0.0041	0.898
	(-0.67)	(-0.30)		(1.22)	(0.19)	(-0.98)	(-0.22)	(0.842)

the model is a significant undertaking.[22] The (unreported) correlation patterns among model risks endorse the empirical obscurity confronted in tracing segregated illiquidity risks and, therefore, in testing the implications of the proposed model requiring uncorrelated factor risks in the regression analysis. Nonetheless, Acharya and Pederson (2005) estimated the unconstrained (unequal) premia to track the (theoretically) segregated impact of each risk on the cross-sectional return variations. They acknowledged that the empirical evidence is weak.

Furthermore, they argued that the models isolating for the separate effect of liquidity or liquidity risks can be reinterpreted as providing the overall specification effect. Therefore, the most robust number is the overall model effect given the severe correlation among pre-estimated beta risks. In respect to the high correlations among the model risks, the model with one of the most representative beta risk among all – that is, the one that is most highly correlated with all the remaining risks – could be tested as well. Ideally, the overall model effect should be manifested in net beta risk, i.e., $\beta^{net,i}$. However, due to empirical difficulties in estimating the beta risks, the overall effect may also be manifested through some other channel of beta risk.[23] In order to improve the estimation difficulties of the unconstrained model with four highly correlated beta risks, we also explore the nested model specifications taking only one beta risk at a time, which are not reported in Acharya and Pederson (2005).

We hypothesize that different liquidity-related risks will manifest their ability, if cover non-overlapping information, to explain the cross-sectional return differences with a particular illiquidity measure. A similar conjecture can also be drawn for differences in the

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[22] Generally, the pre-estimated model risks as in equations (7), (8), (9), and (10) are highly correlated among themselves and pose a serious concern in the empirical implications of the model. This collinearity is also conspicuous for the U.S. market, as reported in Acharya and Pederson (2005). In the presence of such collinearity, finding a distinguishable effect on the returns for each beta risk when taken together is difficult. We also estimate the correlation structure across the yearly model risks (as well as the net beta risk; results of which are available upon request) for both the samples and the illiquidity measures. The cross-correlations (with zero measure) are less severe than correlations among beta risks reported in Acharya and Pederson (2005). The correlations among price impact based betas are substantially larger than the zero measure-based risks and akin to the severe correlation structure provided in Acharya and Pederson (2005) using a Amihud measure-based transaction cost proxy. The cross correlations are even higher in the tranquil period. The correlation among zero measure based illiquidity risks with the market risk and net beta risk follows a similar structure, as witnessed for the full sample. Generally, the correlation patterns show that β^{i3} could be as good as a proxy as $\beta^{net,i}$ for its substantial correlation with other beta risks to capture an overall effect of illiquidity. We note that the overall illiquidity effect after $\beta^{net,i}$ may also be proxied by β^{i2} and β^{i4} as implied by the cross-correlations pattern for the price impact measure based beta risks.

[23] We expect that if this is the case, then the overall effect should be better captured through one of the illiquidity risks rather than the market risk for the latter's reported empirical difficulties (Fama & French, 1992, 1993) in explaining different characteristic-based portfolio returns.

monotonicity of illiquidity risks across the illiquidity portfolio mean returns, as reported in Tables 2 and 3.

4.3. Model testing

We proceed with the estimation of the proposed models as in equation (3) to the equally testable model equation:

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda \beta^{net,i} \tag{14}$$

where $\beta^{net,i} = \beta^{i1} + \beta^{i2} - \beta^{i3} - \beta^{i4}$ shows that the net beta $\beta^{net,i}$ is an overall market risk when illiquidity risk is incorporated. The model in equation (3) is expressed in excess returns, which implies that the constant α should be zero. However, we estimate equation (14) by allowing a nonzero constant for robustness. The estimations using zero measure of illiquidity in all 25 test portfolios are reported in Table 4. The success of the model specifications is gauged under a joint criterion of higher cross-sectional R^2 and ability in suppressing pricing errors (cross-sectional intercept).

Using the level of illiquidity only, the cross-sectional regression in line 1 yields the expected positive estimate and insignificant pricing errors. The lower adjusted R^2 could be argued for the low variability in the zero measure based illiquidity levels for PI, momentum, and BM portfolios (see Table 2 under column heading $E(L^i)$). Nonetheless, the significance of the level of illiquidity shows that the portfolio returns are linked to their illiquidity levels. In line 2, the net beta specification also has a positive and significant price of risk. However, the net beta specification yields significantly large pricing errors. The next specification estimates level of illiquidity and net beta simultaneously. The estimation output shows insignificant pricing errors with only a relatively higher R^2 of 0.45 than the results reported in lines 1 and 2. The coefficient on the expected illiquidity is significant at 10 percent, and the coefficient on the net beta is insignificant even though it retains the positive sign. However, the results show, through lines 1 to 3, that a joint criterion of higher R^2 and insignificant pricing errors is not met.

