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<u>MASTER THESIS:</u>

"ASSET PRICING AND SYSTEMATIC LIQUIDITY RISK: EMPIRICAL EVIDENCE FROM THE GREEK STOCK MARKET"

by

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Abstract

The main purpose of this paper is to examine the significance and magnitude of systematic liquidity risk pricing in the Greek stock market. The motivation for this study was provided by the growing interest in liquidity that has emerged in the asset pricing literature over the recent years. It should be pointed out that besides the recent and relative scant evidence from the U.S. market, there is no evidence regarding the importance of liquidity for asset pricing in the European markets except for the paper of Martinez, Nieto, Rubio and Tapia (2004) who result that systematic liquidity risk is significant priced in the Spanish stock market. For this reason this paper investigates whether market-wide liquidity is a state variable important for asset pricing in the Greek stock market. We analyze whether expected returns of the Greek market are associated cross-sectionally with betas estimated relative to two competing liquidity risk factors. The first one, proposed by Pastor & Stambaugh (2001), is associated with the temporary price fluctuation reversals induced by the order flow (OFL) and the second is the illiquidity ratio (ILLQ), as suggested by Amihud (2002) which is based on the price response to one euro of trading volume. We employ four alternative pricing models: the traditional CAPM, the three-factor Fama and French model and the two CAPM liquidity-based models, in which we add the liquidity factor (either OFL or ILLQ) to the standard CAPM model in order to examine the relation between the liquidity and expected returns.

1. INTRODUCTION

Several asset pricing models have been introduced to the finance literature in order to explain how investors measure risk and value risky assets. At the forefront are the Capital Asset Pricing Model (CAPM), and the subsequent extensions of the CAPM, as well as the Arbitrage Pricing Theory (APT). According to these models expected returns can be predicted given specific related variables. Empirical tests of the CAPM use the risk of the market as measured by beta, which is defined as a measure of the relative variability of a security’s return as compared to the variability of the entire market’s return. The CAPM uses the beta of a security in conjunction with the risk premium on the market to account for the expected risk premium on a specific security, where it attempts to account for the market’s perception of risk and return. However, sceptics of the CAPM posit that in this state the model, by use of beta, does not accurately capture the risk that investors face.

In general, it has been shown that the beta of a security is an incomplete variable in the measuring of risk. This implies that there may be something missing from the model, namely some component of risk. From shortcomings such as this, the extensions of the CAPM and the APT have evolved to bridge this gap and try to account for the missing risk. The majority of the more recent models either remove beta from the model and replace it with a more complete proxy of risk faced by investors or add other variables that may aid beta in capturing the true risk an investor encounters.

In recent years the trend in the literature is toward uncovering factors that accurately predict returns. One such factor is liquidity, where it is defined as the risk that investors face for not being able to readily transfer ownership of a security. Liquidity, by its very nature, is difficult to define and even more difficult to estimate. Kyle (1985) notes “liquidity is a slippery and elusive concept, in part because it encompasses a number of transactional properties of markets. These include tightness, depth and resiliency”. Tightness because the market has many participants, depth because if we look a little above the “current” market price, there is a large incremental quantity available for sale and if we look a little below the current price, there is a large incremental quantity that is sought (by a buyer or buyers) and resiliency because price impacts caused by the trading are small and quickly die out.

Throughout the annals of economic activity the conventional wisdom says the liquidity is one of the most, if not the most, desirable attribute of an asset. A highly liquid asset can be used for any transaction purposes with less or no price discount. Thus, the cash, marketable securities etc. are supposed to be the most liquid of assets. The importance of liquidity comes from the desire of investors to reap more reward for the greater risk they incur. Investors are concerned about liquidity risk. It affects their ability to trade the quantity of stocks they want to buy or sell within their desired time-framework. Most importantly, investors fear that in the event of a financial crisis, they may not be able to exit the market fast enough to contain their losses. These considerations may lead them to shy away from illiquid securities, or require a liquidity-related risk premium to hold them. Specifically, liquidity and asset returns have an inverse relationship, where investors are willing to accept a lower return from securities with a higher level of liquidity.

The importance of liquidity to asset pricing has received substantial attention recently. The question whether liquidity affects asset returns remains unresolved thus far. This issue is important since a vast literature exists in the area of market microstructure of financial markets, which argues that liquidity has a first-order effect upon asset returns. The absence of conclusive results in previous empirical research suggests that asset pricing and liquidity have not been properly addressed in the standard literature. Using a wide variety of liquidity measures, a number of empirical studies have investigated the relation between the level of liquidity and expected returns. An important motive for considering a market-wide liquidity measure, as an important priced factor, is evidence of the existence of commonality across stocks in liquidity fluctuations. If liquidity shocks are non-diversifiable and have a varying impact across individual securities, the more sensitive an asset's return is to such shocks, the greater must be its expected return. Whether and to what extent, liquidity has an important bearing on asset pricing is still in debate.

The underlying difficulty for examining whether liquidity is important in asset pricing is due to the fact that liquidity is unobservable. Liquidity generally denotes the ability of investors to trade large quantities quickly, at low cost, and without substantially moving prices. In this paper, we investigate the relation between stock returns and market-wide liquidity. We investigate whether market-wide liquidity is a state variable important for asset pricing in the Greek stock market. We should regress common stock returns on a proxy for a liquidity factor reflecting market-wide liquidity restrictions. Different liquidity proxies have been employed in the literature. In our research we measure liquidity with two different liquidity factors. The first one, proposed by Pastor & Stambaugh (2001), is associated with the temporary price fluctuation reversals induced by the order flow (OFL) and the second is the illiquidity ratio (ILLQ), as suggested by Amihud (2002) which is based on the price response to one euro of trading volume. Also, in order to examine the relation between the liquidity and expected returns, we employ four alternative pricing models: the traditional CAPM, the three-factor Fama and French model and the two CAPM liquidity-based models, in which we add the liquidity factor (either OFL or ILLQ) to the standard CAPM model.

The rest of the paper is organized as follows. Section 2 makes a review of the common asset pricing models. Section 3 reports the several market liquidity proxies often used in the literature. Section 4 reports the recent literature. Section 5 briefly describes the data and the methodology used for estimating liquidity. It explains the construction of the two liquidity measures and the methodology we use in order to investigate whether the systematic liquidity risk is priced. Section 6 discusses the empirical results on asset pricing with the two market-wide liquidity risk factors. Other results regarding summary statistics of the portfolios employed in our research is also reported. Finally, Section 7 concludes.

2. REVIEW OF THE ASSET PRICING MODELS

Asset pricing theory tries to relate the prices or values of claims to uncertain payments. A low price implies a high rate of return, so one can also think of the theory as explaining why some assets pay higher average returns than others.

To value an asset, we have to account for the delay and for the risk of its payments. The effects of time are not too difficult to work out. However, corrections for risk are much more important determinants of many assets' values. Uncertainty or corrections for risk make asset pricing interesting and challenging. Asset pricing theory all stems from one simple concept: price equals expected discounted payoff.

The foundations for the development of asset pricing models were laid by Markowitz (1952) and Tobin (1958). Early theories suggested that the risk of an individual security is the standard deviation of its returns – a measure of return volatility. Thus, the larger the standard deviation of security returns the greater the risk. An investor's main concern, however, is the risk of his/her total wealth made up of a collection of securities, the portfolio. Markowitz observed that (i) when two risky assets are combined their standard deviations are not additive, provided the returns from the two assets are not perfectly positively correlated and (ii) when a portfolio of risky assets is formed, the standard deviation risk of the portfolio is less than the sum of standard deviations of its constituents. Markowitz was the first to develop a specific measure of portfolio risk and to derive the expected return and risk of a portfolio. The Markowitz model generates the efficient frontier of portfolios and the investors are expected to select a portfolio, which is most appropriate for them, from the efficient set of portfolios available to them.

The computation of risk reduction as proposed by Markowitz is tedious. Sharpe (1964) developed a computationally efficient method, the single index model, where return on an individual security is related to the return on a common index. The common index may be any variable thought to be the dominant influence on stock returns and need not be a stock index (Jones, 1991). The single index model can be extended to portfolios as well. This is possible because the expected return on a portfolio is a weighted average of the expected returns on individual securities.

When analysing the risk of an individual security, however, the individual security risk must be considered in relation to other securities in the portfolio. In particular, the risk of an individual security must be measured in terms of the extent to which it adds risk to the investor's portfolio. Thus, a security's contribution to portfolio risk is different from the risk of the individual security.

Investors face two kinds of risks, namely, diversifiable (unsystematic) and non-diversifiable (systematic). Unsystematic risk is the component of the portfolio risk that can be eliminated by increasing the portfolio size, the reason being that risks that are specific to an individual security such as business or financial risk can be eliminated by constructing a well-diversified portfolio. Systematic risk is associated with overall movements in the general market or economy and therefore is often referred to as the market risk. The market risk is the component of the total risk that cannot be eliminated through portfolio diversification.

Some of the asset pricing models that have been introduced to the finance literature in order to explain how investors measure risk and value risky assets are the following:

2.1 Capital Asset Pricing Model (CAPM)

The Capital Asset Pricing Model (CAPM) of William Sharpe (1964), John Lintner (1965) and J. Mossin (1966) marks the birth of asset pricing theory (resulting in a Nobel Prize for Sharpe in 1990). Four decades later, the CAPM is still widely used in applications, such as estimating the cost of capital for firms and evaluating the performance of managed portfolios.

The CAPM builds on the model of portfolio choice developed by Harry Markowitz (1959). In Markowitz's model, an investor selects a portfolio at time t-1 that produces a stochastic return at t. The model assumes investors are risk averse and, when choosing among portfolios, they care only about the mean and variance of their one-period investment return. As a result, investors choose "mean-variance efficient" portfolios, in the sense that the portfolios: 1) minimize the variance of portfolio return, given expected return and 2) maximize expected return, given variance. Thus, the Markowitz approach is often called a "mean-variance model".

The portfolio model provides an algebraic condition on asset weigh in mean-variance efficient portfolios. The CAPM turns this algebraic statement into a testable prediction about the relation between risk and expected return by identifying a portfolio that must be efficient if asset prices are to clear the market of all assets. The attraction of the CAPM is that it offers powerful and intuitively pleasing predictions about how to measure risk and the relation between expected return and risk.

The CAPM is an equilibrium theory built on the premises of Modern Portfolio Theory. It is, however, an equilibrium theory with a somewhat peculiar structure. This is true for a number of reasons: 1. First, the CAPM is a theory of financial equilibrium only. Investors take the various statistical quantities – means, variances, covariances – that characterize a security's return process as given. There is no attempt within the theory to link the return process with events in the real side of the economy. 2. Second, as a theory of financial equilibrium it makes the assumption that the supply of existing assets is equal to the demand for existing assets and, as such, that the currently observed asset prices are equilibrium ones. There is no attempt, however, to compute asset supply and demand functions explicitly. Only the equilibrium price vector is characterized. 3. Third, the CAPM expresses equilibrium in terms of relationships between the return distributions of individual assets and the return characteristics of the portfolio of assets.

The CAPM is developed in a hypothetical world where the following assumptions are made about investors and the opportunity set:

- Investors are risk-averse individuals who maximize the expected utility of their end-of-period wealth.
- Investors are price takers and have homogenous expectations about asset returns that have a joint normal distribution.

- There exists a risk free asset such that investors may borrow or lend unlimited amounts at the risk-free rate.
- The quantities of assets are fixed. Also, all assets are marketable and perfectly divisible.
- Asset markets are frictionless and information is costless and simultaneously available to all investors.
- There are no market imperfections such as taxes, regulations, or restrictions on short selling.

These assumptions guarantee the efficiency of the market portfolio. Such a condition is necessary for the validity of an exact linear relationship between expected return and risk for individual securities or portfolios at equilibrium. The Capital Asset Pricing Model (CAPM) states that the risk premium of an individual asset equals its beta times the risk premium on the market portfolio.

$$E(R_j) = R_f + \left[E(R_m) - R_f \right] b_j \tag{1}$$

where: $E(R_j)$ = the expected return on security or portfolio j
R_f = the return on the riskless security
$E(R_m)$= the expected return on the market portfolio
b_j = the beta coefficient of security or portfolio j

The $(E(R_m) - R_f)$ is referred to as the market risk-premium, given that it represents the return over the risk free rate required by investors to hold the market portfolio.

The beta coefficient for security j can be defined as the risk of security j in m relative to the total risk of the market portfolio and can be expressed as:

$$b_j = \sigma_{jm} / \sigma_m^2 \tag{2}$$

where: σ_{jm} = the covariance between the rate of return on the market portfolio and the rate of return on security j.
σ^2_m = the variance of rate of return on portfolio m.

