PRICING OF LIQUIDITY RISK: EMPIRICAL EVIDENCE FROM FINLAND

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ABSTRACT

In this study, we investigate the pricing of the liquidity risk in the Finnish stock market using conditional asset pricing models. The estimation is conducted using a modified version of the multivariate GARCH framework of De Santis and Gérard (1998). We test the model using different liquidity risk measures. Our main measure is the value-weighted market-wide bid-ask spread. In addition, we utilize a measure for the trading turnover and the return difference between portfolios of high and low liquidity. The measures have been constructed especially for this study. The results show … (work in process)

Keywords: Conditional asset pricing, liquidity risk, trading volume, bid-ask spread, Finland, Helsinki Stock Exchange

JEL Codes: G12, G14

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1. INTRODUCTION

A key function of securities market is to enable traders to execute orders promptly and smoothly, while keeping the transaction costs low. That is, markets must provide liquidity. However, all markets share periods of lower and higher liquidity, but the benefits of asset diversification or investment regulation requires investors to participate also in markets with lower liquidity. This reveals investors to the liquidity-risk: a risk of being unable to buy or sell assets at the market price at the desired time.

Several studies have studied the volume-price relationship and in particular the effect of the changing liquidity on the pricing of the stocks. Amihud and Mendelson (1986, 1989) found support for the pricing of the liquidity factor measured as the bid-ask spread. Brennan and Subrahmanyam (1996) find a significant relation between required rates of return and their measure of illiquidity after adjusting for Fama and French (1992) risk factors. In addition, several researchers (e.g., Jain and Joh, 1988) have also found evidence of a connection between trading volume and seasonal anomalies in stock returns. Eleswarapu and Reinganum (1993), however, do not find a positive liquidity premium for the non-January months. Gibson and Mougeot (2003) study the pricing of systematic liquidity risk using monthly number of traded shares as a proxy for the liquidity risk.

However, there are still many aspects that need further investigation. First, earlier studies have used mainly unconditional analysis. In this study we investigate the pricing of the liquidity risk using a conditional version of the intertemporal asset pricing model. Second, prior studies use mainly data from large markets where the trading volumes are relatively stable. However, many small and/or emerging stock markets have several unique features. Small stock markets often exhibit large variation in liquidity over time and across companies. Third, there are several definitions for the liquidity and thus the proxies in empirical research have differed across studies. Earlier studies have often used either the number of shares traded, or the trading volume as a proxy for the systematic market-wide liquidity risk. Other studies have used asset specific bid-ask spreads.

In this study we compare and analyze initially five different measures for the liquidity risk. For our asset pricing tests we select the value-weighted market-wide bid-ask spread. It has been constructed especially for this study. In addition, we also utilize liquidity risk factor construction employed e.g. by Fama and French (1992) and trade-weighted average trading volume measure.

We use monthly market and size portfolio data from the Helsinki Stock Exchange (HSE) from 1987 to 2000. The portfolios are also constructed following the guidelines in Vaihekoski (2004). The HSE offers an excellent test laboratory, since it has been referred frequently thinly traded and illiquid market but at the same time the trading volumes have varied considerable over the years.[1] As a test methodology we utilize a modified version of De Santis and Gérard (1998) approach.

There are only a few Finnish studies of the relationship between trading volume and stock returns. Nummelin (1997) uses the change in the market trading volume as an additional source of risk in the three-moment CAPM. Using constant beta approach, he finds that the liquidity does not offer incremental power to explain the return series in the three-moment CAPM. Berglund and Liljeblom (1990) study the impact of trading volume on stock return distributions. They find the trading volume significant factor affecting the stock volatility and other moments. Martikainen et *al.* (1994) find a bi-directional causality between the aggregated share units trading level and market return, where lagged values of volume predict future returns and visa versa. Vaihekoski (2000) tests an unconditional two-factor model where liquidity is proxied with the trading volume. He finds strong support for the pricing of the liquidity risk using size portfolios.

The remainder of this paper is organized as follows. In section 2 we present the theoretical background together with the empirical model and some discussions on the econometric problems. The data and alternative proxies for the liquidity risk are discussed in section 3. Results are presented in section 4 together with some diagnostic tests for the robustness of the results. The final section offers the conclusions and some suggestions for further research.

2. RESEARCH METHODOLOGY

2.1 Theoretical Background

The literature related to volume-price relationship has grown voluminous under the recent years.[2] One reasons for this is certainly the realization that variation in trading volume can offer additional insight into all sides market structure and functionality. In particular, volume can reveal

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[1] The trading turnover reached all time high FIM 31.7 billion (approx. USD 6 billion) in 1989 after which is started to decline until it hit the bottom of FIM 6.3 billion (USD 1.2 billion) in 1991. After 1992, the stock prices started to raise and together with the enormous success of Nokia corporation, the trading turnover reached all-time high FIM 186 billion (USD 34 billion) in 1998.

[2] Good surveys of the area are given, among other, in Baker (1996) and Karpoff (1987).

how the information flows to the market, how the information is disseminated, how market structure affects volume, and how asset prices are affected by the trading volume or liquidity, as studied here.

Earlier studies concentrated mainly on empirical price-volume relation. More recently the theoretical work has also tried to explain the price-volume relation. Morgan suggested even as early as 1976 that volume is associated with the systematic risk. However, Amihud and Mendelson (1986) were one of the first ones to suggest a theoretical explanation, where volume appears as additional risk factor.[3] Their model suggests that asset returns decrease with their liquidity. In their model, assets have different transaction costs and investors have different trading frequencies. Their model suggests a 'trading frequency hypothesis' together with the assumption that the trading frequency is related to observed trading volume imply that the cross-sectional expected return is concave function of liquidity and time-series expected return is an increasing function of turnover.

Merton (1987) proposed an extension of the CAPM, where the assumption of equal information across investors is relaxed. According to his model asset returns are affected, among others, by the fraction of all investors who buy the asset (Merton calls this as the degree of investor recognition) reflecting the investor public availability of information about the asset. Since the investor recognition and liquidity are likely to be related (c.f., Kadlec and McConnell, 1994), the model implies that asset returns should be a decreasing function of liquidity.

The discrete time equilibrium *K*-factor conditional intertemporal capital asset pricing model (ICAPM) can be written in general excess-return form as

$$E\left[r_{it}\middle|\Omega_{t-1}\right] = E\left[\mathbf{f}_t\middle|\Omega_{t-1}\right]\boldsymbol{\beta}_{it}\left(\Omega_{t-1}\right) \tag{1}$$

where the $\mathrm{E}[r_{it}|\boldsymbol{\Omega}_{t-1}]$ is the conditional expected excess return on asset *i*, $\boldsymbol{\beta}_{it}(\boldsymbol{\Omega}_{t-1})$ is a $1\times K$-matrix of conditional betas (or risk-sensitivities) defined as $\mathrm{Cov}_{t-1}(r_{it}, \mathbf{f}_t)\mathrm{Var}_{t-1}(\mathbf{f}_t)^{-1}$ for asset *i* with the risk factors, and $\mathrm{E}[\mathbf{f}_t|\boldsymbol{\Omega}_{t-1}]$ is a $1\times K$-matrix of conditional expected risk-factor premiums, all conditional on the information $\boldsymbol{\Omega}_{t-1}$ available on time. All returns are in excess of the local risk-free rate of return r_{ft-1}.