The not too good performance of net beta specification vindicates the empirical difficulties of the model predictions when the ingredient beta risks do not capture the underlying theoretical direction or are not monotonically sizeable across the illiquidity of test

Table 5 Equally weighted portfolios using Amihud (2002) price impact

This Table provides estimates for the illiquidity related betas and market beta using cross-sectional regression analysis for the period of 1994-2009. In panel A we estimate coefficients for all 25 test portfolios using different variants of following relation between excess returns and explanatory factors

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda^1 \beta^{i1} + \lambda^2 \beta^{i2} - \lambda^3 \beta^{i3} - \lambda^4 \beta^{i4} + \lambda \beta^{net,p}$$

where $\beta^{net,p} = \beta^{i1} + \beta^{i2} - \beta^{i3} - \beta^{i4}$, the total of nine models from above relation are estimated .In panel B the cross-section regressions are performed for equally weighted 15 portfolios which are ranked with some illiquidity related characteristics. The *t*-Statistics is reported in parentheses and these are with corrected standard deviation using Newey and West (1987) method with two lags. R^2 is obtained for each of the estimated model and adjusted R^2 is reported in parentheses.

	Constant	$E(L^i)$	$\beta^{net.i}$	β^{i1}	β^{i2}	β^{i3}	β^{i4}	R^2
Panel A: equally weighted 25 portfolios:								
1	0.0061	0.017						0.605
	(7.32)	(6.58)						(0.588)
2	0.0020		0.0083					0.433
	(0.86)		(3.08)					(0.409)
3	0.0085	0.020	-0.0041					0.623
	(5.42)	(3.52)	(-1.55)					(0.586)
4	-0.0120			0.0371				0.425
	(-3.93)			(6.56)				(0.400)
5	0.0077				0.011			0.386
	(9.352)				(2.69)			(0.360)
6	0.0096					0.0008		0.000
	(0.92)					(0.01)		(-0.043)
7	0.0085						-0.0257	0.137
	(8.13)						(-1.76)	(0.100)
8	-0.0091			0.0186	0.0182	-0.0579	0.0430	0.622
	(-1.37)			(2.40)	(3.91)	(-1.54)	(3.23)	(0.547)
9	-0.0029	0.017		0.0029	0.0069	-0.0677	0.0378	0.698
	(-0.48)	(2.87)		(0.28)	(1.58)	(-2.67)	(3.73)	(0.619)
Panel B: equally weighted 15 illiquidity related portfolios.								
1	0.0064	0.017						0.791
	(8.51)	(5.97)						(0.775)
2	-0.0015		0.0131					0.826
	(-0.97)		(8.29)					(0.812)
3	-0.0025	-0.022	0.0147					0.826
	(-0.756)	(-0.31)	(2.68)					(0.797)
4	-0.0169			0.0457				0.751
	(-6.16)			(10.50)				(0.732)
5	0.0071				0.0196			0.780
	(9.15)				(5.88)			(0.763)
6	0.0128					0.0281		0.005
	(1.00)					(0.28)		(-0.072)
7	0.0067						-0.105	0.722
	(8.58)						(-5.10)	(0.701)
8	-0.0126			0.0123	0.0352	-0.120	0.102	0.884
	(-2.23)			(1.74)	(3.12)	(-4.60)	(1.81)	(0.838)
9	-0.0105	0.038		0.0126	0.0071	-0.091	0.191	0.907
	(-2.25)	(1.68)		(1.80)	(0.28)	(-4.70)	(4.01)	(0.855)