The CAPM indicates that an investor can obtain above the riskless return only by taking on additional risk. In the CAPM, the relevant risk of a security or portfolio is its covariance within the market portfolio (that portion of the total risk which cannot be eliminated by diversification). Investors must be compensated to persuade them to hold an asset with high covariance with the market, and this compensation takes the form of a higher expected return. Since unsystematic risk can disappear via the process of diversification, investors should be rewarded only for taking on systematic risk. The higher the beta of a security or portfolio, the higher it's expected return.

Proof of the CAPM requires that in equilibrium the market portfolio must be an efficient portfolio. One way to establish its efficiency is to argue that so long as investors have homogenous expectations, they will all perceive the same minimum variance opportunity set. Even without a risk-free asset, they will all select efficient portfolios regardless of their individual risk tolerances. Given that all individuals hold positive proportions of their wealth in efficient portfolios, then the market portfolio must be efficient because: 1) the market is simply the sum of all individual holdings and 2) all individuals' holdings are efficient.

Thus, in theory, when all individuals have homogenous expectations, the market portfolio must be efficient. Without homogenous expectations the market portfolio is not necessarily efficient and the equilibrium model of capital markets does not necessarily hold. Thus, the efficiency of the market portfolio and the capital asset pricing model are inseparable, joint hypotheses.

The traditional capital asset pricing model argues that market beta is the only risk factor to explain the cross-sectional variation of expected stock returns, and it was successfully proved in empirical work because every investment strategy, which seemed to provide a high average, turned out to also have a high beta. The contribution of the CAPM is that it relates the expected excess returns to the market portfolio return. When testing the CAPM we are actually testing the following issues: (i) b_j s are true estimates of historical b_j s, (ii) the market portfolio used in empirical studies is the appropriate proxy for the efficient market portfolio for measuring historical risk premium and (iii) the CAPM specification is correct (Radcliffe, 1987).

However, recent research has brought into question the usefulness of the CAPM in describing the cross-section of expected returns because the expected returns from some investment strategies based on firm characteristics cannot be explained by the CAPM beta. Early studies (Lintner[1], 1965; Douglas[2], 1968) on CAPM were primarily based on individual security returns. Their empirical results were discouraging. Miller and Scholes[3] (1972) highlighted some statistical problems encountered when using individual securities in testing the validity of the CAPM. Most studies subsequently overcame this problem by using portfolio returns. Black, Jensen and Scholes[4] (1972), in their study of all the stocks of the New York Stock Exchange over the period 1931-1965, formed portfolios and reported a linear relationship between the average excess portfolio return and the beta, and for beta >1 (<1) the intercept tends to be negative (positive).

Therefore, they developed a **zero-beta version of the CAPM** model where the intercept term is allowed to change in each period. Specifically, the r_f – version of the CAPM assumes that a riskless security exists where investors can borrow or lend at the same rate. Such an assumption is very unrealistic and Black (1972) developed a risk/return exact linear relationship by considering the case where investors can neither borrow nor lend at the riskless rate of interest. Black's model assumes that short-selling of risky securities is permitted and uses two (minimum standard deviation) portfolios: the market portfolio and another portfolio whose rate of return has no correlation with the rate of return of the market portfolio. The rate of return of the market portfolio is

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1. Lintner, John, (1965). "The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets". Review of Economics and Statistics, 47-1, 13-37.
2. Douglas, George W. (1968). "Risk in the Equity Markets: An Empirical Appraisal of Market Efficiency". Ann Arbor, Michigan: University Microfilms, Inc.
3. Miller, Merton, and Myron Scholes. (1972). "Rate of Return in Relation to Risk: A Reexamination of Some Recent Findings," in Studies in the Theory of Capital Markets. Michael C. Jensen, ed. New York: Praeger, pp. 47-78.
4. Black, Fischer, Michael C. Jensen and Myron Scholes.(1972). "The Capital Asset Pricing Model: Some Empirical Tests," in Studies in the Theory of Capital Markets. Michael C. Jensen, ed. New York: Praeger, pp. 79-121.

uncorrelated with the rates of return of an infinite number of portfolios that have the same expected return, but only one lies on the minimum standard deviation portfolio set. This is called the minimum standard deviation zero-beta portfolio. Its beta is zero of course, since it is uncorrelated with the market portfolio.

Extending the Black, Jensen and Scholes (1972) study, Fama and MacBeth (1973) provided evidence (i) of a larger intercept term than the risk-free rate, (ii) that the linear relationship between the average return and the beta holds and (iii) that the linear relationship holds well when the data covers a long time period. Subsequent studies, however, provide weak empirical evidence on these relationships. Moreover, Roll's critique (1977) questioned the usefulness of CAPM. Roll concluded that the mean/standard deviation efficiency of the market portfolio and the validity of the capital asset pricing model are joint hypotheses. Consequently, the only way to test the CAPM directly is to test the following implication: the market portfolio is mean/standard deviation efficient. However, the true market portfolio contains all the risky securities in proportion to their relative value in the market. This implies that one can test the CAPM directly if given all the securities that comprise the market portfolio and the equilibrium proportions of each security in the market portfolio. Since it is not possible to identify all the risky securities and their weighs in the market portfolio, it is impossible to identify the market portfolio itself. This argument led Roll to conclude that it is impossible to test the CAPM.

Among others, Fama and French (1992) update and synthesize the evidence on the empirical failures of the CAPM. Using the cross-section regression approach, they confirm that size, earnings-price, debt-equity and book-to-market ratios add to the explanation of expected stock returns provided by market beta. Also, they confirm the evidence (Reinganum[5](1981), Stambaugh[6] (1982), Lakonishok and Shapiro[7] (1986)) that the relation between average return and beta for common stocks is even flatter after the sample periods used in the early empirical work on the CAPM. The estimate of the beta premium is, however, clouded by statistical uncertainty (a large standard error). If betas do not suffice to explain expected returns, the market portfolio is not efficient, and the CAPM is dead in its tracks. Evidence on the size of the market premium can neither save the model nor further doom it.

The synthesis of the evidence on the empirical problems of the CAPM provided by Fama and French (1992) serves as a catalyst, marking the point when it is generally acknowledged that the CAPM has potentially fatal problems.

All these empirical contradictions of the CAPM point to the need for a more complicated asset pricing model. The CAPM is based on many unrealistic assumptions. For example, the assumption that investors care only about the mean and variance of distributions of one-period portfolio returns is extreme. It is reasonable that investors also care about how their portfolio return covaries with labor income and future investment opportunities, so a portfolio's return variance misses important dimensions of risk. If so,

5. Reinganum, Marc R. (1981). "A New Empirical Perspective on the CAPM." Journal of Financial and Quantitative Analysis. 16:4, pp. 439-462.
6. Stambaugh, Robert F. (1982). "On The Exclusion of Assets from Tests of the Two-Parameter Model: A Sensitivity Analysis." Journal of Financial Economics. 10:3, pp. 237-268.
7. Lakonishok, Josef and Alan C. Shapiro. (1986). Systematic Risk, Total Risk, and Size as Determinants of Stock Market Returns." Journal of Banking and Finance. 10:1, pp. 115-132.

market beta is not a complete description of an asset's risk and we should not be surprised to find that differences in expected return are not completely explained by differences in beta. In this view, the search should turn to asset pricing models that do a better job explaining average returns.

2.2 Intertemporal Capital Asset Pricing Model (ICAPM)

Merton's (1973) intertemporal capital asset pricing model (ICAPM) is a natural extension of the CAPM. The ICAPM begins with a different assumption about investor objectives. In the CAPM investors care only about the wealth their portfolio produces at the end of the current period. In the ICAPM, investors are concerned not only with their end-of-period payoff, but also with the opportunities they will have to consume or invest the payoff. Thus, when choosing a portfolio at time t-1, ICAPM investors consider how their wealth at time t might vary with future state variables, including labor income, the prices of consumption goods, the nature of portfolio opportunities at t and expectations about the labor income, consumption and investment opportunities to be available after t.

In the ICAPM framework, the expected excess return of a risky asset is given by:

$$E(R_j) - R_f = \beta_{jm}\left[E(R_m) - R_f\right] + \sum_{s=1}^{S} \beta_{js}\left[E(R_s) - R_f\right] \tag{3}$$

Like CAPM investors, ICAPM investors prefer high-expected return and low return variance. But ICAPM investors are also concerned with the covariances of portfolio returns with state variables. The ICAPM relates an asset's expected excess return to the covariance of the asset's excess return with each component of the state. As a result, optimal portfolios are "multifactor efficient", which means they have the largest possible expected returns, given their return variances and the covariances of their returns with the relevant state variables.

Fama (1996) shows that the ICAPM generalizes the logic of the CAPM. That is, if there is risk-free borrowing and lending or if short-sales of risky assets are allowed, market clearing prices imply that the market portfolio is multifactor efficient. Moreover, multifactor efficiency implies a relation between expected return and beta risks, but it requires additional betas, along with a market beta, to explain expected returns.

The ICAPM is a linear factor model with wealth and state variables that forecast changes in the distribution of future returns or income. The "state variables" are the variables that determine how well the investor can do in his maximization. Current wealth is obviously a state variable. Additional state variables describe the conditional distribution of income and asset returns the agent will face in the future or "shifts in the investment opportunity set". In multiple good or international models relative price changes are also state variables.

2.3 Three factor Fama-French model

Fama and French (1993) argue that the apparent superior returns of size portfolios and book-to-market portfolios represent compensation for extra-market risk. They argue that though size and book-to-market equity are not themselves state variables, the higher average returns on small stocks and high book-to-market stocks reflect unidentified state variables. These variables produce undiversifiable risks (covariances) in returns that are not captured by the market return and are priced separately from market betas. In support of this claim, they show that the returns on the stocks of large firms and returns on high book-to-market (value) stocks covary more with one another than with returns on low book-to-market (growth) stocks.

This is consistent with Merton's (1973) Intertemporal CAPM where the additional two factors are correlated with relevant state-variables representing the intertemporal changes in the investment opportunity set. As a result, they propose a three factor model in which the three factors are (i) the excess return on a broad market portfolio, (ii) the difference between the return on a portfolio of small stocks (small capitalization) and the return on a portfolio of large stocks (large capitalization), (iii) the difference between the return on a portfolio of high book-to-market stocks and the return on a portfolio of low book-to-market stocks.

Based on this evidence, the three factor model for expected return of Fama and French (1993, 1996) is:

$$E(R_{jt} - R_{ft}) = \beta_{jm}\left[E(R_{mt}) - R_{ft}\right] + \beta_{jsmb}SMB_t + \beta_{jhml}HML_t \qquad (4)$$

In this equation, SMB_t (small minus big) is the difference between the returns on diversified portfolios of small and big stocks, HML_t (high minus low) is the difference between the returns on diversified portfolios of high and low B/M stocks and the betas are slopes in the multiple regression of $R_{jt} – R_{ft}$ on R_{mt} - R_{ft}, SMB_t and HML_t. Fama and French (1995) observed that the two non-market risk factors SMB and HML are useful factors when explaining a cross-section of equity returns.

One implication of the expected return equation of the three factor model is that the intercept a_j in the time series regression,

$$R_{jt} - R_{ft} = \alpha_j + b_{jm}\left(R_{mt} - R_{ft}\right) + b_{js}SMB_t + b_{jh}HML_t + \varepsilon_{jt} \qquad (5)$$

is zero for all assets j. Using this criterion, Fama and French (1993, 1996) find that the model captures much of the variation in average return for portfolios formed on size, book-to-market equity and other price ratios that cause problems for the CAPM.

The three-factor model is now widely used in empirical research that requires a model of expected returns. Estimates of a_j from the time-series regression above are used to calibrate how rapidly stock prices respond to new information.

From a theoretical perspective, the main shortcoming of the three-factor model is its empirical motivation. The small-minus-big (SMB) and high-minus-low (HML) explanatory returns are not motivated by predictions about state variables of concern to investors. Instead they are brute force constructs meant to capture the patterns uncovered by previous work on how average stock returns vary with size and the book-to-market equity ratio. Another strand of research points to problems in both the three factor model and the CAPM. Frankel and Lee[8] (1998), Dechow, Hutton and Sloan[9] (1999), Piotroski[10] (2000) and others show that in portfolios formed on price ratios like book-to-market equity, stocks with higher expected cash flows have higher average returns that are not captured by the three factor model or the CAPM. The authors interpret their results as evidence that stock prices are irrational. They do not reflect available information about expected profitability.