[3] See also Kane (1994).

Equation (1) can be rewritten using the price of risk formulation as follows

$$E_{t-1}\left[r_{it}\right] = Cov_{t-1}\left(r_{it}, \mathbf{f}_t\right)\boldsymbol{\lambda}_t' \tag{2}$$

where $E_{t-1}[r_{it}]$ is the conditional expected excess return on asset *i*, $Cov_t(\cdot)$ is short-hand notation for the conditional covariance operator, $\mathbf{f_t}$ is a *K*-vector of risk factor expectations, and $\boldsymbol{\lambda_t}$ is a *K*-vector of conditional reward-to-risk measures. All parameters and operators are conditional on information Ω_{t-1} available on time *t*-1.

If we consider the liquidity risk as the second source of risk following the discussion earlier, the ICAPM model becomes a two-factor model. Now we can write the expected excess return for asset *i* for month *t* as

$$E_{t-1}\left[r_{it}\right] = \lambda_{mt} Cov_{t-1}\left(r_{it}, r_{mt}\right) + \lambda_{lt} Cov_{t-1}\left(r_{it}, LIQ_t\right) \tag{3}$$

where λ_{mt} is the conditional price of market risk and λ_{lt} is the conditional price of liquidity risk. LIQ_t is our measure of liquidity risk. Price of market risk measures the compensation the representative investor must receive for a unit increase in the variance of the market return (see Merton, 1980). Price of liquidity risk measures the compensation investors require for the liquidity risk.

Since the market portfolio is also a tradable asset, the model gives the following restriction for the expected excess market return

$$E_{t-1}\left[r_{mt}\right] = \lambda_{mt} Var_{t-1}\left(r_{mt}\right) + \lambda_{lt} Cov_{t-1}\left(r_{mt}, LIQ_t\right) \tag{4}$$

where $Var_{t-1}(\cdot)$ is short-hand notation for the conditional variance operator.

2.2 Empirical Model

The empirical testing of the model (5) encounters two problems. First, we have to select a model for the conditional expectations. Second, we have to select a proxy for the liquidity risk. Here we utilize the framework of De Santis and Gérard (1998).[4] They use a multivariate GARCH-in-Mean-approach to model the conditional expectations, covariances, and variances. For the liquidity risk factor, we use five different proxies. Namely, the number of shares traded, the trading volume, value-weighted market bid-ask spread, and finally the high-minus-low liquidity portfolio risk premium.

The empirical model for equation (5) is the following:

$$r_{m,t+1} = \lambda_{m,t+1} h_{t+1}^{m} + \lambda_{l,t+1} h_{t+1}^{m,l} + e_{m,t+1} \tag{5}$$

$$r_{l,t+1} = \mu_l + e_{l,t+1} \tag{6}$$

$$\boldsymbol{\varepsilon}_{t+1} \sim \text{IID}(\mathbf{0}, \boldsymbol{H}_{t+1}).$$

where r_m and r_l are the realized excess market return and the change in the liquidity measere, respectively. Lambdas are the conditional prices of risk and $\boldsymbol{\varepsilon}_{t+1}$ is a 2×1 vector of stacked innovations, i.e., $\boldsymbol{\varepsilon}_{\mathbf{t+1}} = [e_{m,t+1}\ e_{l,t+1}]'$. $\boldsymbol{H}_{t+1}$ is the variance-covariance matrix.

If we use the high-minus-low liquidity portfolio risk premium as our proxy for the liquidity risk, we can use the following specification for the premium instead of equation (6)

$$r_{l,t+1} = \lambda_{m,t+1} h_{t+1}^{m,l} + \lambda_{l,t+1} h_{t+1}^{l} + e_{l,t+1} \tag{7}$$

since this proxy is a tradable asset.

There are several alternatives to specify the two-variate covariance process of $\boldsymbol{\varepsilon}_{t+1}$. Financial returns often exhibit features like clustering, time-variation and non-normality. Variance-covariance specifications in the family of (Generalized) Autoregressive Conditional Heteroskedasticity (henceforth GARCH) capture these features. The drawback of the first multivariate extension by Bollerslev et al. (1988) is the large number of parameters to estimate, the difficulties to obtain a stationary covariance process and the problems to get a positive-

[4] The estimation is conducted using a Gauss program originally written by Bruno Gerard. Modifications to the original program are made by the authors.

definite (co)variance matrix. Many of these problems are circumvented by the BEKK (Baba, Engle, Kraft and Kroner) parameterization proposed by Engle and Kroner (1995):

$$\mathbf{H}_{t+1} = \mathbf{C}'\mathbf{C} + \mathbf{A}'\boldsymbol{\varepsilon}_t\boldsymbol{\varepsilon}'_t\mathbf{A} + \mathbf{B}'\mathbf{H}_t\mathbf{B}, \tag{8}$$

where the matrices can be written as follows for the bivariate case

$$\mathbf{C} = \begin{bmatrix} c_{11} & c_{12} \\ 0 & c_{22} \end{bmatrix}, \ \mathbf{A} = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}, \text{ and } \mathbf{B} = \begin{bmatrix} b_{11} & b_{12} \\ b_{21} & b_{22} \end{bmatrix}. \tag{9}$$

While specification (8) allows for rich dynamics and a positive-definite covariance matrix, the number of parameters still grows fairly large in higher-dimensional systems. Therefore, parameter restrictions are often imposed, for example diagonality or symmetricity restrictions. In order to simplify the estimation process, we adopt the covariance stationary specification of Ding and Engle (1994):

$$\boldsymbol{H}_{t+1} = H_0 \times (ii' - \boldsymbol{aa}' - \boldsymbol{bb}') + \boldsymbol{aa}' \times \varepsilon_t\varepsilon'_t + \boldsymbol{bb}' \times H_t, \tag{10}$$

where $\boldsymbol{a}$ and $\boldsymbol{b}$ contain the diagonal elements of $\boldsymbol{A}$ and $\boldsymbol{B}$, respectively. $\boldsymbol{H}_0$ the unconditional variance-covariance matrix.