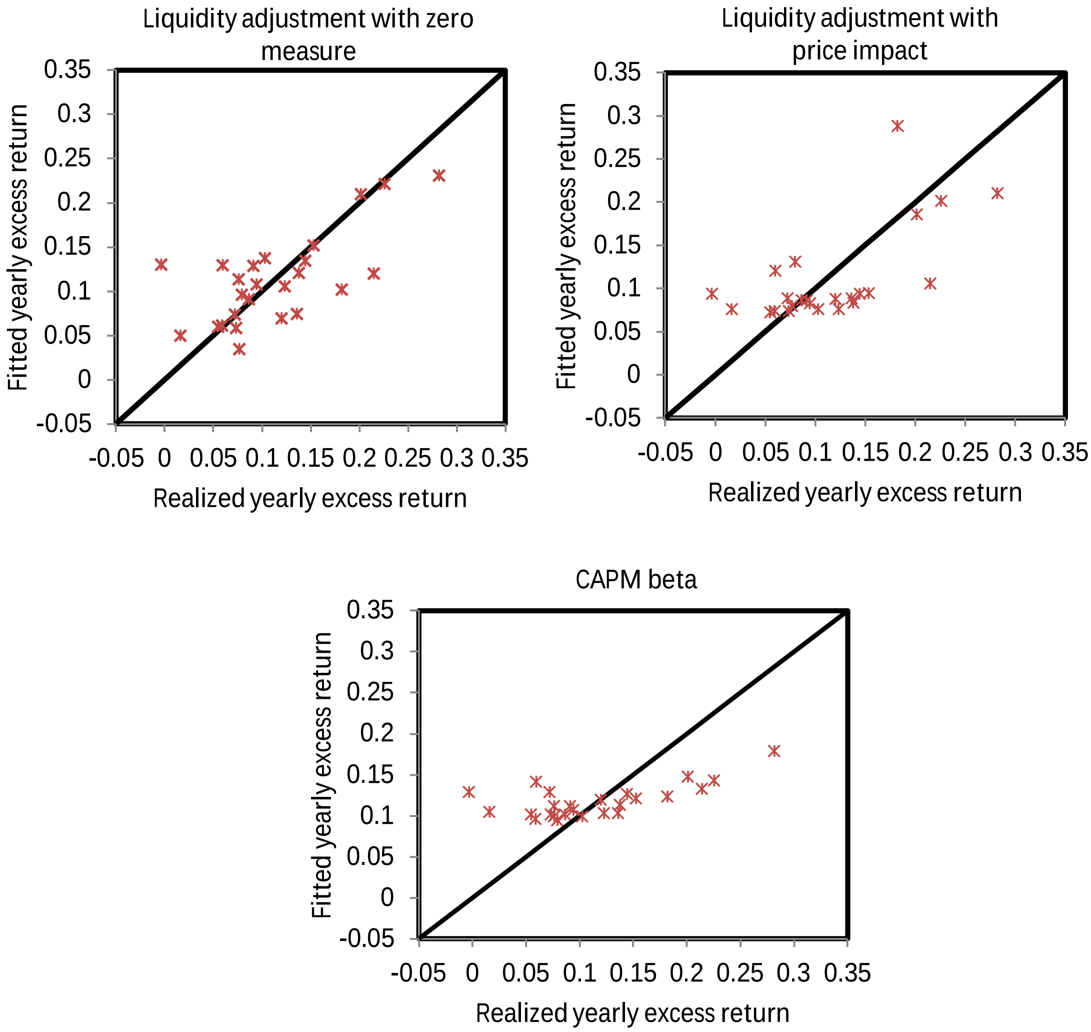

Figure 3. Empirical fit for 25 portfolios: the empirical fit depicted at the top left corner is when a relevant measure of illiquidity is estimated as zero measure, at the right of it is an empirical fit when relevant measure of illiquidity is estimated by Amihud (2002) price impact. Below is empirical fit by CAPM beta. The period of estimation is 1994-2009.

portfolios. The same is argued for the beta risks estimated with zero measure (for example, the commonality effect; see Table 2). Nonetheless, the plausible coefficient estimates on expected illiquidity levels are an improvement on Acharya and Pederson (2005), as the illiquidity level, when allowed to have a free parameter value, was often implausibly estimated in their work.

The price of risk associated with either of the beta risk can also be interpreted to capture the overall model effect, as argued earlier. The individual beta risk specification incorporates the possibility to pinpoint which beta is a more relevant risk in suppressing cross-sectional pricing errors. Therefore, given the highlighted estimation difficulties and the strong correlation patterns among beta risks, we test the following cross-sectional specifications along with the nested single beta representations for the described analysis:

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda^1 \beta^{i1} + \lambda^2 \beta^{i2} - \lambda^3 \beta^{i3} - \lambda^4 \beta^{i4} \qquad (15).$$

In line 4, a CAPM specification is tested and the price of risk associated with β^{i1} is positively significant. The significant model pricing errors over predict the average portfolio returns by 1.20 percent per month, which is substantially large. The price of risk for the commonality effect is expected to be positive. However, we find an insignificantly negative coefficient, which once again highlights the inability of the commonality effect to not account for the particular contemporaneous association between idiosyncratic and aggregate illiquidity shocks. The specification with flight to liquidity risk produces insignificantly small pricing errors. It also yields the highest adjusted R^2 across specifications using only one explanatory variable. The estimated price of risk for β^{i4} is insignificantly theoretical. Acharya and Pedersen (2005) reported that the depressed wealth effect risk has the largest and most significant compensation across all the illiquidity risks for the U.S. stock returns.

The regression in line 8 retains a strong impression for β^{i3}, as in line 6, and is significant even in the presence of other model risks. The model comparison, under the established criteria, suggests that the specification using only flight to liquidity risks performs better than all others. The β^{i3} risk can explain the largest variability in the portfolio mean returns while maintaining the model parsimony with almost similar adjusted R^2 as in lines 8 and 9. In brief, when illiquidity is measured by zero measure, illiquidity risk is best captured through β^{i3} to proxy the overall illiquidity effect in the Finnish market. The result signifies the pervasiveness of illiquidity risk, which is attributed to flight to liquidity, also reported in Vaihekoski (2009) for the Finnish market.

The estimations using price impact measure based illiquidity risks are reported in panel A of Table 5. The results show that the level of illiquidity is significantly related to expected returns with a larger model R^2 than the corresponding zero measure specifications. The increased explanation vindicates the larger variability (information content) in the price impact measured portfolio illiquidity levels in conjunction with expected portfolio returns compared to the zero measure (see column headers $E(L^i)$ and $E(A^i)$ in Table 2 and 3). However, the specification with the expected illiquidity has significant pricing errors and fails on the model success criteria. The net beta specification does not have high model R^2, although it has insignificantly estimated small pricing errors. Using the level of illiquidity along with the net beta deteriorates the model in terms of the significant cross-sectional pricing errors.

The β^{i2} has positive and significant coefficients in the single beta risk specifications. However, the commonality risk alone is not a sufficient risk factor as pricing errors are significant. The flight to liquidity specification cannot replicate the performance it has with zero measure and is neither significant nor plausible. In line 7, the last illiquidity-related risk also has a negatively significant estimate of the price of risk. The performance of the net beta specification, among other single beta specifications, is relatively better under the model selection criterion for suppressing cross-sectional mispricing. The model estimations highlight the key differences in measuring illiquidity between zero measure and price impact through the significance of alternating illiquidity betas to explain expected portfolio returns, as hypothesized earlier.