In truth however one can’t tell whether the problem is bad pricing or a bad asset pricing model. A stock’s price can always be expressed as the present value of expected future cash flows discounted at the expected return on the stock. It follows that if two stocks have the same price, the one with higher expected cash flows must have a higher expected return. And this is true whether pricing is rational or irrational. Thus, when one observes a positive relation between expected cash flows and expected returns that is left unexplained by the CAPM or the three factor model, one can’t tell whether this is the result of irrational pricing or a mis-specified asset pricing model.

2.4 Arbitrage Pricing Theory (APT)

Ross (1976) has proposed a new and different approach to explain the pricing of assets. He has developed a mechanism that, given the process that generates security returns, derives asset prices from arbitrage arguments analogous to (but more complex than) those used to derive CAPMs. Arbitrage pricing theory is a new and different approach of determining asset prices. It is based on the law of one price: two items that are the same can’t sell at different prices. The strong assumptions made about utility theory in deriving the CAPM are not necessary. In fact, the APT description of equilibrium is more general than that provided by a CAPM-type model in that pricing can be affected by influences beyond simply means and variances. An assumption of homogenous expectations is necessary. The assumption of investors utilizing a mean variance framework is replaced by an assumption of the process generating security returns. The CAPM predicts that security rates of return will be linearly related to a simple common factor – the rate of return on the market portfolio.

The APT starts by assuming that there are k factors which cause asset returns to systematically deviate from their expected values. It simply assumes that these k factors cause returns to vary together. Based on these assumptions, Ross shows that, in order to

8. Frankel, Richard and Charles M.C. Lee. (1998). “Accounting Valuation, Market Expectation, and Cross-Sectional Stock Returns.” Journal of Accounting and Economics. 25:3, 283-319.

9. Dechow, Patricia M., Amy P. Hutton and Richard G. Sloan. (1999). “An Empirical Assessment of the Residual Income Valuation Model.” Journal of Accounting and Economics. 26:1, 1-34.

10. Piotroski, Joseph D. (2000). “Value Investing: The Use of Historical Financial Statement Information to Separate Winners from Losers.” Journal of Accounting Research. 38, pp.1-51.

prevent arbitrage, an asset's expected return must be a linear function of its sensitivity to the k common factors:

$$E(R_{jt}) = R_f + \beta_{j1t}F_{1t} + \beta_{j2t}F_{2t} + \ldots + \beta_{jkt}F_{kt} + \varepsilon_{jt} \tag{6}$$

where: R_j = the random rate of return on the jth asset.
$E(R_j)$ = the expected rate of return on the jth asset.
b_{jk} = the sensitivity of the jth asset’s return to the kth factor.
F_k = the risk premium for factor k.
ε_j = a random zero mean noise term for the jth asset and variance equal to σ^2_{ej}

The theory requires that the number of assets under consideration be much larger than the number of factors, k, and that the noise term, ε_j, be the unsystematic risk component for the jth asset. It must be independent of all factors and all error terms for other assets.

The principal strength of the APT approach is that it is based on the no arbitrage condition. Because the no arbitrage condition should hold for any subset of securities, it is not necessary to identify all risky assets or a “market portfolio” to test the APT. An important characteristic of the APT theory is that it is extremely general. This generality is both strength and a weakness. Although it allows us to describe equilibrium in terms of any multi-index model, it gives us no evidence as to what might be an appropriate multi-index model. Furthermore, APT tells us nothing about the size. This makes interpretation of tests difficult.

The CAPM is seen to be a special case of the APT (where asset returns are assumed to be joint normal). But the arbitrage pricing theory is much more robust than the capital asset pricing model for several reasons:

1. The APT makes no assumptions about the empirical distribution of asset returns.
2. The APT makes no strong assumptions about individual’s utility functions (at least nothing stronger than greed and risk aversion).
3. The APT allows the equilibrium returns of assets to be dependent on many factors, not just one (beta).
4. The APT yields a statement about the relative pricing of any subset of assets, hence one need not measure the entire universe of assets in order to test the theory.
5. There is no special role for the market portfolio in the APT, whereas the CAPM requires that the market portfolio be efficient.
6. The APT is easily extended to a multi period framework.

2.5 Consumption CAPM (CCAPM)

The basic model of asset pricing is Consumption-CAPM (CCAPM) proposed by Lucas (1978), Rubinstein (1978) and Breeden (1979). In the basic CCAPM model, prices (and as a consequence, returns) of assets are given as the solution to the optimization problem of a representative consumer-investor. The central pricing formula defines the price of an asset as the expected discounted payoff, using the investor’s marginal utility to discount the payoff. The marginal utility loss of consuming a little less today and investing the result should equal the marginal utility gain of selling the investment at some point in the future and eating the proceeds. If the price does not satisfy this relation, the investor should buy more of the asset, until the condition holds.

The consumer seeks to make sure that he has a constant flow of consumption over time, in other words, he wants to reduce the volatility of consumption over time. He can accomplish this by holding an asset whose payoffs are negatively correlated with consumption. If this is the case, the investor can reduce the volatility of his future consumption. For example, if the payoff of the asset is higher when GDP are lower as a consequence of a recession, the investor can increase his consumption by spending the payoff of the asset.

The central role of assets is that they stabilize consumption over time. In other words, they act as insurance in cases when income drops unexpectedly. Given that assets have returns, which depend on the state of the business cycle, we would like to hold assets, which have higher returns, when income (consumption) is low (economic recession) and low returns when income is high (economic boom). In this sense, we are prepared to pay a higher price for an investment with returns, which are negatively correlated with income.

This model is based on the intuition that an extra dollar of consumption is worth more to a consumer when the level of aggregate consumption is low. When things are going really well and many people can afford a comfortable standard of living, another dollar of consumption doesn't make us feel very much better off. But when times are hard, a few extra dollars to spend on consumption goods is very welcome. Based on this "diminishing marginal utility of consumption," securities that have high returns when aggregate consumption is low will be demanded by investors, bidding up their prices (and lowering their expected returns). In contrast, stocks that co-vary positively with aggregate consumption will require higher expected returns, since they provide high returns during states of the economy where the high returns do the least good.

Based on this line of reasoning, they derived a consumption-based capital asset pricing model (CCAPM) of the form:

$$E(R_j) = R_f + \beta_{jC}\left[E(R_m) - R_f\right] \tag{7}$$

where β_{jC} measures the sensitivity of the return of asset j to changes in aggregate consumption. β_{jC} is referred to as the consumption beta of asset j, and the CCAPM's main result is that expected returns should be a linear function of consumption betas.

Finally a point worth remembering is that all factor models are derived as specializations of the consumption-based model. Many authors of factor model papers disparage the consumption-based model, forgetting that their factor model *is* the consumption-based model plus extra assumptions that allow one to proxy for marginal utility growth from some other variables.

3. Market Liquidity Proxies

The power of the asset-pricing tests is enhanced by using large samples. Hence, we concentrate on those liquidity proxies constructed from daily data, instead of from high-frequency data, which has a relatively short time period. Normally, the construction of aggregate market-wide liquidity proxies starts with a definition of firm-specific liquidity, and then aggregates to a market-wide liquidity proxy by taking the cross-sectional average after excluding the two most extreme observations at both ends of the cross-section. In the literature, there are several alternative measures of liquidity.

3.1 Bid-Ask Spread

The proportional quoted bid-ask spread, typically calculated as the difference between the bid and ask price divided by the bid-ask midpoint, is a widely used measure of market liquidity. It directly measures the cost of executing a small trade. The spread contains two components. The first component compensates market-makers for inventory costs, order processing fees, and/or monopoly profits. This component is transitory since its effect on stock price is unrelated to the underlying value of the securities. The second component, an adverse selection component, arises because market-makers may trade with unidentified informed traders. In order to recover from loses to the informed traders who may have superior information, rational market-makers in a competitive environment widen the spread to recover profits from uninformed traders. Specifically, the bid-ask spread compensates the market dealer for the order processing cost and liquidity risk associated with holding an illiquid asset. Hence, the bid-ask spread is positively related to market liquidity risk.

$$PQSPR_{jt} = \frac{1}{D_{jt}} \sum_{d=1}^{D_{jt}} \left(p^{A}_{jdt} - p^{B}_{jdt}\right) \Big/ \left(0{,}5\,p^{A}_{jdt} + 0{,}5\,p^{B}_{jdt}\right) \tag{8}$$

where p^{A}_{jdt} and p^{B}_{jdt} are the ask and bid prices for stock j on day d in month t.

D_{jt} is the number of days for stock j in month t.

The market-wide proportional quoted bid-ask spread is taken to be the cross sectional average of these stock's monthly proportional quoted spreads.

As a proxy for liquidity, the bid-ask spread has certain shortcomings. Brennan and Subrahmanyam (1996) argue that the bid-ask spread is a noisy measure of liquidity because large trades tend to occur outside the spread while small trades tend to occur inside, which means that bid-ask quotes are only good for limited quantities. People often use intraday data to compute bid-ask spreads. The market wide relative spread is taken to be the cross sectional average of these stocks' monthly relative spreads.

Another limitation of the bid-ask spread as a measure of liquidity is that it does not incorporate the key element of time or immediacy. It measures exactly the market maker's return for providing immediacy only in the special case in which the market maker simultaneously "crosses" (executes both sides of) the trade, one at the bid and one at the ask. But in that case, the spread could not also serve as a valid measure of the cost of supplying immediacy to each of its customers. It is simply a charge by the market maker for executing their orders, rather than for providing them liquidity services. Also, the data on the bid-ask spread is hard to obtain on a monthly basis over long periods of time (Amihud & Mendelson (1986) and Eleswarapu & Reinganum (1993) use the average of the bid-ask spread at the beginning and at the end of the year as a proxy for the liquidity of a stock through that year).

3.2 Stock Turnover

Stock turnover is given by the ratio of trading volume to the number of shares outstanding. It is a trading activity measure that is often used as a proxy for liquidity. The advantage of using the turnover rate as a proxy for liquidity is two-fold. First, it has strong theoretical appeal. *Amihud and Mendelson (1986)* show that assets with higher spreads are allocated in equilibrium to portfolios with (the same or) longer expected holding periods. They argue that in equilibrium, the observed market (gross) return must be an increasing function of the relative spread, implying that the observed asset returns must be an increasing function of the expected holding periods. Given the fact that the turnover is the reciprocal of a representative investor’s holding period and is negatively related to other liquidity costs such as bid-ask spreads, one can use it as a proxy for liquidity and the observed asset return must be a decreasing function of the turnover rate of that asset. Intuitively, in an intertemporal setting with zero transaction costs, investors will continuously rebalance their portfolios in response to changes in the investment opportunity set. In the presence of transaction costs, such rebalancing will be performed more infrequently, resulting in reduced liquidity. Second, the data on turnover rates is relatively easy to obtain. This enables to capture month-by-month variation in the liquidity of assets and allows the examination of liquidity effects across a large number of stocks over a long period of time.

The monthly turnover measure is the average of daily share turnover:

$$stov_{jdt} = \frac{1}{D_{jt}} \sum_{d=1}^{D_{jt}} \frac{vol_{jdt}}{no_{jdt}} \tag{9}$$

where vol_{jdt} is the euro/dollar value of shares traded-volume (or the number of shares traded) of stock j on day d in month t

no_{jdt} is the number of shares outstanding

$D_{j,t}$ is the number of observations for stock j in month *t*.

The market-wide stock turnover liquidity measure is calculated as the cross-sectional of the stocks’ monthly stock turnover.

$$stov_t = \frac{1}{N_t} \sum_{j=1}^{N_t} stov_{jdt} \tag{10}$$

However, *Lee and Swaminathan (2000)*[11] question the interpretation of turnover as a proxy for liquidity because the relationship between turnover and expected returns depends on how stocks have performed in the past. More specifically, they find that high volume stocks are generally glamour stocks and low volume stocks are generally value or neglected stocks. Also high volume firms and low volume firms differ significantly in terms of their past operating and price performance.

3.3 Illiquidity Ratio

The illiquidity ratio of *Amihud (2002),* which is defined to be the absolute return divided by the euro trading volume, reflects the absolute (percentage) price change per euro of trading volume, and is a low frequency analog to microstructure high frequency liquidity measures. While the bid-ask spread captures the cost of executing a small trade, the illiquidity ratio, as a price impact proxy, captures the cost associated with larger trades.