The parameters are estimated by maximum likelihood. Assuming conditional normality, and defining the residuals from equations (5)–(6), and $\boldsymbol{H}_{t+1}$ as specified in equation (10), the model yields the following time *t* log likelihood function (omitting the constant):

$$\ln L_t = -\frac{1}{2}\ln|\mathbf{H}_t| - \frac{1}{2}e_t'\mathbf{H}_t^{-1}\mathbf{e}_t. \tag{11}$$

Although asset returns are often non-normal, we choose the normal distribution. However, we use the quasi-maximum likelihood (QML) approach of Bollerslev and Wooldridge (1992) to calculate the standard errors. Given that the conditional mean and conditional variance are correctly specified, QML yields consistent and asymptotically normally distributed parameter estimates. Further, robust Wald statistics can straightforwardly be computed. We use the Berndt-Hall-Hall-Hausman (BHHH, 1974) algorithm for the optimization.

We can also assume following earlier studies that the prices of risks are time-varying. A commonly used approach is to model the price of risk as a linear function of conditioning information variables. This implies the following formulation for the price of liquidity risk:

$$\lambda_{l,t+1} = Z_t \kappa_l , \tag{12}$$

where $\mathbf{Z}_t$ is an ($1 \times L$) data vector for the information variables at t, $\boldsymbol{\kappa}_l$ is a vector of linear regression coefficients, and L is the number of information variables, including the constant. We can use the same formulation for the market risk, but if we wish the price of market risk to be positive, one often uses the following formulation instead of (12):

$$\lambda_{mt+1} = \exp(Z_{t-1}\kappa_m) \tag{13}$$

If the conditioning information variables approach is used, we have to decide the variables that are used to model the time-variation in the price of risk. In addition, we have to decide if we want to use the same information for the market and liquidity price of risk. Unfortunately, there is still no consensus on the metric to use in selecting between the variables and models. Simply maximizing the explanatory power of the model and variables raises the question of data mining. In addition, that approach is bound to be theoretically questionable and econometrically difficult to implement. The question of selecting the right information variables is even more problematic. In general, the question of relevant information variables should be addressed by economic reasoning. In practice, one hopes to select theoretically justified variables that are also able to capture at least a part of the predictability in the prices of risk.

3. DATA

Our estimation period covers 168 months of data from January 1987 to December 2000. The beginning of the sample was selected due to the availability of risk-free return series for Finland. During the sample period several steps were taken in Finland to increase the trading volumes and liquidity in the market. The first one was the abolishment of the stamp tax (1.6 percent) on trades from the beginning of November, 1992. Another step was taken in the beginning of 1993 when all restrictions on foreign ownership were abolished. At the same time the taxation of all capital income was harmonized in Finland (see Vaihekoski, 1997, for details).

We use continuously compounded excess asset returns throughout, since these returns more accurately describe price changes during a volatile time period. Risk-free return is calculated as the one-month holding period return on the one-month Euribor (Helibor for pre-1998 period) interbank money market rate on the last trading day of month t–1. [5] All returns in estimations are in percentage – not decimal – form so that they are more convenient to report.

3.1 Liquidity Risk Factor

A number of proxies for the liquidity measures have been proposed in the literature (see, e.g., Amihud, 2002; Hasbrouck, 2005). A common understanding is that there is no single theoretically correct measure that would reflect all sides of the liquidity (Groth and Dubofsky, 1992; Berstein, 1987). The most often used measures are based either on the bid-ask spreads or the trading volume. In this study, we consider initially five different proxies in the estimation partly to compare the results.

Our first proxy is the value-weighted average of the companies bid-ask spread at the end of the month (*BASpread*). This series have been created specially for this study and is the main liquidity measure in this study. However, the bid-ask spread is not without problems. Laux (1993) argues that the bid-ask is insensitive to trade size. Huang and Stoll (1996) argue that the spread data is empirically quite poor measure the actual transaction cost. Lee (1993) point out that many large trades occur outside the spread and many small trades within the spread. Furthermore, Chen and Kan (1989) find the spread-return relation sensitive to the estimation method.

Our second and third proxies are the total number of shares traded (*TNST*) and the value of the trading volume (*TVOL*) during a month. They are commonly used measures since they are both readily available. Gibson and Mougeot (2003) support the former measure. They argue that the bid-ask spread is more appropriate for short-horizon analysis whereas the number of shares traded is a better measure of the long horizon liquidity shocks. Furthermore, empirical evidence have shown that there is a connection between the number of shares traded and the aggregate inventory risk (Chordia et al., 2000).

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[5] The one-month risk-free rate is changed to continuously compounded using the following equation: $ln(1 + r \times$ (number of days between month-end observations)/360).

However, both measures have the drawback that they does not take into account appropriate the changes in the number of listed companies or in the market values of the companies. To see this, let us assume that there are two time periods 0 and 1. During periods 0, there is only one company X with market value and trading volume 100 shares or units of currency. Company Y with market value 50 becomes listed in the beginning of period 1, but no actual trading occurs with its shares. The traditional measure does not see any change in the liquidity in from period 0 to 1, even though the market on average is clearly less liquid, since there are two companies one of which is liquid and another one which is not liquid.

To circumvent this problem, we define an alternative value-weighted measure of the average trading volume (*VWTVOL*) which is the fourth measure used in this study. Volume is first calculated for every stock series as the number of shares times the last transaction price and summed over the days of the month to get the monthly series.[6] After this we calculate the value-weighted average of the series to get our market-wide liquidity measure using the following equation

$$VWTVOL_t = \frac{\sum_{i=1}^{N} MV_{it} Vol_{it}}{\sum_{i=1}^{N} MV_{it}} \tag{14}$$

where MV_{it} is the market value of the company i at the end of month t, Vol_{it} is the trading volume of the company i during month t, and N is the number of companies listed at the end of month t. Here the trading This measure take into account the changes in the market values.[7]

There is also another weakness in the traditional trading volume based liquidity measures that is circumvented with the use of *VWTVOL*. They cannot compare states where trading varies between companies with different market values. If there are two companies X and Y with market values, say, 100 and 50, it makes a difference whether the trading occurs on the stocks of company X or Y. If the trading is one hundred units during both periods 0 and 1, but in the first period the trading occurs only in company X and in the second period only in company Y, the traditional volume based measures would show unchanged liquidity. The value-weighted measure (14), however, would show a reduction of 33 percent in liquidity, which reflects that the trading in company X is more important for the whole market's liquidity.

[6] A similar measure using number of shares traded could also be constructed.

[7] For example, in the previous example, this new measure would give a negative effect of 33 percent on the liquidity, which reflects the change in the market value relative to the trading volume.

Our fifth and last liquidity risk proxy is the created similarly to Fama and French (1993), namely calculating the risk premium for a portfolio including the most liquid listed companies over a portfolio of the most illiquid companies, i.e., high-minus-low liquidity portfolio (*HMLLiq*). Three portfolios are formed using the guidelines in Vaihekoski (2004). Companies are ranked each month to one of the companies on the basis of their percentage bid-ask spread at the end of the month. Portfolio returns are the value-weighted average of the companies in the group. Weights are market value of the company (sum of the market value of the listed shares) during the end of the previous month and they are updated monthly. Companies are included in the portfolios as soon as the (lagged) market value is available until the one period before they are removed from the exchange list. Stock returns are the logarithmic difference in using last transaction prices.