We graph cross-sectional pricing error plots using the best model specifications, under the employed model performance criteria, for zero measure and price impact measure separately. The predicted returns are the multiple of the selected model price of risk with corresponding time series portfolio beta (as reported in Table 2 and 3). We use line 6 of Table 4 (panel A) for zero measure and the net beta price of risk as in line 2 of Table 5 (panel A) for price impact based model predictions. Similarly, we also plot the standard CAPM specification predictions.

All the selected models use only one explanatory variable; hence, no model is given any statistical advantage. In Figure 3, we provide the empirical fits of the models against actual portfolio returns. The model projections with liquidity adjustment are obviously better than the market beta.[24] The model predictions show that the difference between the actual and predicted yearly average returns is 3.5 percent with zero measure, while with price impact measure, this differential is 3.8 percent. The market model specifications performs the poorest and the differential is alarmingly high, i.e., 14.38%.

The generated plots are the outcome of a stringent test to explain returns on (non-illiquidity) momentum and BM ratio portfolios. Therefore, the average annual differentials

[24] A reason for the out of place empirical fit of CAPM is significant mispricing, as shown in Table 4 and 5 line 4, which is economically equivalent to 1.20 percent of the monthly return off from the target.

between model-predicted and actual returns are encouraging on the part of successful specifications.

4.4. Model testing for illiquidity-related portfolios

Numerous studies report that illiquidity risk matters for asset returns, which are a function of the level of the idiosyncratic illiquidity. Accordingly, we reduce the cross section of twenty five portfolios to fifteen portfolios and test the hypothesis for the Finnish market. All the regressions reported in panel A of Tables 4 and 5 are re-estimated and presented in panel B of the Tables 4 and 5. The estimations with zero measure retain the overall structure of significance or insignificance of particular beta risks and pricing errors, as we have across the specifications in panel A. The notable differences in the panel B specifications include the significance of large pricing errors in line 3, the significant risk premium on net beta in specification in line 3 with significantly large cross-sectional pricing errors, the significance of market risk in line 8 also with significant cross-sectional errors. However, the most striking difference is the larger cross-sectional R^2 values across all the specifications. Importantly, the flight to liquidity risk specification shows greater ability in suppressing the pricing errors (although insignificantly estimated) and obtains a R^2 of 80.90 percent.

In panel B of Table 5, we report that the specification regressions using price impact measure based illiquidity risks. Here again, in line 2, the net beta significantly affects the cross-sectional return variations, although with insignificantly small pricing errors and with an adjusted R^2 of 81.20 percent. In line 3, the specification using the level of illiquidity along with the net beta yields insignificant pricing errors, but the coefficient on expected illiquidity is implausibly estimated and counter-intuitive. Furthermore, the adjusted R^2 in line 3 is actually decreased when compared with only the net beta specification. Generally, individual liquidity risks with price impact measure perform better for illiquidity-related portfolios. The main difference between the estimations reported in panels A compared to those in panels B of Tables 4 and 5 is the larger explanation of cross-sectional variance of the mean returns by the employed specification risks. To highlight this effect, see the model R^2 for the successful specifications in Table 4 and 5 across the panels (line 6 and line 2). The estimations in B panels have approximately 78 percent and 100 percent higher model R^2values to the corresponding R^2 levels in A panels of these tables.