Furthermore, the advantage of using the illiquidity ratio is two-fold. First, it has a strong theoretical appeal. Hasbrouck (2004) finds that this measure appears to be the best among the usual proxies constructed from daily data. Second, the data on illiquidity rates is relatively easy to obtain. This enables us to capture, month-by-month, variations in the illiquidity of assets and allows the examination of illiquidity effects across a large number of stocks over a long period of time.
The monthly firm-specific illiquidity ratio is given by

$$ILLQ_{jt} = \frac{1}{D_{jt}} \sum_{d=1}^{D_{jt}} \frac{|R_{jdt}|}{V_{jdt}} \tag{11}$$

where $r_{j,d,t}$ and $v_{j,d,t}$ are the return and the euro volume for stock j on day d in month t, and $D_{j,t}$ is the number of observations for stock j in month t. Then the market-wide illiquidity ratio is the cross-sectional average of individual stocks’ illiquidity ratios in each month.

3.4 Liquidity ratio

This illiquidity measure (ILLIQ) is strongly related to the liquidity ratio known as the Amivest measure, the ratio of the sum of the daily volume to the sum of the absolute return. The Amivest liquidity ratio for a stock is

$$L_{jt} = \frac{1}{D_{jt}} \sum_{d=1}^{D_{jt}} V_{jdt} \Big/ |R_{jdt}| \tag{12}$$

11. Lee, Charles M., & Swaminathan, B., (2000). “Price momentum and trading volume”. Journal of Finance, 55, 2017-2069.

where R_{jdt}: is the return on day d
V_{jdt}: is the volume (euro or share) on day d
The average is taken over all days in the sample where $R_{jdt} \neq 0$

The originator of the ratio, Amivest, was a money management and broker/dealer concern. It was taken over by the North Fork Bank (New York) in 1998. This measure has been used in the cross-sectional studies of comparative liquidity across markets (e.g., Cooper et al., 1985; Khan and Baker, 1993). Also, Amihud et al. (1997) and Berkman and Eleswarapu (1998) used the liquidity ratio to study the effects of changes in liquidity on the values of stocks that were subject to changes in their trading methods. The liquidity ratio, however, does not have the intuitive interpretation of measuring the average daily association between a unit of volume and the price change, as does the ILLIQ.

3.5 Return Reversal

Pastor and Stambaugh (2002) suggest that a reasonable liquidity risk factor should be associated with the strength of volume-related return reversals since order flow induces greater return reversals when liquidity is lower. This measure is motivated by the Campbell, Grossman, and Wang (1993) (CGW) model and its empirical findings. In the CGW symmetric information setting, risk-averse market makers accommodate trades from liquidity or non-informational traders. In providing liquidity, market makers demand compensation in the form of a lower (higher) stock price and a higher expected stock return, when facing selling (buying) order from liquidity traders. Such trades thus cause higher volume return-reversals when current trading volume is high.

This return reversal measure reflects only temporary price fluctuations arising from the inventory control effect of price impact. It does not capture the permanent effect on price arising from asymmetric information like Amihud's illiquidity ratio.

The monthly firm-specific return reversal measure (henceforth referred to as PS) is computed by performing the following OLS regression using daily data within a month:

$$R^{e}_{j,d+1,t} = a_{jt} + b_{jt} R_{jdt} + \gamma_{jt} sign\left(R^{e}_{jdt}\right) vol_{jdt} + u_{j,d+1,t} \qquad (13)$$

where $R^{e}_{jd+1,t}$ is the excess return with respect to the value weighted market return for firm j on day $t + 1$

R_{jdt} is the return for firm j on day t

vol_{jdt} is euro volume for stock j on day d in month t.

Firm months with less than 15 daily return observations are excluded. γ_{jt} measures the expected return reversal for a given euro volume. The greater the expected reversal is, the lower the stock's liquidity. $\gamma_{jt} > 0$ would suggest that the market did not fully respond to the preceding day's order flow. On the other hand, $\gamma_{jt} < 0$ would suggest that the market over-reacted, perhaps due to limited capacity of market makers to absorb the order flow.

Therefore γ_{jt} should be generally negative and larger in absolute value when liquidity is lower. The cross-sectional average of monthly individual stocks' return reversal measures is the market-wide return reversal measure.

4. RELATED LITERATURE

The question of whether liquidity determines expected returns has been widely documented in the financial literature. Using a variety of liquidity measures, studies analyze whether less liquid stocks have higher average returns than expected.

4.1 Cross-sectional liquidity

One of the first published researches that examine the relationship between liquidity and asset pricing is the paper by **Amihud and Mendelson (1986)**. They provided a seminal paper in introducing liquidity to academic research, even though liquidity had long been an issue looked at by practitioners. They analyzed the relationship between stock returns and bid-ask spreads and found empirical evidence related to the existence of a liquidity premium. Illiquidity can be measured by the cost of immediate execution. An investor willing to transact faces a tradeoff: He may either wait to transact at a favorable price or insist on immediate execution at the current bid or ask price. The quoted ask (offer) price includes a premium for immediate buying and the bid price similarly reflects a concession required for immediate sale. Thus, a natural measure of illiquidity is the spread between the bid and ask prices which is the sum of the buying premium and the selling concession.

Using bid-ask spread as a measure of illiquidity, they developed a theoretical model predicting that higher spread assets yield higher return, and that there is a clientele effect whereby investors with longer investment horizons will select assets with higher average spreads. As a result of this horizon clientele, they argued that the observed asset returns must be an increasing and concave function of the transaction costs.

Their data consisted of monthly securities returns provided by the CRSP and relative bid-ask spreads collected for NYSE stocks from Fitch's Stock Quotations on the NYSE. Using the data for the period 1961-1980, they empirically test by using cross-section and time-series methodology as well, the implications of their theoretical model using a CAPM framework and their evidence confirms that there is a positive relationship between expected stock return and illiquidity. However, the design of their empirical tests does not permit the exploration of potential monthly seasonality in the relation between expected returns and bid-ask spreads.

Because of contrary studies **Amihud and Mendelson (1989)** revisit their liquidity-return relationship and provide a joint test of risk factors that are thought to be important to expected returns. They show that three of four factors identified by Merton (1987) as significantly related to risk-adjusted returns are no longer significant when the relative bid-ask spread is included as an explanatory variable. Only beta remains significant. They look at beta, residual risk, size and liquidity. They conclude that expected asset returns are a function of beta and liquidity and, in the presence of liquidity, returns are not significantly related to residual risk and firm size.

However, **Eleswarapu and Reinganum (1993)**, who extended the sample period by 10 years, examined the effect of seasonality on bid-ask spreads and returns. Using the same liquidity measure as Amihud and Mendelson (1986), they found that the relationship between bid-ask spreads and asset returns is mainly limited to the month of January. The purpose of their paper was twofold: 1) to investigate the relation between average returns and bid-ask spreads in January and in non-January months and 2) to determine if Amihud & Mendelson’s empirical results are sensitive to their restrictive portfolio selection criteria.

They tested the cross-sectional relation between monthly returns, betas and the relative bid-ask spread over the 1961-1990 period using NYSE firms. Monthly NYSE stock returns are obtained from tapes provided by the CRSP. The evidence reveals a positive relation between bid-ask spreads and average returns, but only during the month of January (the liquidity premium is reliably positive only during the month of January). The lack of such a positive relation between spreads and average returns outside of January may well be part of a broader puzzle.

Also, unlike the original Amihud & Mendelson’s study, the evidence in their paper suggests a significant size effect even after controlling for spreads and beta. The restrictive sample selection criteria of Amihud & Mendelson tend to systematically exclude smaller firms and hence bias the results against finding a size effect. By modifying the portfolio formation technique, the number of firms included in the analysis increases by 45%. However, the quoted bid-ask spread is a noisy measure of illiquidity because many large trades occur outside the spread and many small trades occur within the spread.

Brennan and Subrahmanyam (1996) refute the findings of Eleswarapu and Reinganum (1993) and find some support for the Amihud and Mendelson (1986) study. In their paper, they bring together diverse empirical techniques from asset pricing and market microstructure research to examine the return-illiquidity relation. Specifically, instead of using bid-ask spreads as a proxy for liquidity they measure stock illiquidity by price impact, measured as the price response to signed order flow (order size) and by the fixed cost of trading. They estimate measures of illiquidity from intraday transactions data, take the Fama-French model as their null hypothesis and test whether variables related to the cost of transacting have additional explanatory power for the cross-section of returns.

Since their measures require intraday data, which is available only after 1983, their sample period is short. They use intraday data from the Institute for the Study of Securities Markets for the years 1984 and 1988. The use of transactions data enables them to estimate both the variable (trade-size-dependent) and the fixed costs of transacting. By empirically examining the effects of both variable and fixed components of illiquidity on asset returns they are able to shed light on the importance of the empirical measures of adverse selection in influencing asset returns.

Their main findings are that there is a significant return premium associated with both the fixed and variable elements of the cost of transacting. The relation between the premium and the variable cost is concave, which is consistent with clientele effects caused by small traders concentrating in the less liquid stocks. However, the relation between the premium and the estimated fixed cost component is convex. This is inconsistent with the horizon clientele effect proposed by Amihud and Mendelson (1986), and may be the result of their inability to estimate this parameter accurately on account of price discreteness. Alternatively, it may be due to incomplete risk adjustment by the three-factor Fama and French model they use. They also address the issue of seasonality raised by Eleswarapu and Reinganum (1993). A likelihood ratio test of seasonality leads them to conclude that there are no significant monthly seasonal components in the compensation for their transaction cost measures, the bid-ask spread, or the inverse price level variable, after allowing for the effect of the Fama and French risk factors. Finally, an interesting byproduct of their analysis is the finding that controlling for firm size, there appears to be a negative relation between the variable and fixed costs of transacting.

Given the lack of robustness of empirical results, several investigators have re-examined the relationship between liquidity and asset returns using alternative measures of liquidity that allow to approach the concept of liquidity employed by investors in their financial decisions. In this sense, a large number of papers have focused on the use of liquidity measures based on trading activity, such as trading volume (Brennan, Chordia, and Subrahmanyam, (1998)), turnover ratio (Datar, Naik, Radcliffe, (1998), and Chan and Faff, (2004)) or illiquidity ratio (Amihud, (2002)).

Brennan, Chordia and Subrahmanyam (1998) examine the relation between stock returns, measures of risk, and several non-risk security characteristics, including the book-to-market ratio, firm size, the stock price, the dividend yield, and lagged returns. Their primary objective is to determine whether non-risk characteristics have marginal explanatory power relative to the arbitrage pricing theory (APT) benchmark, with factors determined using, in turn the Connor and Korajcyzk (1988)[12] and the Fama and French (1993) approaches. They use trading volume as a measure of liquidity and they find a negative and significant relationship between returns and trading volume for both NYSE and NASDAQ stocks, which is consistent with a liquidity premium in asset prices. However, this liquidity measure has two potential problems. First, the number of shares traded by it is not a sufficient statistic for the liquidity of a stock since it does not take into account the difference in the number of shares outstanding or the shareholder base. Second, the use of the euro volume has a size bias. The basic data consist of monthly returns and other characteristics for a sample of the common stock of companies for the period January 1966 to December 1995.

Jacoby, Fowler and Gottesman (2000) developed a theoretical approach about the capital asset pricing model and the liquidity effect. They derive a liquidity-adjusted version of the CAPM based on returns calculated after taking into account the effect of the bid-ask spread. Their model demonstrates that the measure of systematic risk should incorporate liquidity costs (the bid-ask spread).

The contribution of their paper is to demonstrate that beta and liquidity are inseparable. They develop a CAPM-based model, which is a one period model, under which all securities, liquid and illiquid, are held for the whole period. This means that they do not allow the more liquid asset to be traded more frequently during the period, thereby eliminating the clientele effect and the concavity obtained by Amihud and

12. Connor, G., & Korajczyk, R., (1988). "Risk and return in an equilibrium APT: application of a new test methodology". Journal of Financial Economics 21, 255–290.

Mendelson. They adopt Amihud and Mendelson's (1989) conclusion that the bid-ask spread is the true reason for the existence of the size effect. Their model shows that the true measure of systematic risk, in a world with uncertainty with regard to the future spread, is one calculated on the basis of the net (after-spread) returns. This theoretical conclusion anticipates that the beta measure and the spread effect are inseparable. By identifying a significant size effect, described by Fama and French (1992), with the spread effect, they suggest that an after-spread beta may produce significant results for the same period (1963-1990).

The after-spread beta measure they derive is non-linear in the traditional beta. The non-linear specification indicates that rejection of the traditional CAPM is expected, especially when the liquidity effect is significant. This point allows them to contrast the early empirical success of the CAPM obtained by Black et al. (1972), and Fama and MacBeth (1973) against the Fama and French (1992) study. The earlier studies only used data from the highly liquid NYSE, while the data used by Fama and French (1992) also includes securities from the less liquid AMEX and NASDAQ. This can be explained by the fact that liquidity costs proxied by the bid-ask spread are more prominent for shorter (monthly) holding periods, while their relative importance weakens for longer (annual) holding periods.