The time series for the first four measures can be seen from Figure 1. The effect of the economic recession in the early 1990s on the liquidity can be clearly seen from the Figure. All measures show lower liquidity. For example, the average bid-ask spread increased from approximately two percent to more than five percent. Similarly, all measures show higher liquidity in the late 1990s following the strong bull market.

The summary statistics for the liquidity measures (*HMLLiq* is missing at the moment) are given in Panel A in Table 1. The mean bid-ask spread has been 2.1 percent during the sample period. All series show evidence of non-normality and high autocorrelation. Panel B in Table 1 presents the correlation matrix of the liquidity risk factor proxies. The bid-ask spread series show negative correlation with the other series since the higher trading volume, the lower bid-ask spread. The magnitude of the correlation is clearly lower than what the other series have with each other. This suggests that the bid-ask spread based liquidity measures and the trading volume based measures are not complete substitutes. On the other hand, the volume-based variables high correlation. As a results, for closer empirical analysis, we choose two measures: variables: *BASpread* and *VWTVOL*.

3.2 Market Risk Factor and Test Assets

We test the asset pricing model using local risk factor. It acts also a test asset in the estimation. The local market portfolio return is proxied by the return on the HEX-index obtained from the

Helsinki Stock Exchange.[8] It is value-weighted, adjusted for splits and issues, and includes (gross) dividends All returns are calculated as the difference in the logarithms of the relevant index and in excess of continuously compounded risk-free rate, which is calculated from the 1-month Helibor-rate (prior to 1998; Euribor used after 1998).

Using aggregate market index, however, one naturally looses some of the cross-sectional variation in the stocks' behavior. Therefore, we test the model also using size portfolios. The portfolios are constructed from the stocks listed on the Main List of the Helsinki Stock Exchange (HEX) between January 1987 and December 2000. Size portfolios are created sorting listed companies every month according to their market value during the end of the previous month to six groups. Portfolio returns are the value-weighted average of the companies in the group. Weights are market value of the company (sum of the market value of the listed shares) during the end of the previous month and they are updated monthly. Companies are included in the portfolios as soon as the (lagged) market value is available until the one period before they are removed from the exchange list. Stock returns are the logarithmic difference in using last transaction prices. For more information see Vaihekoski (2004).

The summary statistics for the market portfolio and the size portfolios are given in Table 2. Mean and standard deviation have been annualized by multiplying with 12 and square root of 12, respectively. The Finnish market index shows an average of 19.9 percent annual continuously compounded return with an annual standard deviation of 26.3 percent. Realized returns have thus been quite high during the sample period, but so has the volatility. The HEX index shows surprisingly high first order autocorrelation coefficient (0.246). It is clearly higher what has been observed in more mature markets (typically less than 0.1). The autocorrelation also shows surprisingly high persistence (or predictability) if tested using Q(12) test statistic (not reported). This could be driven by infrequent trading.

We can also see that Finnish size portfolios show, contrary to the US findings, that the mean realized return is generally lower for the smaller companies. This is probably due to the recession in the Finnish economy in the early 1990s, which seems to have hit the small companies more

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8 Since the HEX-index is not available prior to 1990, the WI-index is used instead. Both indexes are value-weighted and corrected for cash dividends, splits, stock dividends and new issues. The main difference between the WI-index and the HEX-index is how the dividends are handled. In the WI-index the dividends are reinvested to the particular stock, whereas in the HEX-index the dividends are reinvested in the market. Other smaller differences include, among others,. what price is used when no transaction price is available (See Berglund et. *al.*, 1983).

severely than larger companies since smaller firms are typically more dependent on the success of the domestic markets.

Most assets' returns show evidence of non-normality. The Bera-Jarque test for the normality rejects the null hypothesis of normal distribution for five out of six size portfolios. Furthermore, there is evidence of significant first and in one case even third-order serial correlation in the portfolio returns. Panel B shows the cross-correlation matrix for the market and portfolio returns. As expected, the largest size portfolio exhibits the highest cross-correlation with the market index (0.969). Size portfolios exhibit in general higher cross-correlations with each other as one would expect.

3.3 Information variables

The selection of the information variables to model the variation in the prices of risks is always problematic. Naturally, the variables given by the theory are the most prominent choices. They should also be easily observable and available before the investment period. However, the amount of the variables cannot be too large, since redundant variables could reduce the power of the tests and deteriorate small sample properties of the ML estimation. On the other hand, the omission of right conditioning information can lead to erroneous conclusions regarding the conditional mean-variance efficiency of a portfolio (Hansen and Richard, 1987).

The time-aggregation level and the availability of data also limit plausible alternatives. A more frequent data usually gives fewer alternatives (e.g., more frequent than monthly data practically causes one to exclude economic variables from the study). Thus, the choice of the variables also depends partly what are the objectives of the information variables and what risk factors are used.

For the time-varying price of market risk, we select variables that has been used earlier in similar studies in Finland (see, e.g., Nummelin and Vaihekoski, 2002; Antell and Vaihekoski, 2006). The selected variables are a constant, lagged market return, a measure of term structure, a measure of market integration and devaluation expectations, and a January dummy. For the time-varying price of liquidity risk, the selected variables should reflect the value of liquidity. Liquidity is *a priori* more valuables during recessions and when the stock market shows negative development. To keep the system manageable, we select only two variables: lagged market return and lagged trading volume (TVOL).[9]

$R_{m,t-1}$ is the lagged equity market return. It is selected following previous studies (see, e.g., Evans, 1994). Theoretically, past returns are the first reasonable prediction of the expected returns if expected returns follow some kind of autoregressive process. Table 3 shows that realized market returns exhibit high degree of first-order serial correlation, which is well known by the market participants. In addition, market returns should reflect investors expectations of future economic development which could be reflected into the price of liquidity risk.

SD_{t-1} is a measure of the interest rate term premia (yield spread), where the term premia is proxied by the difference between one and twelve month Euribor/Helibor rates. It can be shown that the yield spread is related to the expected interest rate changes and to the long bond returns. It has been found to be a significant predictor of the stock returns for example by Campbell (1987). The term structure also contains information of the expected inflation, economic growth and economic activity (see Estrella and Hardouvelis, 1991).

$IRDIFF_{t-1}$ is a proxy for the money market integration between Finland and central Europe and Germany in particular. It is calculated as the difference between Finnish rate one month money market rate (Helibor) and the corresponding German rate (Fibor). After 1998 when Finland adopted the euro, the interest rate difference is zero. It is expected to capture some of the devaluation expectations that can be argued to be reflected in the stock market during the beginning of the sample period.[10] On the other hand, this variable is expected to reflect the increased global integration of the Finnish stock market and overall stabilization in the Finnish economy.