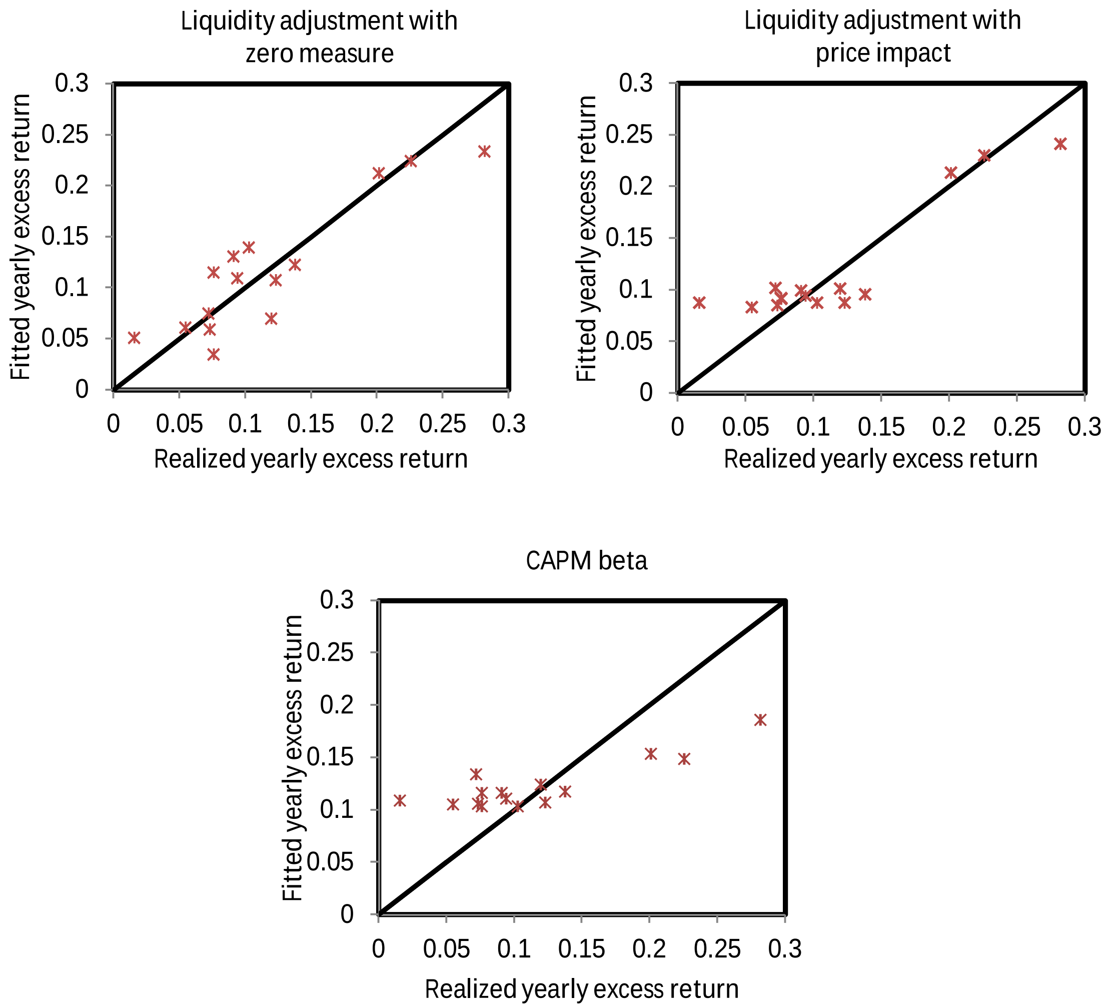

Figure 4. Empirical fit for 15 portfolios: the empirical fit depicted at the top left corner is when a relevant measure of illiquidity is estimated as zero measure, at the right of it is an empirical fit when relevant measure of illiquidity is estimated by Amihud (2002) price impact. Below is empirical fit by CAPM beta. The period of estimation is 1994-2009.

The model predictions, for the return differentials between the most illiquid and liquid portfolios, show that illiquidity risk matters the most for illiquidity-related portfolios. We make use of the most successful price of risk specification across Tables 4 and 5 (panels B). The reported price of risk associated with β^{i3} is -0.0823. Using the flight to liquidity price of risk, a predicted return differential on the most illiquid and illiquid is estimated as:

$$\lambda^3(\beta^{3,L-5} - \beta^{3,L-1})12 = 14.84\%$$

where $(\beta^{3,L-5} - \beta^{3,L-1})$ is the difference between the betas of these two portfolios. The subsequent calculations yield an annualized return differential of 14.84 percent. The prediction is near the yearly difference between realized returns on these portfolios, which is 15.37 percent for the period of 1994–2009.

Table 6 Equally weighted portfolios using zero measure of illiquidity

This Table provides estimates for the illiquidity related betas and market beta using cross-sectional regression analysis for the period of 1996-2007. In this Table we estimate these coefficients for all 15 test portfolios using different variants of following relation between excess returns and explanatory factors

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda^1 \beta^{i1} + \lambda^2 \beta^{i2} - \lambda^3 \beta^{i3} - \lambda^4 \beta^{i4} + \lambda \beta^{net,p}$$

where $\beta^{net,p} = \beta^{ip} + \beta^{2p} - \beta^{3p} - \beta^{4p}$, the total of nine models from above relation is estimated. The *t*-statistics is reported in parentheses and these are with corrected standard deviation using Newey and West (1987) method with two lags. R^2 is obtained for each of the estimated model and adjusted R^2 is reported in parentheses.

	Constant	$E(L^i)$	$\beta^{net.i}$	β^{i1}	β^{i2}	β^{i3}	β^{i4}	R^2
1	0.0060	0.0279						0.561
	(4.47)	(6.85)						(0.527)
2	-0.0132		0.0267					0.839
	(-5.39)		(12.07)					(0.827)
3	-0.0119	0.0042	0.0242					0.844
	(-4.97)	(0.95)	(9.09)					(0.818)
4	-0.0045			0.0402				0.746
	(-2.31)			(10.80)				(0.726)
5	0.0263				-0.0288			0.056
	(1.84)				(-0.84)			(-0.017)
6	0.0041					-0.0770		0.871
	(5.11)					(-18.70)		(0.861)
7	0.0123						-0.0650	0.229
	(13.26)						(-3.17)	(0.170)
8	-0.0017			0.0126	0.0061	-0.0555	-0.0094	0.882
	(-0.21)			(1.29)	(0.37)	(-2.92)	(0.49)	(0.835)
9	0.0051	-0.0113		0.0004	-0.0011	-0.0927	-0.0164	0.889
	(0.30)	(-0.63)		(0.02)	(-0.04)	(-1.51)	(-0.85)	(0.828)