They further examine the relationship between the expected return and the future spread cost within the CAPM framework. This positive relationship in their model is found to be convex. This finding differs from Amihud and Mendelson's (1986), whose model suggests a positive and concave relationship between the expected gross return and the future spread.

Another related measure is turnover, the ratio of trading volume to the number of shares outstanding, which can employ as a measure of the asset trading frequency. Datar, Naik and Radcliffe (1998) and Chordia, Subrahmanyam and Anshuman (2001) found that cross-sectionally, stock returns decrease in stock turnover, which is consistent with a negative relationship between liquidity and expected return.

Datar, Naik and Radcliffe (1998) attempt to shed light on the relation between liquidity and asset returns using a proxy for liquidity that is different from the bid–ask spread measure widely used by researchers. The reason for proposing a new proxy for liquidity is two-fold. First, the data on bid–ask spread is hard to obtain on a monthly basis over long periods of time (Amihud & Mendelson (1986) and Eleswarapu & Reinganum (1993) use the average of the bid–ask spread at the beginning and at the end of the year as a proxy for the liquidity of a stock through that year). Second, researches have shown that the quoted spread is a poor proxy for the actual transactions costs faced by investors and call for an alternative proxy, which may do a better job of capturing the liquidity of an asset.

For these reasons they propose the turnover rate of an asset as a proxy for its liquidity. They define the turnover rate of a stock as the number of shares traded divided by the number of shares outstanding in that stock and think of it as an intuitive metric of the liquidity of the stock. The advantage of using the turnover rate as a proxy for liquidity is two-fold. First, it has strong theoretical appeal. Amihud and Mendelson (1986) prove that in equilibrium liquidity is correlated with trading frequency. So, if one cannot observe liquidity directly but can observe the turnover rate, then one can use the latter as a proxy for liquidity. Second, the data on turnover rates is relatively easy to obtain (it can be constructed from the CRSP tapes on a monthly basis). This enables to capture month by month variation in the liquidity of assets and allows the examination of liquidity effects across a large number of stocks over a long period of time.

Using the turnover rate as a proxy for liquidity they examine whether stock returns are negatively related to liquidity as predicted by Amihud and Mendelson's (1986) model. They investigate if this relation persists after controlling for the firm size, book to market ratio and the firm beta. They employed a modified Fama-MacBeth (1973) methodology in their analysis of the cross-sectional returns of stocks. Since Eleswarapu & Reinganum (1993) find that liquidity premium is mainly restricted to the month of January, they examine the relationship with and without the month of January. Finally, they subdivide the sample into two halves and examine the robustness of the relation between the stock returns and turnover over time.

Their dataset consists of all non-financial firms on the NYSE from 31 July 1962 through 31 December 1991. Monthly data on returns is collected from the CRSP and the book value is extracted from the COMPUSTAT tapes. In their dataset, on average there are about 880 stocks in each month.

Their results support the predictions of Amihud and Mendelson's (1986) model. They find that the stock returns are strongly negatively related to their turnover rates confirming the notion that illiquid stocks provide higher average returns. In general, they find that a drop of 1% in the turnover rate is associated with a higher return of about 4.5 basis points per month, on average. In contrast to the findings of Eleswarapu & Reinganum (1993), they do not observe any evidence of January seasonality. In particular, they find that the stock returns are strongly related to the turnover rates throughout the year. They conclude that the size-return relationship reported by Fama and French (1992) is a reflection of the liquidity-return relationship, with size simply one of a number of possible surrogates for liquidity. Finally, when they subdivide their dataset into two halves, they observe that the liquidity effect is significant in the first as well as in the second half. In summary, they find that the liquidity effect predicted by Amihud and Mendelson's (1986) model is robust and plays an important role in explaining the overall cross-section of stock returns.

Fama and French (1992) argue that liquidity is an important issue but it does not need to be specifically measured and accounted for because it is subsumed by the combination of size and book-to-market factors. However, other cross-sectional studies such as **Chordia, Subrahmanyam and Anshuman (2001)** show that liquidity needs to be accounted for individually and that after controlling for size, book-to-market and other variables, liquidity is still very much an important factor in returns. They document a negative and surprisingly strong relation between average returns and both the level as well as the variability of trading activity, after controlling for the well-known size, book-to-market ratio, and momentum effects, as well as the price level and dividend yield for a sample of NYSE and AMEX common stocks-listed companies for the period January 1966 to December 1995. This negative relation is statistically and economically significant. Theoretically, the relationship between expected returns and liquidity, and more importantly the relationship between expected returns and the variability of liquidity, is motivated by the idea that agents are risk averse and have an aversion to variability in liquidity. Consequently, securities with higher variability should yield higher expected returns.

They empirically investigate the relationship between expected returns and the volatility of liquidity using the Brennan, Chordia and Subrahmanyam (1998) methodology. Since they do not have data on bid-ask spreads for a length of time sufficient to run asset pricing tests, they proxy for liquidity by using two measures of trading activity, the dollar volume and the share turnover. The turnover rate is related to the representative investor's holding period and the dollar trading volume is related to how quickly a dealer expects to turn around her position. In addition, they make use of the Fama and French (1993) factors as a risk adjustment. Of course, there is always the possibility that these measures are actually picking up some unknown and as yet undiscovered risk factor, or some behavioral anomaly. However, they believe this concern is mitigated both by the fact that they adjust returns for risk using the Fama-French factors, and that they have also controlled for well-known return determinants such as size, book-to-market ratio, momentum, price, and dividend yield.

Chan and Faff (2004) examine the role of liquidity (proxied by share turnover) in explaining stock returns in the context of the Fama-French three factor cross-sectional framework for the Australian equity market for the period January 1989 to December 1999.

Following recent papers such as Datar, Naik and Radcliffe (1998) and Chordia, Subrahmanyam and Anshuman (2001), their paper uses the cross-sectional regression approach of Fama and MacBeth (1973). Specifically, they examine whether cross-sectional variations in individual stock returns can be explained by differences in liquidity (proxied by share turnover), in the context of the Fama-French variables of size, book-to-market and stock beta. They use Generalized Methods of Moments (GMM) methodology to overcome the errors-in-variables problem in the traditional Fama-MacBeth cross sectional regression. Their GMM tests fail to reject the over identifying and form portfolios based on various criteria such as industry, size, book-to-market ratios, and co-skewness with a market portfolio. Their results show that conditional skewness helps explain the cross sectional variation of expected returns. Their proxy for liquidity, the turnover variable for each stock is computed as the average of the monthly trading volume divided by the number of shares on issue for the previous three months (updated monthly) and is similar to that used by Datar, Naik and Radcliffe (1998).

Their main findings all relate to the asset pricing role of turnover/liquidity and can be summarized as follows. First and foremost, they find for the full sample period, for the two sub periods, for all months and for the liquidity augmented Fama-French model that stock returns are strongly negatively related to turnover, as proxied by liquidity. Second, while the role of turnover may be weakened by January and/or July seasonality, it is not seriously so. Third, the importance of turnover is robust to the inclusion of a momentum factor. The significance of this finding is that it rebuts the argument of Lee and Swaminathan (2000)[13] who suggest that turnover is less a proxy for illiquidity and more a proxy for 'value/glamour'. By the inclusion of a momentum variable, they are controlling for the value/glamour effect, and the fact that turnover retained its strong negative relationship with returns in this setting, gives added credence to the view that turnover proxies liquidity in their study.

In short, they conclude that in Australia over the time of their sample period there has been a significant asset pricing role for turnover. Moreover, their evidence suggests that it is much more likely that turnover proxies liquidity than it is proxies

13. Lee, Charles M., & Swaminathan, B., (2000). "Price momentum and trading volume". Journal of Finance, 55, 2017-2069.

‘value/glamour’. As such, they believe that liquidity has been an important priced factor, forming a strong negative relationship with returns.

4.2 Literature on Commonality in Liquidity

It is important to distinguish between liquidity level and liquidity risk of assets. Most of the studies that investigate liquidity and asset prices, often make the argument that stocks with low liquidity level, measured by bid-ask spreads, dollar volume, etc., earn higher expected returns (see, e.g., Amihud and Mendelson (1986), Brennan and Subrahmanyam (1996), Chordia, Subrahmanyam, and Anshuman (2001), and Easley, Hvidkjaer, and O’Hara (2002)). Only a few recent studies investigate whether there exists a systematic component of liquidity (see, e.g., Chordia, Roll, and Subrahmanyam (2000), Huberman and Halka (2001), Hasbrouck and Seppi (1999)).

Commonality in liquidity could arise from several sources. Trading activity generally displays market-wide intertemporal response to general price swings. Since trading volume is a principal determinant of dealer inventory, its variation seems likely to induce co-movements in optimal inventory levels which lead in turn to co-movements in individual bid-ask spreads, quoted depth, and other measures of liquidity. Across assets, inventory-carrying costs must also co-move because these costs depend on market interest rates. The risk of maintaining inventory depends also on volatility, which could have a market component. One might think that little covariation in liquidity would be induced by asymmetric information because few traders possess privileged information about broad market movements. Trading costs should be cross-sectionally related to expected returns before costs simply because after-cost returns should be equilibrated in properly functioning markets (Amihud and Mendelson, (1986); Brennan and Subrahmanyam, (1996)).

But commonality in liquidity raises the additional issue of whether shocks in trading costs constitute a source of non-diversifiable priced risk. If covariation in trading costs cannot be completely anticipated and has a varying impact across individual securities, the more sensitive an asset is to such shocks, the greater must be its expected return. Hence, there are potentially two different channels by which trading costs influence asset pricing, one static and one dynamic: a static channel influencing average trading costs and a dynamic channel influencing risk.

Specifically, **Chordia, Roll, and Subrahmanyam (2000)** were the first who empirically documented the commonality in liquidity. They use transactions data for New York Exchange (NYSE) stocks, obtained from the Institute for the Study of Securities Markets (ISSM) during the most recently available calendar year, 1992. Corresponding to every transaction, five different liquidity measures are computed: the quoted and effective bid-ask spreads, the proportional quoted and effective spreads and quoted depth.

Recognizing the existence of commonality in liquidity allows them to uncover evidence that inventory risks and asymmetric information both affect individual stock liquidity. A stock's spread is positively related to the number of individual transactions but negatively related to the aggregate level of trading in the entire market. They interpret this pattern as a manifestation of two effects (a) a diminution in inventory risk from greater market-wide trading activity, most plausibly by uninformed traders, and (b) an increase in asymmetric information risk occasioned by informed traders attempting to conceal their activities by breaking trades into small units, thus increasing the number of transactions. Although commonality is the instrument used to reveal asymmetric information effects on liquidity, they have no evidence that asymmetric information itself has common determinants. Co-movements in liquidity also suggest that transaction expenses might be better managed with appropriate timing. When spreads are low, managed portfolio turnover can be larger without sacrificing performance. However, they do not yet know whether common variations in trading costs are associated with other market phenomena, such as price swings, which might offset the benefits of time-managed trading.

Huberman and Halka’s (1999) goal is to document the presence of a systematic component of liquidity and to explore variables that may be correlated with it. They conjecture that a systematic component of the temporal variation of liquidity emerges because of the presence and effect of noise traders. Since they cannot offer a model of the motivation, incidence and effect of noise traders on stock returns, volatility, trading volume and, most relevant here, liquidity, they consider it useful to record empirical regularities until they develop a model of liquidity. They wish to abstract from time-of-day effects; hence, they sample liquidity proxies once a day, at noon. Moreover, because liquidity proxies are highly auto correlated, they control for the expected component so they can concentrate on the cross-sectional correlations of the innovations in liquidity proxies.

Their primary data source is the 1996 Trade and Quotes (TAQ) Database provided by the NYSE, which reports all trades and quotes, time-stamped. They sort all NYSE stocks by size and select a random sample of 60 stocks from each size-based quartile. They use prices from the CRSP and number of shares from Standard & Poor’s Compustat at the end of 1995 to compute market capitalization (size).

They consider four proxies of liquidity: spread, spread/price ratio, quantity depth (depth measured as number of shares) and dollar depth (depth measured in dollars). They divide their 240-stock sample into two mutually exclusive subsets and compute the series of daily averages of the four liquidity proxies for each of the two subsets. Each of these series exhibits a high degree of autocorrelation. They estimate their autoregressive structure, thereby deriving the series of innovations for each of the four liquidity proxies, for each of the two mutually exclusive subsets.