JAN_{t-1} is an indicator variable for January. It gets a value one during January, zero otherwise. It has been selected following previous studies (see, e.g., Keim, 1983; in Finnish market Nummelin

[9] Gibson and Mougeot (2004) use three different variables, namely the recession index, change in the default premium, and change in the slope of the term structure.

[10] Finnish stock market experienced a long period of negative realized returns following deep economic recession during a period from 1989 to 1994. There are several possible explanations for this. From theoretical perspective, low realized returns should be accompanied with low expected returns. This implies that asset returns have low market risk sensitivity or exposure to other sources of risk. Berglund and Löflund (1996) conclude that the negative realized returns in Finnish market can be explained as a premium on a currency risk related to the devaluation or Peso (jump) risk. Alternatively it could be explained by the higher liquidity risk premium.

and Vaihekoski, 2002). Furthermore, Jain and Joh (1988) find a connection between January and market volume. January-dummy is used in a similar asset pricing tests, among other, by Evans (1994).

Table 3 presents the descriptive statistics for the conditioning information variables (except January dummy and the liquidity variables shown in Table 1. Panel B shows that the selected variables show low pairwise correlation so *a priori* none of them is redundant. All financial information variables are measured with a one-period lag, and considered to be publicly known information. Variables (except January dummy) are standardized to have zero unconditional mean and unit variance (portfolio specific variables are standardized jointly), so that the estimated constant can be interpreted as the unconditional mean.

4. EMPIRICAL RESULTS

4.1 Preliminary Regressions

To test if the selected information variables are potentially able to predict variation in the prices of risks, we test run regressions where asset and market returns as well as liquidity measure are regressed on the information variables with and without the January variable. Table 4 summarizes the results from the forecasting regressions (not done).

4.2 Unconditional Multifactor ICAPM

Our initial model is a standard unconditional two-factor beta asset pricing model where the liquidity risk factor is used as the second source of risk. This model is tested here to analyze size portfolios' different sensitivities towards liquidity risk. Results are reported for the three different liquidity measure in Table 5.

The results show … (not done at the moment)

4.3 Constant Prices of Risks

In our first asset pricing model with the price of risk specification we assume that the price of both market and liquidity risks has remained the same throughout the sample period. In the estimation the price of risk is assumed to be constant whereas the variance and covariance terms are time-varying. This corresponds to equations (5) and (6). Table 6 shows the results first for the market portfolio and then for the size portfolios. Size portfolios have been estimated one asset at a time in order to obtain convergence in the estimation. *BASpread* has been used as the proxy for the liquidity risk.

The results show … (not done at the moment)

4.4 Time-varying Prices of Risks

Table 7 presents the ML estimation results for the model where the prices of market and liquidity risks have been allowed to be time-varying. Both prices are modeled linear on the conditioning information variables. *BASpread* has been used as the proxy for the liquidity risk in the estimation.[11]

The results show … (not done at the moment)

We also estimated the model with the positivity constrain for the price of market risk, i.e., equation (13). The results (not reported) show … (not done at the moment)

5. SUMMARY AND CONCLUSIONS

In this paper we study the intertemporal capital asset pricing model and the pricing of liquidity risk in the Finnish stock market using monthly market and size portfolio data from 1987 to 2000. Finnish stock market offers an interesting test laboratory since it has shown prolonged periods of illiquidity but also times of extremely high growth in the turnover. The sample period includes also some institutional changes to promote the stock trading, including, for example, a gradual liberalization of the Finnish financial markets (completed in the end of 1992) and removal of the stamp duty on stock trades on the stock exchange. Many emerging markets have or are currently experiencing similar development.

We also analyze different measures for the liquidity risk. Our main liquidity measure is the value-weighted market-wide bid-ask spread. It has been constructed especially for this study. In addition, we utilize value-weighted average trading turnover. Finally, we use risk factor construction employed e.g. by Fama and French (1992). Namely, we construct three portfolios with respect to the liquidity and calculate the difference in returns between the portfolios with the highest and lowest liquid companies.

In our empirical specification, we utilize the multivariate GARCH-M framework of De Santis and Gerard (1998) allowing a time-varying variance-covariance process. First, we estimate the unconditional ICAPM with constant prices of risks. Second, we allow the prices of market and liquidity risks to be time-varying with respect to information variables. All models are estimated both including and excluding an asset specific risk component.

The results show …

[11] The model was also estimated using *VWTVOL* and *HMLLiq* as proxies for the liquidity risk. The results (not reported) show …

REFERENCES

Amihud, Yakov – Mendelson, Haim: The Effect of Beta, Bid-Ask Spread, Residual Risk, and Size of Stock Returns. *Journal of Finance*, 1989, Vol. 44, No. 2, 479-486.

Amihud, Yakov – Mendelson, Haim: Asset Pricing and the Bid-Ask Spread. *Journal of Financial Economics*, 1986, Vol. 17, No. __, 223-248.

Amihud, Yakov: Illiquidity and stock returns: Cross-section and time-series effects. Journal of Financial Markets, 2002, vol. 5, 31-56.

Baker, H. Kent: Trading Location and Liquidity: An Analysis of U.S. Dealer and Agency Markets for Common Stocks. *Financial Markets, Institutions & Instruments*, 1996, Vol. 5, No. 4.

Berglund, Tom – Wahlroos, B. – Grandell, L.: The KOP and the UNITAS indexes for the Helsinki Stock Exchange in the light of a New Value Weighted Index. *Finnish Journal of Business Economics*, 1983, Vol. 32, 30-41.

Berglund, Tom – Liljeblom, Eva: The Impact of Trading Volume on Stock Return Distribution. *Finnish Economic Papers*, 1990, Vol. 3, No. 2, 108-124.

Berndt, E., B. Hall, R. Hall and J. Hausman, 1974: "Estimation and Inference in Nonlinear Structural Models. *Annals of Economic and Social Management* 3/4, 653–665.

Bernstein, P. L.: Liquidity, Stock Market, and Market Makers. *Financial Management*, 1987, Vol. 16, No. 2, 54-62.

Bollerslev, T., R. F. Engle and J. M. Wooldridge, 1988: A Capital Asset Pricing Model with Time-varying Covariances. *Journal of Political Economy* 96, 116–131.

Bollerslev, T. & J. M. Wooldridge, 1992: Quasi-Maximum Likelihood Estimation and Inference in Dynamic Models with Time-Varying Covariances. *Econometric Reviews* 11, 143–172.

Brennan, Michael J. – Subrahmanyam, Avanidhar: Market Microstructure and Asset Pricing: On the Compensation for Illiquidity in Stock Returns. *Journal of Financial Economics*, 1996, Vol. 41, No. __, 441-464.