Using our second measure of illiquidity, we repeat the procedure. The price of risk associated with $\beta^{net,i}$, in panel B line 2 of Table 5, is 0.0131. This yields a predicted return differential as:

$$\lambda\ (\beta^{netbeta,L-5} - \beta^{netbeta,L-1})12 = 14.48\%$$

The tested specifications explain almost all the return difference across illiquidity portfolios. Imposing the constancy constraint on the net beta price of risk, we determine which beta best explains the return differentials. To conserve space, we show only the winner component, which is β^{2i} , the commonality in illiquidity. Using the reported net beta specification price of risk, the part coming from commonality effect (while using commonality betas) is calculated:

$$\lambda(\beta^{2,L-5} - \beta^{2,L-1})12 = 11.06\%.$$

Similarly, market beta makes 1.09 percent of the overall return differential, whereas the flight to liquidity explains only 0.15 percent. The remaining difference of 1.34 percent is

Table 7 Equally weighted portfolios using Amihud (2002) price impact

This Table provides estimates for the illiquidity related betas and market beta using cross-sectional regression analysis for the period of 1996-2007. In this Table we estimated these coefficients for all 15 test portfolios using different variants of following relation between excess returns and explanatory factors

$$E(R^i) = \alpha + \psi^i E(C^i) + \lambda^1 \beta^{i1} + \lambda^2 \beta^{i2} - \lambda^3 \beta^{i3} - \lambda^4 \beta^{i4} + \lambda \beta^{net,p}$$

where $\beta^{net,p} = \beta^{ip} + \beta^{2p} - \beta^{3p} - \beta^{4p}$, the total of nine models from above relation is estimated. The *t*-statistics is reported in parentheses and these are with corrected standard deviation using Newey and West (1987) method with two lags. R^2 is obtained for each of the estimated model and adjusted R^2 is reported in parentheses.

	Constant	$E(L^i)$	$\beta^{net.p}$	β^{i1}	β^{i2}	β^{i3}	β^{i4}	R^2
1	0.0113	0.034						0.774
	(16.98)	(7.55)						(0.757)
2	-0.0009		0.0155					0.800
	(-0.66)		(16.17)					(0.784)
3	0.0035	0.014	0.0097					0.819
	(0.88)	(1.26)	(1.87)					(0.788)
4	-0.0045			0.0216				0.746
	(-2.31)			(10.80)				(0.726)
5	0.0121				0.122			0.783
	(17.81)				(7.63)			(0.767)
6	-0.0022					-0.282		0.741
	(-1.25)					(-11.03)		(0.721)
7	0.0122						-0.0852	0.630
	(17.14)						(-6.99)	(0.602)
8	0.0046			0.0044	0.0964	-0.0786	0.0265	0.836
	(1.02)			(0.64)	(1.53)	(-0.89)	(0.72)	(0.771)
9	0.0040	0.024		0.0066	0.0317	-0.0447	0.0376	0.840
	(0.94)	(0.34)		(0.61)	(0.19)	(-0.26)	(0.60)	(0.751)

attributed to β^{4i}. The liquidity risks account for nearly 92 percent of the total model-predicted risk premium and only 8 percent is associated with the market (CAPM) risk. Acharya and Pederson (2005) reported the comparable return differential between the most illiquid and liquid portfolio for the U.S. stock returns as:

$$\lambda \ (\beta^{netbeta,L-25} - \beta^{netbeta,L-1})12 = 6.40\%$$

Of this yearly return differential, the three illiquidity-related betas explain almost 1.10 percent, whereas the market beta explains 5.30 percent. The illiquidity premium accounts for only 17 percent of the model projection compared to 92 percent reported for the Finnish stock market, given the equality of model premia across the beta risks. These results clearly suggest that market-related risk is dominant for the U.S. market, whereas otherwise is true for the Finnish stock returns. The larger liquidity premium rather than market premium shows the importance of accounting for liquidity risk as propagated by numerous theories. Moreover, the evidence also confirms our hypothesis that illiquidity effects can be more pronounced for illiquid markets, even if the markets are developed, as in our case.