The innovations of the time series of liquidity proxies are positively correlated for each liquidity proxy, which indicates the presence of a common liquidity factor. The results hold when they control for returns, volatility, trading volume, interest rates and other variables and they think could be correlated with common co movements in liquidity. They seem similarly valid across a wide spectrum of firm sizes and betas. Moreover, the temporal variation in the liquidity proxies is positively correlated with return and negatively correlated with volatility.

Also, **Hasbrouck and Seppi (1999)** explore the commonality in liquidity. By taking as their starting point, a linear microstructure specification in which returns are driven by signed order flows and public news, they assess the extent and role of cross-firm common factors in returns, order flows, and market liquidity. The data used is from the NYSE's TAQ database, which contains all trades and quotes for stocks listed on the NYSE, the AMEX, and NASDAQ's National Market System. Their sample is limited to the 30 Dow stocks in 1994 using time-aggregated trade and quote data over 15-minute intervals. This selection is motivated by (1) their intention to include firms for which common factors in liquidity trading (e.g., because of indexation) and information are plausible a priori and (2) the fact that the rapid pace of trading there allows them to construct high-frequency trading measures which approximate the idea of contemporaneous (i.e., simultaneous) order flow across stocks as well as giving them frequently updated prices. The sample covers the 252 trading days in 1994. They measure price changes using the quote midpoints at the beginning and end of each interval.

First, by using principal components and canonical correlation analyses they find that both returns and order flows are characterized by common factors. Commonality in the order flows explains roughly two-thirds of the commonality in returns. Second, they examine variation and common covariation in various liquidity proxies and market depth (trade impact) coefficients. They find some evidence of a common factor in quote-based proxies for liquidity, and to a lesser degree, in inferred price impact coefficients, after controlling for previously documented time-of-day seasonalities

Their findings are less supportive of economically significant common factors in liquidity. After removing time-of-day effects, the strength of any common factors in spreads and related liquidity measures, as judged by the first principal components, is modest. This is confirmed by cross-sectional regressions in which price impact coefficients are projected on various explanatory variables. In contrast to Chordia, Roll and Subrahmanyam (1999) and Huberman and Halka (1999), Hasbrouck and Seppi (1999) do not find conclusive evidence of the existence of such common factors. Own-firm variables dominate the principal component (common factor) and daily liquidity shock estimates. Thus, the systematic liquidity fluctuations visible during market crises such as 1987 and 1998 do not appear to characterize normal trading.

The work of **Jones (2001)** is closely related to the nascent literature on systematic liquidity, including Hasbrouck and Seppi (2001), Huberman and Halka (2001), and Chordia, Roll, and Subrahmanyam (2000). Their goal is to predict changes in liquidity at short horizons. In contrast, the goal of Jones’s paper is to document systematic, cyclical changes in liquidity over a much longer time period at much longer wavelengths. This paper is concerned with the link between asset pricing and variation in aggregate liquidity, but over time rather than in the cross-section. Specifically, by assembling a long time series on liquidity, it becomes possible to explore low frequency time variation in liquidity. This raises the tantalizing possibility, also independently suggested in Amihud (2002), that time-variation in spreads, turnover, and other liquidity measures may be closely associated with time-varying expected returns.

His paper provides the first comprehensive look at some of the frictions faced by equity investors over the past 100 years. He introduces three annual time series related to US equity market trading frictions and liquidity. The time series include:
(1) quoted bid-ask spreads on large stocks from 1900 through 2000,
(2) the weighted-average explicit costs associated with trading NYSE stocks, including commissions and other fees, since 1925, and
(3) turnover in NYSE stocks since 1900, collected in order to judge the overall incidence of these other frictions.

He takes these time series of liquidity variables and investigates whether liquidity, broadly defined, might account for some of the apparent time variation that has been observed in expected stock returns. He finds that spreads and turnover both predict excess stock returns up to three years ahead. Over the entire 20th century, these liquidity variables dominate traditional predictor variables, such as the dividend yield.

The main results are as follows. Bid-ask spreads on Dow Jones stocks gradually declined over the course of the century but are punctuated by sharp rises during periods of market turmoil. Proportional one-way commissions rise dramatically to a peak of nearly 1% in the late 1960’s and early 1970’s, and fall sharply following commission deregulation in 1975. Turnover is extremely high in the first decade of the 1900’s, and plunges in the wake of the Great Depression, remaining low for several decades thereafter. The sum of half-spreads and one-way commissions, multiplied by annual turnover, is an estimate of the annual proportional cost of aggregate equity trading. This cost drives a wedge between gross equity returns and net equity returns. This wedge can account for a small part of the observed equity premium, but suggests that the gross equity premium is perhaps 1% lower today than it was early in the 1900’s.

Finally, and perhaps most importantly, his paper presents evidence that these measures of liquidity – spreads and turnover – predict stock returns one year ahead. High spreads predict high stock returns; high turnover predicts low stock returns. This suggests that liquidity is an important determinant of conditional expected returns.

Aggregate arguments associated with liquidity restrictions have been put forward by many authors. Their papers develop either theoretical or empirical arguments implying a covariance between returns and some measure of aggregate liquidity. Their work may be understood as attempts to rationalize the consequences of commonality in liquidity and to justify the need for empirical research analyzing the impact of aggregate liquidity shocks on asset pricing.

More specifically, **Domowitz and Wang (2002)** measure liquidity as a functional of supply and demand schedules and measure commonality in liquidity as functional covariance (correlation). By addressing commonality in liquidity in a functional setting, they can connect liquidity commonality with the underlying supply and demand functions and provide a direct reason for commonality in liquidity: the commonality in supplies and demands of different securities. They show that liquidity commonality is due to supply and demand co-movements, through which order types play an important role, order types include market and limit orders. Contrarily, return commonality is mainly caused by order flow co-movements, order flows include order directions and sizes. Both their simulation results and empirical evidence from the Australian Stock Exchange data, during 3/1/2000 to 12/31/2000 for the 19 stocks that were consistently in the ASX 20 index, support the above statement.

All the results demonstrate that return commonality and liquidity commonality are not due to the same reason: order type determines liquidity and order flow determines return. Therefore, it is possible for stocks to have negative or little correlations in returns but strong positive correlations in liquidity. If this is true, then implementing the traditional diversification strategy faces one potential obstacle: the co-movements in liquidity for stocks that cancel out with each other in returns. The traditional Markowitz mean-variance portfolio theory focuses on the first and second moments of returns, and assumes no transaction cost. Past research has added the first moment of transaction cost, the liquidity level, into expected returns. They believe the second moment of transaction cost also matters in the sense that it may enter as a separate risk that needs to be minimized together with the variance of portfolio return. With this change in the objective function, the optimal portfolio is certainly going to change. Therefore, they conjecture that liquidity, or more general, transaction cost, matters to asset pricing not only through its first moment – the liquidity level, but also through its second moment – the liquidity variance/covariance.

4.3 Recent Literature on Systematic Aggregate Liquidity

In contrast to the majority of the literature, which examines the liquidity-return relationship in cross-sectional studies, **Amihud (2002)** adds to the importance of liquidity by showing the existence of a statistically significant time-varying relationship between liquidity and expected returns. Specifically, he uses a new measure based on trading activity as a proxy for liquidity, the illiquidity measure. The ILLIQ is the daily ratio of absolute stock return to its dollar volume, averaged over some period. It can be interpreted as the daily price response associated with one dollar of trading volume, thus serving as a rough measure of price impact.

There are finer and better measures of illiquidity, such as the bid ask spread (quoted or effective), transaction-by-transaction market impact or the probability of information based trading. These measures, however, require a lot of microstructure data that are not available in many stock markets. And, even when available, the data do not cover very long periods of time. The measure used by Amihud (2002) enables to construct long time series of illiquidity that are necessary to test the effects over time of illiquidity on ex ante and contemporaneous stock excess return. This would be very hard to do with the finer microstructure measures of illiquidity. ILLIQ should be positively related to variables that measure illiquidity from microstructure data. Therefore, while it is coarser and less accurate, it is readily available for the study of the time series effects of liquidity.

The results show that both across stocks and over time expected stock returns are an increasing function of expected illiquidity. Across NYSE stocks during 1964–1997, ILLIQ has a positive and highly significant effect on expected return. Stock excess return, traditionally called ‘‘risk premium’’, has been considered a compensation for risk. His paper proposes that expected stock excess return also reflects compensation for expected market illiquidity, and is thus an increasing function of expected market illiquidity. The results are consistent with this hypothesis.

Market illiquidity is the average ILLIQ across stocks in each period, and expected illiquidity is obtained from an autoregressive model. In addition, unexpected market illiquidity lowers contemporaneous stock prices. This is because higher realized illiquidity raises expected illiquidity that in turn raises stock expected returns and lowers stock prices (assuming no relation between corporate cash flows and market liquidity). This hypothesis too is supported by the results.

The effects of illiquidity on stock excess return remain significant after including in the model two variables that are known to affect expected stock returns: the default yield premium on low-rated corporate bonds and the term yield premium on long-term Treasury bonds. The effects over time of illiquidity on stock excess return differ across stocks by their liquidity or size: the effects of both expected and unexpected illiquidity are stronger on the returns of small stock portfolios. This suggests that the variations over time in the ‘‘small firm effect’’ – the excess return on small firms stocks - is partially due to changes in market illiquidity. This is because in times of dire liquidity, there is a ‘‘flight to liquidity’’ that makes large stocks relatively more attractive. The greater sensitivity of small stocks to illiquidity means that these stocks are subject to greater illiquidity risk which, if priced, should result in higher illiquidity risk premium. The results suggest that the stock excess return, usually referred to as ‘‘risk premium’’, is in part a premium for stock illiquidity.

However, all the above studies have left open the question as to whether illiquidity is a systematic risk factor, in which case stocks that are more sensitive to unexpected market illiquidity shocks, should offer higher expected returns. An exception is to be found in **Pastor and Stambaugh (2001)** who investigate whether market-wide liquidity is a state variable important for asset pricing by employing a four-factor asset pricing model (the three Fama-French factors plus a momentum factor). They focus on an aspect of liquidity associated with temporary price fluctuations induced by order flow. They find that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity. Stocks that are more sensitive to aggregate liquidity have substantially higher expected returns, even after accounting for exposures to the market return as well as size, value, and momentum factors.

They construct a measure of market liquidity in a given month as the equally weighted average of the liquidity measures of individual stocks on the NYSE and AMEX, using daily data within the month. Their monthly liquidity measure relies on the principle that order flow induces greater return reversals when liquidity is lower. Their liquidity measure captures a dimension of liquidity associated with the strength of volume-related return reversals. Over the last four decades, this measure of market-wide liquidity exhibits a number of sharp declines, many of which coincide with market downturns and apparent flights to quality. Their liquidity measure is also characterized by significant commonality across stocks, supporting the notion of aggregate liquidity as a priced state variable. Smaller stocks are less liquid, according to their measure, and the smallest stocks have high sensitivities to aggregate liquidity. Over a 34-year period, the average return on stocks with high sensitivities to liquidity exceeds that for stocks with low sensitivities by 7.5% annually, adjusted for exposures to the market return as well as size, value, and momentum factors.

Gibson and Mougeot (2002) also attempt to examine the significance and magnitude of systematic liquidity risk pricing for an actively traded well-diversified US stock portfolio that is the S&P 500 stock market index. They focus on a broader definition of systematic liquidity in order to examine whether long term – in their case monthly – random movements in market liquidity affect stock prices to the extend that their returns covary with changes in market liquidity.

They need a proxy for longer horizons market-wide liquidity shocks. For that purpose, they chose to define the market liquidity as the number of traded shares in the S&P 500 Index during a month. They rely on a bivariate Garch (1,1)-in-mean specification for the stock market excess returns in order to examine whether systematic liquidity risk is priced and whether the sign of the unitary liquidity risk premium is negative. The bivariate Garch (1,1)-in-mean specification is tested on monthly excess market returns of the S&P 500 Index during the period January 1973–December 1997. Overall, the results suggest that liquidity risk is indeed priced during the entire as well as over sub-periods in the US. The sign of the liquidity risk premium is significantly negative and time varying. Furthermore, according to these preliminary results, the unitary market risk premium becomes insignificant within the general bivariate Garch (1,1)-in-mean model with constant risk premia. According to their results, systematic liquidity risk dominates market risk and is insensitive to the introduction of extreme liquidity events such as the October '87 crash.

It is interesting to mention that using a different market ''illiquidity'' risk measure, as we mentioned earlier, Amihud (2002) finds a positive relationship between expected market illiquidity and expected stock returns. The latter is consistent with their findings given their specific proxy for systematic ''liquidity''.