Campbell, J. Y.: Stock Returns and the Term Structure. Journal of Financial Economics, 1987, Vol. 18, 373-400.

Chen, Nai-fu – Kan, Raymond: Expected Returns and the Bid-Ask Spread. University of Chicago, Working Paper 265, 1989.

Chortia, T. – Roll, R. – Subrahmanyam, A.: Commonality in Liquidity. *Journal of Financial Economics*, 2000, 56, 3-28.

De Santis, G. – Gérard, B.: How big is the premium for currency risk? *Journal of Financial Economics*, 1998, vol. 49, 375-412.

Ding, Z. and R. F. Engle, 1994: Large scale conditional covariance matrix modeling, estimation and testing. USCD Discussion Paper.

Eleswarapu, Venkat R. – Reinganum, Marc R.: The Seasonal Behavior of the Liquidity Premium in Asset Pricing. *Journal of Financial Economics*, 1993, Vol. 34, No. __, 373-386.

Engle, R. F. and K. Kroner, 1995: Multivariate Simultaneous Generalized ARCH. *Econometric Theory* 11, 122–150.

Estrella, Arture – Hardouvelis, Gikas A.: The Term Structure as a Predictor of Real Economic Activity. *Journal of Finance*, 1994, Vol. 46, No. 2, 555-576.

Evans, Martin D.: Expected returns, time-varying risk, and risk premia. *Journal of Finance*, 1994, Vol. 49, No. 2, 655-679.

Fama, Eugene F. – French, Kenneth R.: Common Risk Factors in the Returns on Stocks and Bonds. *Journal of Financial Economics,* 1993, Vol. 33, 3-56.

Fama, Eugene F. – French, Kenneth R.: The Cross-Section of Expected Stock Returns. *Journal of Finance*, 1992, Vol. 47, 427-465.

Gibson, Rajna – Mouguet, Nicolas: The Pricing of Systematic Liquidity Risk: Empirical Evidence from the US Stock Market. *Journal of Banking and Finance*, 2003, vol. 28, 157-178.

Groth, J. C. – Dubofsky, D. A.: The Liquidity Factor. In D. F. Parrillo, E. R. Hobbing, M. V. Porter, and J.G. Gutman (Eds.): *The NASDAQ Handook*. Chicago: Probus Publishing Company, 1992.

Hansen, Lars P. – Richard, Scott F.: The role of conditioning information in deducing testable restrictions implied by dynamic asset pricing models. *Econometrica*, 1987, Vol. 55, No. 3, 587-613.

Hasbrouck, Joel: Trading costs and returns for US equities: The evidence from daily data. New York University, Stern School of Business, unpublished manuscript.

Huang, Roger D. – Stoll, Hans R.: Revenues of Immediacy Suppliers versus Execution Costs of Investors: Evidence from the NYSE. Vanderbilt University, Working Paper, 1996.

Jain, P. C. – Joh, G.: The Relation between Hourly Prices and Trading Volume. Wharton School, Working Paper, 1986.

Jarque, C. M. and Bera, A. K., 1987: A Test for Normality of Observations and Regression Residuals. *International Statistical Review*, 55, 163-172.

Keim, Donald B.: Size-Related Anomalies and Stock Returns Seasonality: Further Empirical Evidence. *Journal of Financial Economics*, 1983, Vol. 12, June, 13-32.

Kane, Alex: Trading Cost Premiums in Capital Asset Returns – A Closed Form Solution. *Journal of Banking and Finance*, 1994, Vol. 18, No. __, 1177-1183.

Karpoff, Jonathan: The Relation Between Price Changes and Trading Volume: A Survey. *Journal of Financial and Quantitative Analysis*, 1987, Vol. 22, No. __, 109-126.

Laux, P. A.: Trade Sizes and Theories of Bid-Ask Spread. *Journal of Financial Research*, 1993, Vol. 16, No. 3, 237-249.

Lee, Charles: Market Fragmentation and Price-Execution in NYSE-listed Securities. Journal of Finance, 1993, Vol. 48, 1009-1038.

Ljung, G. M. & Box, G. E. P., 1978: On a Measure of Lack of Fit in Time Series Models. *Biometrika*, 65, 297-303.

Martikainen, Teppo – Puttonen, Vesa – Luoma, Martti – Rothovius, Timo: The Linear and Non-linear Relationship between Stock Returns and Trading Volume in the Finnish Stock Market. Applied Financial Economics, 1994, Vol. 4, No. 2, 159-169.

Merton, Robert C.: A Simple Model of Capital Market Equilibrium with Incomplete Information. Journal of Finance, 1987, Vol. 42, No. __, 483-510.

Merton, Robert C., 1980: On Estimating the Expected Return on the Market. *Journal of Financial Economics*, 8, 323-361.

Newey, W. K. – West, K. D.: A Simple, Positive Semi-Definite, Heteroscedasticity and Autocorrelation Consistent Covariance Matrix. Econometrica, 1987, Vol. 55, 703-708.

Nummelin, Kim: Global Coskewness and the Pricing of Finnish Stocks: Empirical Tests. Journal of International Financial Markets, Institutions and Money, 1997, vol. 7, no 2, 137-155.

Nummelin, K. and M. Vaihekoski, 2002: International Capital Markets and Finnish stock returns. *European Journal of Finance*, 8, 322–343.

Vaihekoski, Mika: Global market and currency risks in Finnish stock market. Unpublished working paper. Available from SSRN.

Vaihekoski, Mika: The Finnish stock market: Recent trends and important events. The Finnish Journal of Business Economics, 1997, 46, 4, 526-543.

Vaihekoski, Mika: Unconditional international asset pricing models: Empirical tests. The Finnish Economic Papers, 2000, 13, 2, 71-88.
Vaihekoski, Mika: Portfolio construction for tests of asset pricing models. Financial Markets, Institutions & Investors, 2004, 13, 1 (February), 1-39.

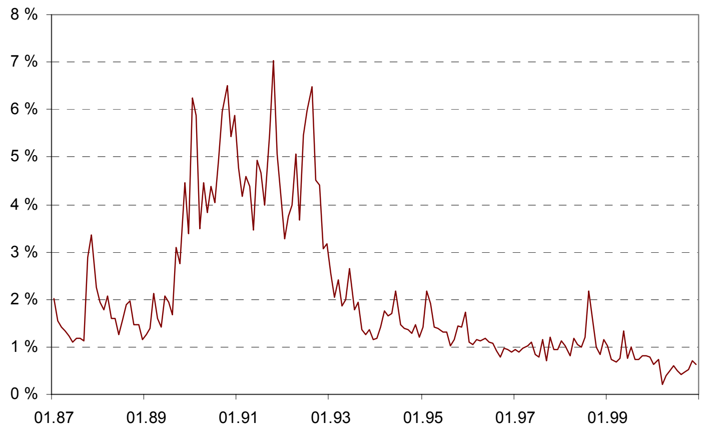

Figure 1a. Value-weighted bid-ask spread.