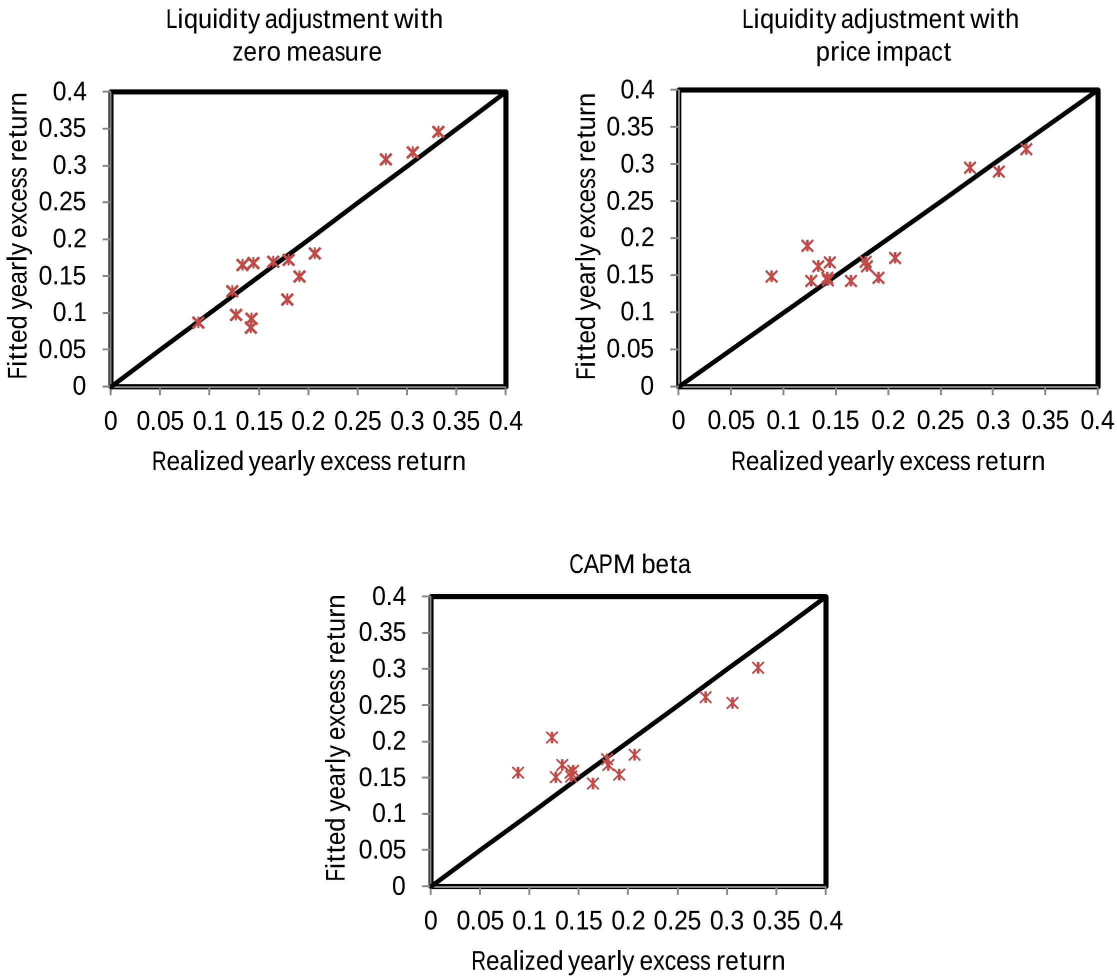

Figure 5. Empirical fit for 15 portfolios: the empirical fit depicted at the top left corner is when a relevant measure of illiquidity is estimated as zero measure, at the right of it is an empirical fit when relevant measure of illiquidity is estimated by Amihud (2002) price impact. Below is empirical fit by CAPM beta. The period of estimation is 1996-2007.

The pricing error plots for the illiquidity portfolio estimations are shown in Figure 4 with the earlier noted specifications (lines 6 and 2 in panel B of Tables 6 and 7 respectively). The graphs show much nicer empirical fits. The difference between the predicted and actual yearly-realized returns decreases compared to the specifications with non-illiquidity test portfolios. The zero measure yields a yearly difference of 2.5 percent, whereas with price impact, the yearly difference is 2.8 percent. The prediction errors are lower by approximately 1 percent per annum across the combination of test portfolios.

4.5 Model testing for 1996–2007

To report the persistence of the illiquidity-related betas across samples, we run the cross-sectional regressions for the sample period spanning from 1996–2007.[25] Table 6 reports the results with zero measure beta risks. The coefficient on expected illiquidity is positive and significant, implying higher expected returns for illiquid assets. Nonetheless, the specification with expected illiquidity fails yet again in suppressing mispricing. The problem of significant pricing errors also undermines the net beta and the net beta along with the level of illiquidity specifications. Other comparable differences than the full sample estimations include the fewer pricing errors equaling -0.45 percent per month for the market model specification and the larger pricing errors from the $\beta^{3,i}$ specification. Moreover, the cross-sectional pricing errors from both the specifications are significant at 1% critical t-values.

The best model in the reduced sample is in line 8, in which all the beta risks are taken together, whereas only β^{3i} is significantly priced. Under the employed model selection criteria, none of the single beta specifications outperform each other on both fronts. However, for possessing the largest adjusted model R^2 values across all specifications and economically, the smallest pricing errors across single beta specification – the flight to liquidity risk – still manage to stand out. Nonetheless, the specification including illiquidity-related betas with market risk reduces the cross-sectional mispricing (insignificantly estimated), although it suffers for using additional degrees of freedom and thus lower adjusted R^2 values.

The results for the price impact based liquidity risks estimations in the tranquil period, reported in Table 7, are similar to what we report in Table 5 panel B. The noted differences include the significance of net beta in line 3 at 10 percent critical t-values, the significance of flight to liquidity risk, and insignificantly estimated pricing errors for the specifications in lines 8 and 9. Moreover, the specifications in lines 8 and 9 do not have any other significant prices for the remaining model risks, whereas all the risk premia are significant at 10 percent or less critical t-values, with the exception of the commonality effect (in line 9 only) in the full period comparable settings.

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[25] As indicated in section 3.2, the Finnish market has a higher price impact and slightly reduced zero returns for 1996–2007. The descriptive behavior of the Finnish aggregate market illiquidities motivated the selection of the reduced sample. We only report the results for illiquidity-related portfolios. The estimations using the cross-section of 25 portfolios are able upon request.

Figure 5 plots the empirical fit of the successful models in the calmer period. Visible improvement is noted in the performance of the CAPM beta compared to the full period. The evidence implies that a CAPM beta may be a better candidate for explaining return variations in illiquidity portfolios in calmer periods rather than periods involving high illiquidity. The improvement is such that the average annualized difference between the model-predicted returns and the realized returns is 5.41 percent. The lower prediction errors are a substantial drop from the annualized difference of 20 percent in the whole sample for the illiquidity portfolios. The annualized difference with the illiquidity adjustment, from both measures of illiquidity, is 2.5 percent, and, on average, is similar for the 15 illiquidity test portfolios across the samples.