Acharya and Pedersen (2003) present a simple theoretical model that helps explain how asset prices are affected by liquidity risk and commonality in liquidity. The model provides a unified theoretical framework that can explain the empirical findings that return sensitivity to market liquidity is priced (Pastor and Stambaugh, 2001), that average liquidity is priced (Amihud and Mendelson, 1986), and that liquidity comoves with returns and predicts future returns (Amihud, 2002; Chordia et al., 2001a; Jones, 2001).

In their model, risk-averse agents in an overlapping generation's economy trade securities whose liquidity varies randomly over time. They solve the model explicitly and derive a liquidity-adjusted capital asset pricing model (CAPM). Their model of liquidity risk complements the existing theoretical literature on asset pricing with constant trading frictions. In the liquidity-adjusted CAPM, the expected return of a security is increasing in its expected illiquidity and its ''net beta,'' which is proportional to the covariance of its return, r^i, net of its exogenous illiquidity costs, c^i, with the market portfolio's net return, r^M _ c^M. The net beta can be decomposed into the standard market beta and three betas representing different forms of liquidity risk. These liquidity risks are associated with: (i) commonality in liquidity with the market liquidity, $cov(c^i, c^M)$, (ii) return sensitivity to market liquidity, $cov(r^i, c^M)$ and, (iii) liquidity sensitivity to market returns, $cov(c^i, r^M)$.

They explore the cross-sectional predictions of the model using NYSE and AMEX stocks over the period 1963 to 1999. They use the illiquidity measure of Amihud (2002) to show that expected stock returns are a function of expected stock illiquidity, and covariances of stock return and illiquidity with the overall market return and illiquidity. They find that the liquidity-adjusted CAPM fares better than the standard CAPM in terms of R^2 for cross-sectional returns and p-values in specification tests, even though both models employ exactly one degree of freedom. Further, they find weak evidence that liquidity risk is important over and above the effects of market risk and the level of liquidity. The model has a good fit for portfolios sorted on liquidity, liquidity variation, and size, but the model cannot explain the cross-sectional returns associated with the book-to-market effect.

An interesting result that emerges from their empirical exercises based on Amihud's illiquidity measure is that illiquid securities also have high liquidity risk, consistent with ''flight to liquidity'' in times of down markets or generally illiquid markets. In particular, a security that has high average illiquidity, c^i, also tends to have high commonality in liquidity with the market liquidity, high return sensitivity to market liquidity, and high liquidity sensitivity to market returns.

The model also shows that since liquidity is persistent, liquidity predicts future returns and liquidity co-moves with contemporaneous returns. This is because a positive shock to illiquidity predicts high future illiquidity, which raises the required return and lowers contemporaneous prices. This may help explain the empirical findings of Amihud et al. (1990), Amihud (2002), Chordia et al. (2001a), Jones (2001), and Pastor and Stambaugh (2003) in the U.S. stock market.

Finally, the model provides a framework in which they can study the economic significance of liquidity risk. We find that liquidity risk explains about 1.1% of cross-sectional returns when the effect of average liquidity is calibrated to the typical holding period in the data and the model restriction of a single risk premium is imposed. About 80% of this effect is due to the liquidity sensitivity to the market return, $cov(c^{i}_{t+1}, r^{M}_{t+1})$, an effect not previously studied in the literature. Freeing up risk premia leads to larger estimates of the liquidity risk premium, but these results are estimated imprecisely because of collinearity between liquidity and liquidity risk.

Avramov, Chao and Chordia (2002) show that including a market liquidity proxy in the risk factor set, moves the market portfolio closer to the multifactor mean-variance efficiency frontier, thus reducing mispricing.

Specifically they examine whether accounting for a market-wide liquidity state variable improves the performance of the different models. They compare three different asset pricing models, (i) CAPM, (ii) the three factor Fama-French model and (iii) the Fama-French model augmented by a momentum factor. Each of these models is also augmented by two state variables that proxy for liquidity risk. Their empirical framework takes the maximal expected return loss caused by holding the market portfolio instead of a multifactor efficient portfolio as a measure of model misspecification, and they seek to evaluate and compare asset pricing models by analyzing the posterior distribution of this measure under alternative model specifications. The results strongly suggest that liquidity has pervasive effect on the consumption investment opportunity set. Regardless of whether portfolio constrains are imposed, including a proxy for liquidity improves the performance of the CAPM, the Fama-French model, and the FF model augmented with a momentum factor WML (Winner Minus Loser).

They also allow for different degrees of short sale constraints. With short sales prohibited, the CAPM augmented with the liquidity state variables dominates the three-factor Fama-French model as well as the Fama-French model augmented by a momentum factor. Moreover, the market portfolio appears multifactor efficient when investors are allowed to hedge against a market-wide liquidity risk. The results strongly suggest that in the presence of short sale constraints, investors are concerned about and hedge against liquidity risk because as shown by Chordia, Roll and Subrahmanyam (2001), the aggregate, daily market liquidity declines when returns are negative.

Sadka (2003) demonstrate the importance of liquidity for asset pricing. He shows empirically that liquidity varies over time, which raises the possibility of a premium associated with liquidity risk. Investors may be impatient to execute their trades or they might be subject to liquidity shocks, forcing them to liquidate their positions. His paper finds that transaction costs can impose a first order effect on prices. Unique measures of firm-level liquidity, based on fundamental microstructure models, are proposed and estimated using intraday data for the period January 1983 to August 2001. The empirical analysis utilizes several different databases, starting with intraday data for the estimation of execution costs, and daily/monthly/annual data for the asset pricing analysis. In contrast to Jones (2002), who constructs a time series of annual bid-ask spreads of the Dow Jones stocks for the past century, his paper focuses on a large cross-section of NYSE firms for the last two decades.

His paper is mostly related to Pástor and Stambaugh (2003) and Acharya and Pedersen (2003), insofar as it finds that systematic liquidity risk is priced, yet there are several substantial differences. First, the papers utilized different measures of liquidity, each carrying a different economic interpretation: Pástor and Stambaugh (2003) focus on transitory price effects of trades (which can be viewed as non-informational costs of trading), Acharya and Pedersen (2003) measure the total price effects, and his paper focuses on permanent price effects (which can be viewed as informational costs of trading). A priori, it is not clear which part of liquidity may be priced–he shows permanent effects are also priced. Second, the papers differ in the data used to estimate liquidity. Pástor and Stambaugh (2003) and Acharya and Pedersen (2003) use daily data, while he utilize intraday data. The use of intraday data increases the precision of the liquidity estimates, especially if liquidity is to be estimated on a monthly basis. In his paper, the monthly estimates of liquidity are mostly based on hundreds and even thousands of observations, while the other papers have 22 observations at best. Pástor and Stambaugh (2003) only use the aggregate measure of liquidity for their analysis, while the estimates in his paper also allow the testing of liquidity on a firm-specific level. Third, it is important to note that the estimated measures of liquidity in his paper rely on fundamental concepts from the microstructure literature.

An economy-wide liquidity factor is then constructed using these measures. Many view financial anomalies as strong rejections of the efficient market hypothesis. However, if these anomalies are associated with some type of risk and/or are too costly to exploit, then their significance is reduced. The liquidity factor can be used to test whether asset-pricing anomalies carry a premium for liquidity risk, which may practically explain their persistence. Also, anomalies may exhibit high levels of illiquidity, which may indicate a possibility of limits to arbitrage. The portfolios that are formed to test these anomalies in the literature often require frequent rebalancing, and, therefore, are likely to be subject to liquidity concerns. The liquidity risk factor may also be added in the evaluation of portfolio managers (active versus passive funds). Systematic liquidity risk, rather than the absolute level of liquidity, is shown to be important in explaining cross-sectional variation of expected returns. Applying the framework developed here to the momentum anomaly suggests that profits are associated with liquidity risk.

It should be pointed out that, besides the recent and relatively scant evidence from the US market, to the best of our knowledge, there is no evidence regarding the importance of illiquidity as a risk factor in any European country. Thus, Martinez, Nieto, Rubio and Tapia (2004) thought important to report empirical results from other data sets to check the robustness of the available results and to support the conviction that it is not due to a data-snooping problem. In this sense, the Spanish market is set to play a decisive role in the shaping of the stock market map in Europe.

The paper of **Martinez, Nieto, Rubio and Tapia (2004)** is mostly related to Pastor & Stambaugh (2001), who develop a measure of market-wide liquidity based on price reversals and test whether assets that highly covary with their factor obtain higher average returns, and Sadka (2003), who uses the estimated price impact to introduce a liquidity factor based on innovations to aggregate liquidity. Both papers suggest that liquidity risk is a factor priced in the market. Their empirical work analyze whether Spanish expected returns during the nineties are associated cross-sectionally with betas estimated relative to three competing liquidity risk factors.

The first one, proposed by Pastor and Stambaugh (2002), is associated with the strength of volume-related return reversals (OFL) since order flow induces greater return reversals when liquidity is lower. The second market-wide liquidity factor they propose is defined as the difference between returns of stocks highly sensitive to changes in the relative bid-ask spread less returns from stocks with low sensitivities to those changes (HLS). In particular, they argue that stocks with positive covariability between returns and this factor are assets whose returns tend to go down when aggregate liquidity is low, and hence do not hedge a potential liquidity crisis. Consequently, investors will require a premium to hold these assets. Their empirical results show that neither of these proxies for systematic liquidity risk carries a premium in the Spanish stock market. Finally, the third is the one proposed by Amihud (2002). In particular, illiquidity is defined for each individual stock as the ratio of the daily absolute return to the euro trading volume on that day. Then, and for each month in the sample period, this measure is averaged out across days and stocks to obtain an aggregate measure of illiquidity. When a particular stock has a high value of ILLIQ, it indicates that the price moves quite a lot in response to trading volume and, therefore, the stock is considered to be illiquid. Interestingly, both in time-series and in the traditional cross-sectional framework, they find evidence consistent with market-wide liquidity risk being priced on either unconditional or conditional versions of liquidity-based asset pricing models in the Spanish stock market. Therefore, given an adequate illiquidity risk factor, it seems that the stochastic discount factor should be linearly related not only to the aggregate wealth return and to state variables predicting future returns, but also to aggregate illiquidity risk.

Moreover, this is the first paper that simultaneously analyzes competing market-wide liquidity factors. They have individual daily and monthly returns for all stocks traded on the Spanish continuous market from January 1991 through December 2000. Of course, it must be recognized that their sample period is short in comparison to the available evidence on asset pricing. This is not a problem in itself, but the results should be taken as valid just for the period being studied, and more general conclusions should be left for future research when longer series of data will be readily available.

They employ five alternative pricing models: the traditional CAPM, the three factor Fama and French model and the three CAPM liquidity-based models, in which they add the liquidity factor (either HLS,OFL or ILLQ) to the standard CAPM model. Also, they concluded that the level of liquidity does not seem to be the relevant variable in asset pricing; rather, the sensitivity of the returns to market-wide liquidity risk factor is what is priced by the market.

Also, **Marcelo and Quiros's (2005)** examine the importance of illiquidity as a risk factor in the Spanish market. Their main purpose is to construct an illiquidity risk factor and to analyze pricing implications for the Spanish stock market over the 1994–2002 period. Because of the absence of consensus in empirical research about the most appropriate liquidity measure, they applied the Amihud (2002) illiquidity ratio that shows the price response associated with one euro of trading volume. They examine the asset-pricing role of illiquidity, proxied by Amihud's ratio, in the context of the standard CAPM and the Fama and French three-factor model. They generated a mimicking portfolio for illiquidity by extending the approximately orthogonalizing procedure of Fama and French (1993) and analyzed whether it enters the stochastic discount factor as an additional state variable. This illiquidity-mimicking factor is created by obtaining the difference between the mean return on a set of illiquid stock portfolios (*I*) and the mean

return on a set of very liquid (*V*) stock portfolios, named IMV (illiquid minus very liquid). The advantage of this construction is that each factor is formed while controlling for the effect of the other Fama and French factors.
They have individual daily and monthly returns for stocks traded on the Spanish Continuous market from January 1994 to December 2002. They also include companies that belong to a high technology sector and traded on the Spanish “Nuevo Mercado” from January 2000. The number of stocks in the sample range from 140 to 159
during the period analyzed. For the same set of common stocks, they also have daily data on the trading volume (2016 average daily observations per security). This daily data is employed for the monthly calculation of firms’ illiquidity ratios.