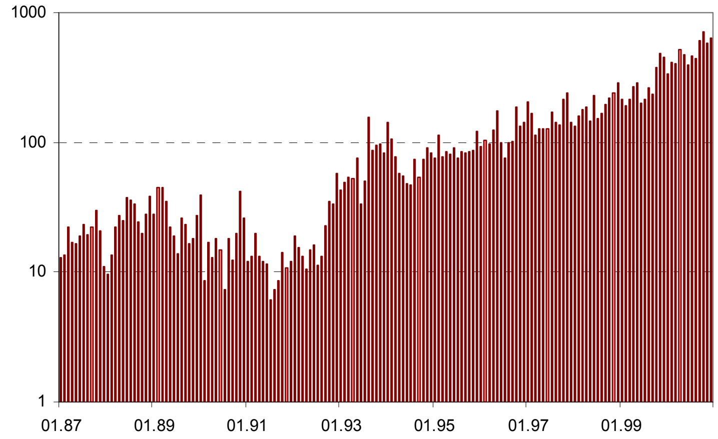

Figure 1b. Total number of shares traded (log scale).

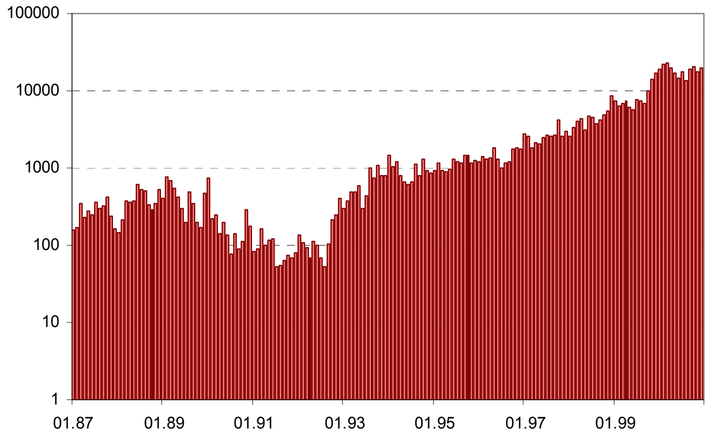

Figure 1c. Total value of shares traded (turnover; log scale)

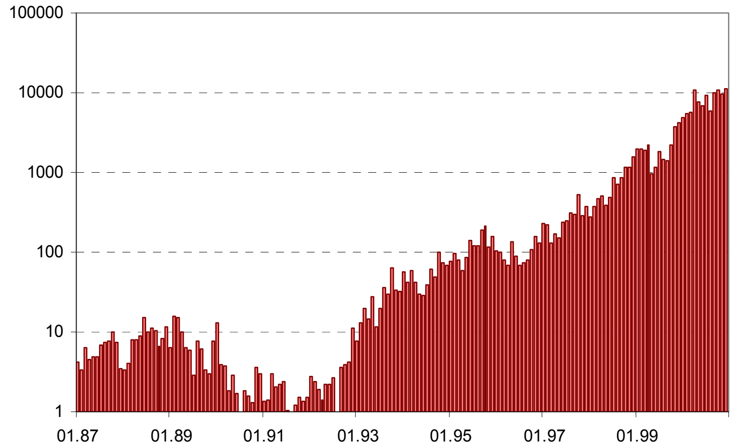

Figure 1d. Value-weighted average trading turnover (log scale).

Figure 1. Liquidity measures for the Finnish equity market during 1987–2000.

Table 1. Descriptive statistics for the liquidity measures.

Descriptive statistics are calculated for the five monthly liquidity measures. BASpread is the value-weighted bid-ask spread. TNST is the total number of shares traded. TVOL is trading turnover. VWTVOL is the value-weighted average trading turnover. HMLLiq is the logarithmic difference in the high-minus-low liquidity portfolios' returns. The *p*-value for the Jarque-Bera test statistic of the null hypothesis of normal distribution is provided in the table. Q(12) is the Ljung-Box (1978) statistics for the returns. The sample size is 168 monthly observations from January 1987 to December 2000.

Liquidity series	**Mean** (%)	**Std. dev.** (%)	**Skewness**	**Excess Kurtosis**	**Normality** (p-value)	**Autocorrelation**[a] ρ_1	ρ_2	ρ_3	ρ_{12}	**Q(12)**[b]
Panel A. Summary statistics										
BASpread	0.021	0.015	1.259	0.415	<0.001	0.927*	0.894*	0.853*	0.658*	<0.001
TNST (millions)	2115.231	138.447	2.041	4.104	<0.001	0.921*	0.866*	0.809*	0.576*	<0.001
TVOL (millions)	2851.728	5081.029	2.521	5.487	<0.001	0.948*	0.909*	0.853*	0.460	<0.001
VWTVOL (millions)	825.809	2207.313	3.360	10.686	<0.001	0.890*	0.840*	0.777*	0.263	<0.001
HMLLiq	-	-	-	-	-	-	-	-	-	-

a) Autocorrelation coefficients significantly (5%) different from zero are marked with an asterisk (*).

b) The *p*-value for the Ljung and Box (1978) test statistic for the null that autocorrelation coefficients up to 12 lags are zero.

Table 1. *Continued*

Panel B. Cross-correlation coefficients					
	BASpread	TNST	TVOL	VWTVOL	HMLLiq
BASpread	1.000				
TNST	-0.540	1.000			
TVOL	-0.442	0.939	1.000		
VWTVOL	-0.346	0.897	0.928	1.000	
HMLLiq	0.	0.	0.	0.	1.000

Table 2. Descriptive statistics for the monthly asset returns.

Descriptive statistics for the market portfolio and six size portfolio returns are given below. Mean and standard deviation of the returns are annualized. The normality of the return series is tested using Bera-Jarque test (p-value provided in the table). Sample size is 168 monthly observations from January 1987 to December 2000.

PORTFOLIO	Return Mean	Std. Dev.	Skew-ness	Excess Kurtosis	Bera-Jarque	Autocorrelation[a] ρ_1	ρ_2	ρ_3
Panel A: Sample statistics								
Market portfolio								
HEX index	19.9 %	0.263	0.028	0.584	0.300	0.246*	0.001	0.054
Size portfolios								
1 – Largest	17.7 %	0.280	-0.040	0.245	0.793	0.207*	0.056	0.063
2	5.5 %	0.247	-0.125	1.000	0.024	0.277*	-0.021	0.095
3	4.6 %	0.259	-0.256	1.570	<0.001	0.291*	-0.094	0.005
4	7.9 %	0.244	0.350	1.961	<0.001	0.311*	0.041	0.139
5	3.3 %	0.221	-0.099	1.102	0.012	0.270*	-0.007	0.063
6 – Smallest	3.6 %	0.239	0.670	2.949	<0.001	0.174*	0.046	0.096

[a] Significant autocorrelation coefficients are marked with an asterisk (*).