Nevertheless, illiquidity risks still have explanatory power above the market beta in the reduced sample period and are more visible through price impact measure based model projections. To highlight the improvement, we also check for the relative contribution of the liquidity effect in the total model risk premium in the calm period by price impact measure:

$$E(R^i) = \alpha + \lambda^{i1}\beta^{i1} + \lambda\beta^{net,p} \tag{16}$$

We do not control for illiquidity level as we intend to compare price of risk for liquidity risks and for market beta. The estimation of equation (16) yields the following results:

$$E(R^i) = 0.002 - 0.014\beta^{i1} + 0.025\beta^{net,p} \tag{17}$$

In equation (17), pricing errors are insignificantly small and the price of risk associated with the net beta is significant with Newey and West (1987) corrected standard errors at the 10 percent level, whereas the corresponding market beta is insignificant. The negative risk premium associated with the market beta does not mean that risk is negative and is exemplified, similar to Acharya and Pederson (2005), as:

$$E(R^i) = 0.002 + 0.011\beta^{i1} + 0.025(\beta^{i2} - \beta^{i3} - \beta^{i4}).$$

The negative sign on market premia indicates that, under the model assumptions, a greater risk premium is associated with illiquidity beta risks. This evidence highlights the importance of liquidity adjustment in the static CAPM. The annualized difference between the illiquid portfolio, L-5, and the liquid portfolio L-1 returns is 18.29 percent for the sample period from 1996–2007. Using the price of risk associated with the net beta as shown at line 2 of Table 7, the model-predicted annualized return differential is 10.32 percent. Although the model prediction is not as precise as reported for the full period, we focus on the proportional part coming from illiquidity-related risks rather than market risks, while maintaining *ceteris paribus*.

The calculations show that market-related risk explains 4.34 percent of the annual return differential out of the total model prediction, and the remaining model risk premium is associated with the illiquidity-related risks. The proportional illiquidity effect is not as substantial as reported in the full period; yet it accounts for approximately 60 percent of the model-predicted risk premium. The evidence highlights time variation in illiquidity premia. However, illiquidity-related risks are more important than market risks, regardless of the market conditions, and constitute a major part of the model-projected risk premium. Arguably, if the sample includes the illiquidity period, then illiquidity risk compensation is enough to make the whole model risk premium (approximately).

The estimations display the overall model effect is captured through net beta specification using price impact measure illiquidity risks, whereas zero measure based flight to liquidity risk specification performs equally good. Moreover, the results show that the sensitivity of expected returns across the price impact illiquidity risks compared to zero measure illiquidity risks is more often theoretical. The whole impact of illiquidity risk is thus manifested through net beta. The model restriction of the equality of premium is also met strongly in estimations using the price impact measure based illiquidity risks when tested with a Wald test (results available upon request). However, the restriction is more often rejected for estimations with zero measure beta risks. Finally, the main evidence is the sizeable pricing of illiquidity premium for the Finnish market, even if we cautiously assume no change to illiquidity across the samples.

5. Conclusions

In this paper, we simplify the liquidity-adjusted model by Acharya and Pedersen (2005) to determine asset prices and account for the total cost of trade in a single period equilibrium model. The liquidity-adjusted model is purposefully tested for the Finnish stock market. We emphasize the testing to show the higher relevance of illiquidity-related theories and models to comparably more illiquid stock markets, rather than the standard practice of testing for the most liquid U.S. market. The liquidity adjustment in the model is incorporated through two different measures to proxy transaction costs. The selection of two separate illiquidity measures is employed to analyze if the effect of illiquidity on asset pricing is captured any differently via a particular measure. We show that proxy measures capture asset illiquidity while checking the key illiquidity characteristics of firm size, turnover, and PI ratio following Demsetz (1968), Datar et al. (1998), and Brennan and Subrahmanyam (1996), among others.

The central finding of the paper is the substantial risk premium related to illiquidity risks for Finnish stocks (92 percent in full periods and 60 percent in calm periods) in the total model risk premium. The illiquidity premium is far larger than the reported illiquidity premium (17 percent) in the U.S. market as inferred from a comparable study (Acharya & Pederson, 2005). The remaining empirical evidence can be divided into three parts. First, the estimations using the illiquidity measures show that different model (illiquidity) risks are important to explaining variations in expected returns and in reducing model mispricing across samples. Therefore, we argue that the empirical significance of depressed wealth effect in Acharya and Pederson (2005) is more of a dimensional effect than the systematic wholesomeness of the risk, given the non-availability of exacting illiquidity proxies that cover all aspects of concept liquidity. Nonetheless, the altering ability of illiquidity risks across specifications does not undermine the performance of the illiquidity measures in capturing the overall effect of illiquidity. Second, time variation in the illiquidity premium is documented in the samples, which include and exclude illiquid periods. Third, liquidity-adjusted CAPM performs remarkably better in comparison to the simple CAPM specifications across the samples, including and excluding illiquidity periods. We suggest that the illiquidity premium across the stock markets (both developed and emerging) should be quantified for further generalizations.

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