Table 2. *Continued*

Panel B: Cross-correlation coefficients

	HEX-Index	1	2	3	4	5	6
HEX Market Index	1.000						
1 – Largest	0.969	1.000					
2	0.803	0.705	1.000				
3	0.713	0.623	0.778	1.000			
4	0.649	0.532	0.710	0.750	1.000		
5	0.671	0.572	0.714	0.799	0.782	1.000	
6 – Smallest	0.584	0.487	0.671	0.635	0.685	0.709	1.000

Table 3. Descriptive statistics of the monthly information variables data.

The information set contains: market return (R_m), measure of term structure (SD), and the difference between Finnish and German one month money market rates (IRDIFF), a January dummy (JAN), and trading turnover (TVOL). All variables are lagged by one month except JAN. The sample size is 168 monthly observations from December 1986 to November 2000.

	Mean	Standard Deviation	Skewness	Excess Kurtosis	Normality (p-value)	Autocorrelation[a] ρ_1	ρ_2	ρ_3	Q(12)[b]
Panel A. Summary statistics									
R_m	0.017	0.076	0.021	0.516	0.391	0.248*	0.091	0.088	<0.001
SD	0.003	0.009	-1.519	4.268	<0.001	0.653*	0.475*	0.322*	<0.001
IRDIFF	0.024	0.027	0.808	-0.050	<0.001	0.905*	0.882*	0.846*	<0.001
Panel B. Pairwise correlations	R_m	SD	IRDIFF						
R_m	1.000								
SD	-0.011	1.000							
IRDIFF	-0.194	-0.168	1.000						

a) Autocorrelation coefficients significantly (5%) different from zero are marked with an asterisk (*).

b) The *p*-value for the Ljung and Box (1978) test statistic for the null that autocorrelation coefficients up to 12 lags are zero.

Table 4. Preliminary Regressions

OLS regressions of excess test asset and risk-factor returns on the forecasting variables and a constant. *BASpread* is the value-weighted bid-ask spread. *VWTVOL* is the value-weighted average trading turnover. *HMLLiq* is the difference in the high-minus-low liquidity portfolios' returns. The information set contains: market return (R_m), a measure of term structure (*SD*), the difference between Finnish and German one month money market rates (*IRDIFF*), trading turnover (*TVOL*), and a January dummy (JAN). Sample is January 1987 to December 2000 with 168 monthly observations.

	All information			Exclude JAN	
	R^2 adj.	**F (5,162)**	***p*-value**	**F (1,168)**	***p*-value**
Panel A. Size portfolio returns					
Size 1 – largest	0.	0.	0.	0.	0.
Size 2	0.	0.	0.	0.	0.
Size 3	0.	0.	0.	0.	0.
Size 4	0.	0.	0.	0.	0.
Size 5	0.	0.	0.	0.	0.
Size 6 – smallest	0.	0.	0.	0.	0.
Panel B. Risk factor returns					
R_{mt}	0.	0.	0.	0.	0.
BASpread	0.	0.	0.	0.	0.
VWTVOL	0.	0.	0.	0.	0.
HMLLiq	0.	0.	0.	0.	0.

Table 5. Two-factor beta pricing model

Two factor beta asset pricing model is tested. The equity market portfolio and a measure of liquidity act as risk factors. In Model I, the liquidity risk is proxied with the value-weighted bid-ask spread. In Model II, the liquidity is proxied with the value-weighted average trading volume. In Model III, the liquidity is proxied with the difference in the high-minus-low liquidity portfolios' returns. Reported results include the risk factor betas and Jensen's alpha using six size portfolio returns. All returns are in excess of the one-month Helibor/Euribor rate. Parameter estimates are from the OLS estimation where we have used a Newey-West (1987) heteroskedasticity and autocorrelation consistent estimator with three lags. Standard errors are in parenthesis below parameter values. The cross-sectional Wald test statistic is also given with *p*-value in parenthesis. The sample size is 168 monthly observations from 1987 to 2000.

TIME SERIES	Model I			Model II			**Adj. R^2**	
	α_0	β_m	β_l	α_0	β_m	β_l	Model I	Model II
Largest	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
3	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
4	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
5	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Smallest	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Wald-test	0.000	0.000	0.000	0.000	0.000	0.000		
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		

Table 5 *continued.*

TIME SERIES	Model III			Adj. R^2
	α_0	β_m	β_l	Model III
Largest	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
3	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
4	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
5	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
Smallest	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000
Wald-test (p-value)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	

Table 6. Conditional ICAPM with constant prices of risks

Quasi-maximum likelihood estimates of the conditional APM with constant prices of market and liquidity risks. Each asset is estimated separately. Finnish market portfolio (measured using the HEX-index) and six size portfolios are used as the test asset. The liquidity risk is proxied with the value-weighted bid-ask spread (*BASpread*). QML standard errors are in parentheses. Coefficients significantly (5% or 1%) different from zero are marked with two an asterisk (*) or asterisks (**).The sample size is 168 monthly observations from January 1987 to December 2000.

	Market	Size portfolio					
	Portfolio	Largest	2	3	4	5	Smallest
Panel A: Parameter estimates							
Price of market risk, λ_m							
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price of liquidity risk, λ_l							
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance parameters							
a_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Diagnostic tests							
Likelihood function	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Av. standardized residual	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Av. mean pricing error	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Table 7. Conditional ICAPM with time-varying prices of risk

Quasi-maximum likelihood estimates of the conditional APM with time-varying prices of market and liquidity risk. Each asset is estimated separately. Finnish market portfolio (measured using the HEX-index) and six size portfolios are used as the test asset. The liquidity risk is proxied with the value-weighted bid-ask spread (*BASpread*). The information set contains: market return (R_m), a measure of term structure (*SD*), the difference between Finnish and German one month money market rates (*IRDIFF*), trading turnover (*TVOL*), and a January dummy (JAN). QML standard errors are in parentheses. Coefficients significantly (5% or 1%) different from zero are marked with two an asterisk (*) or asterisks (**).The sample size is 168 monthly observations from January 1987 to December 2000.

	Market	Size portfolio					
	Portfolio	Largest	2	3	4	5	Smallest
Panel A: Parameter estimates							
Price of market risk, λ_m							
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R_m	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
SD	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
IRDIFF	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
JAN	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Price of liquidity risk, λ_l							
Constant	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R_m	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
TVOL	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Variance parameters							
a_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
b_i	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Panel B: Diagnostic tests							
Likelihood function	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Av. standardized residual	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Av. mean pricing error	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Etc.	0.000	0.000	0.000	0.000	0.000	0.000	0.000