Their results for the Spanish stock market indicate that time varying expected excess asset returns, from January 1994 to December 2002, can be explained by the two asset-pricing models considered when they include the illiquidity risk factor as an augmenting variable. However, their cross-sectional empirical results show the payment for assuming higher illiquidity risk is mainly limited to the month of January. The conclusions obtained in their work have important implications, not only for the Spanish stock market in particular but also for stock markets in general, since their results support the recent evidence found with U.S. market data and provide additional evidence to support the assumption that market-wide illiquidity should be a key ingredient of asset-pricing models. Nevertheless, this result must be interpreted with care given the short period of time covered by this research.

5. Data and Methodology

5.1 Data

Our sample uses data for the period January 1991-December 2005 and includes all stocks of the Co AC’s WSCOPE GREECE Index. This is an Index made by Datastream database and contains 373 stocks and we believe that is a representative sample of the Greek stock market. Daily and monthly prices of all stocks are obtained from Datastream. The price data are used to calculate daily and monthly returns, controlling for splits and dividends. The return of the market is an equally-weighted portfolio comprised of all stocks available either in a given month or on a particular day in the sample. The gr three month Treasury Bill rate is used as the risk-free rate when monthly data is needed. For the same set of stocks we obtain from Effect Finance database daily data on the bid-ask prices and volume, defined as the euro value of shares traded.

It should be pointed out that for the first twenty four months of our sample period (January 1991-December 1992) the euro volume of each stock included in the Co AC’s WSCOPE GREECE Index was zero or NaN. To alleviate the potential influence due to “stale price”, we only considered observations with positive trading volume data, so our data period starts at January 1993.

Moreover, two additional variables have been used to construct risk factors in different asset pricing models. In particular, for the Fama-French three factor model we employed a size proxy (ME) and the book-to-market ratio (B/M). As a measure of size for each company in a single month we used the market value of that company, calculated by multiplying the number of shares of each firm in December of the previous year by their price at the end of each month. For the sample period, the market value and the book-to-market ratio of each company were obtained from Datastream. The market value was expressed in millions of euros. These data were employed to construct the well-known SMB and HML Fama-French portfolios, following Fama and French paper “Common risk factors in the returns on stocks and bonds” (1992).

Specifically, for the construction of the factors of Fama and French we constructed six portfolios formed from sorts of stocks on market value (ME-size) and on book-to-market (B/M). In January of each year from 1993 to 2005, all stocks included in the Index are ranked according to the size and sorted on two groups, small and big. Also in January of each year from 1993 to 2005, stocks are ranked according to their book-to-market values and sorted into three book-to-market equity groups. The sorting procedure is based on the breakpoints for the bottom 30% (Low), middle 40% (Medium) and top 30% (High) of the ranked values of B/M of all stocks. So, we constructed six portfolios (S/L, S/M, S/H, B/L, B/M, B/H) from the intersections of the two ME and the three B/M groups. For example, the S/L portfolio contains the stocks in the small-ME group that are also in the low B/M group and the B/H portfolio contains the big-ME stocks that also have high B/Ms. Monthly value-weighted returns on the six portfolios are calculated from January of year t to December of year t and the portfolios are reformed in January of t+1.

The portfolio SMB (small minus big), meant to mimic the risk factor in returns related to size, is the difference each month, between the simple average of the returns on the three small-stock portfolios (S/L, S/M and S/H) and the simple average of the returns of the three big-stock portfolios (B/L, B/M and B/H). Thus, SMB is the difference between the returns on small and big stock portfolios with about the same weighted-average book-to-market equity. This difference should be largely free of the influence of B/M, focusing instead on the different return behaviors of small and big stocks.

The portfolio HML (high minus low), meant to mimic the risk factor in returns related to book-to-market equity, is defined similarly. HML is the difference, each month, between the simple average of the returns on the two high-B/M portfolios (S/H and B/H) and the average of the returns on the two low-B/M portfolios (S/L and B/L). The two components of HML are returns on high and low-B/M portfolios with about the same weighted average size. Thus the difference between the two returns should be largely free of the size factor in returns, focusing instead on the different return behaviors of high and low-B/M firms.

Finally, the proxy for the market factor in stock returns is the excess market return, R_m-R_f, R_m is the return on the value-weighted portfolio of the stocks in the six size – B/M portfolios and R_f is the three-month Treasury bill rate. In the Appendix in Tables 9, 10 and 11 we report the three factors constructed by following the methodology of Fama and French.

5.2 Methodology

The methodology we used is mostly related to that of Martinez, Nieto, Rubio and Tapia (2004), who result that systematic liquidity risk is significant priced in the Spanish stock market. Our empirical work analyzed whether expected returns of the stocks included in the Co AC’s WSCOPE GREECE Index are associated with betas estimated relative to two competing liquidity risk factors.

5.2.1 Evidence on commonality in liquidity

Initially in order to confirm that there exists commonality in liquidity in the Greek stock market, we regress the monthly percentage change in the quoted bid-ask spread for each of the companies available in the sample, DSP_{jt}, on a cross-sectional equally-weighted average of the same variable representing the market-wide quoted spread, DSP_{mt}. Some stocks are rarely traded and would not provide reliable observations. For this reason to be included, we require that a stock has more than 2500 observations during the whole period (the number of daily observations for the period 1991-2005 for a stock is 3252) and at least five transactions on the month.

$$DSP_{jt} = a_j + \beta_j DSP_{mt} + \varepsilon_{jt} \tag{14}$$

where DSP_{jt} is the percentage change from month t-1 to t in liquidity, as proxied by the quoted spread of stock j and DSP_{mt} is the concurrent change in a cross-sectional average of the same variable or the market-wide (equally weighted) quoted spread.

If the average sensitivity of changes in the bid-ask spread relative to changes in the aggregate measure of liquidity is significant and the most of the individual coefficients are positive and significantly different from zero, this will indicate that individual liquidity commoves with market liquidity and that commonality in liquidity exists in the Greek stock market.

5.2.2 Liquidity risk factors

a) The Illiquidity Ratio (ILLIQ)

The illiquidity ratio (ILLQ) proposed by Amihud (2002) is a proxy for the price impact of a trade. In particular, Amihud proposes measuring illiquidity for a given stock on a given day as the ratio of absolute percentage price change per euro of daily trading volume. Thus the illiquidity of stock j in month t is given by:

$$ILLIQ_{jt} = \frac{1}{D_{jt}} \sum_{d=1}^{D_{jt}} \frac{\left|R_{jdt}\right|}{V_{jdt}} \tag{15}$$

where R_{jdt} and V_{jdt} are, respectively, the return and euro volume on day d in moth t and D_{jt} is the number of days with observations in month t of stock j. The intuition behind this illiquidity measure is as follows. A stock is illiquid, that is, it has a high value of $ILLIQ_{jt}$ if the stock's price moves quite a lot in response to little volume and therefore the stock is considered to be illiquid.

This measure is computed for stocks with more than 2500 daily observations during the whole period and at least 15 return and volume observations during a month and then we excluded the extreme values of $ILLIQ_{jt}$. Those outliers were caused by some companies which entered the market during the sample period or had their quotation suspended. In those cases, the low volume traded caused a value of $ILLIQ_{jt}$ far higher than the average value reached by the rest of companies in normal circumstances. Therefore, we considered it reasonable to eliminate those observations from the months that they appear.

The market-wide illiquidity ratio is then the cross-sectional average of these monthly firm-specific $ILLIQ_{jt}$ which is then multiplied by a scale factor 10^6.

$$ILLIQ_t = \left(\frac{1}{N_t}\right)\sum_{j=1}^{N_t} ILLIQ_{jt} \qquad (16)$$

where N_t is the number of stocks available in month t in our sample.

When this factor increases, we may understand that there is an adverse shock to aggregate liquidity. Stocks that tend to pay lower returns when this measure increases (negative betas relative to this factor) do not provide the desirable hedging behaviour to investors and therefore an extra compensation is required to hold these stocks. This implies that the premium associated to this liquidity factor in a cross section should be negative.

b) The Pastor & Stambaugh factor (OFL)

The liquidity risk factor proposed by Pastor and Stambaugh (2002) is associated with the strength of volume-related return reversals (OFL) since order flow induces greater return reversals when liquidity is lower. The market-wide liquidity factor in a given month is obtained as the equally weighted average of the liquidity measures of individual stocks, which are calculated with daily return and volume data within that particular month. This measure is computed for stocks with more than 2500 daily observations during the whole period. Specifically, we calculated the liquidity measure for stock j in month t by performing the following ordinary-least-squares (OLS) regression using daily data:

$$R^e_{j,d+1,t} = a_{jt} + b_{jt}R_{jdt} + \gamma_{jt} sign\left(R^e_{jdt}\right) vol_{jdt} + u_{j,d+1,t} \qquad (17)$$

where quantities are defined as follows:

R_{jdt} : the return on stock j on day d in month t
$R^e_{j,d+1,t}$: $r_{i,d+1,t} - r_{m,d+1,t}$, where $r_{m,d+1,t}$ is the return on the equal-weighted market return on day d+1 in month t
vol_{jdt} : the euro volume for stock j on day d in month t

The sign$\left(R^e_{jdt}\right)$ variable is equal to 1 when lagged excess returns are positive and equal to -1 when lagged excess returns are negative. We also define vol_{jdt} as the value of shares traded, measured in billions of euro. The signing of the trading volume is meant to distinguish whether trades are driven by selling pressure from investors or by buying pressure. When investors are selling shares in a company to market makers or other short-term liquidity providers such as speculators, excess returns on that company should be negative. When investors are buying from market makers, excess returns should be positive. The lagged return is included to capture inertia effects that are not volume-related. A stock’s liquidity is computed in a given month only if there are more than 15 observations with which to estimate the above regression and the daily observations are not required to be consecutive (except that each observation requires data for two successive days).

The basic idea behind the model is that a financial market may be considered liquid if it is able to quickly absorb large amounts of trading without distorting prices. In other words, when a big change in the price of a stock is needed to accommodate its demand, the asset is considered to be illiquid. So, the “order flow”, constructed here as volume signed by the contemporaneous return on the stock in excess of the market, should be associated with a return that we expect to be reversed in the future if the stock is not sufficiently liquid. We therefore expect γ_{jt} to be negative and larger in absolute value when liquidity decreases. The greater the order flow the greater the change in the expected return will be. The market-wide average liquidity in month t is estimated more precisely.

$$\hat{\gamma}_t = \left(1/N\right)\sum_{j=1}^{N}\hat{\gamma}_{j,t} \tag{18}$$

We constructed the above market-wide measure for each month from January 1993 through December 2005[14]. The number of stocks in the index (N) ranges from 60 to 138.

Also, to construct innovations in liquidity, we scaled the monthly difference in liquidity measures, averaged across the N_t stocks with available data in both the current and the previous month.

$$\Delta\hat{\gamma}_t = \left(\frac{m_t}{m_1}\right)\frac{1}{N_t}\sum_{j=1}^{N_t}\left(\hat{\gamma}_{j,t} - \hat{\gamma}_{j,t-1}\right) \tag{19}$$

where m_t is the total euro value at the end of month t-1 of the stocks included in the average in month t, and month 1 corresponds to January 1993. The scaled series

14. The sample period starts at January 1993 through December 2005 because the first 24 months (January 1991-December 1992) the volume of each stock is either zero or NaN.

$\left({m_t}/{m_1} \right)\hat{\gamma}_t$ can be viewed as an estimate of the liquidity cost. We then regressed $\Delta\hat{\gamma}_t$ on its lag as well as the lagged value of the scaled level series and the liquidity factor is given by the residuals in the following expression:

$$\Delta\hat{\gamma}_t = a + b\Delta\hat{\gamma}_{t-1} + c\left(\frac{m_{t-1}}{m_1}\right)\hat{\gamma}_{t-1} + u_t \tag{20}$$

The final systematic liquidity factor, OFL_t, is taken as the fitted residual divided by 10, simply to obtain more convenient magnitudes of the liquidity market-wide factor:

$$OFL_t = \frac{1}{10}\hat{u}_t \tag{21}$$

Stocks that covary positive with OFL have a large liquidity risk and investors will demand a higher return from them. Hence, we expect a positive premium associated with this risk factor in asset pricing models.

5.2.3 Construction of portfolios

We constructed 10 size-sorted portfolios according to the market value of each security at the end of each year, named MV1 (smallest) to MV10 (largest). Size or the market value of the stock is also related to liquidity since a larger stock issue has smaller price impact for a given order flow. Stock expected returns are negatively related to size (Fama and French (1992)), which is consistent with it being a proxy for liquidity. Specifically, stocks with small market values tend to have higher returns than stocks with big market values. Barry and Brown (1984) propose that the higher return on small firm’s stock is compensation for less information available on small firms that have been listed for a shorter period of time. This is consistent with the illiquidity explanation of the small firm effect since illiquidity costs are increasing in the asymmetry of information between traders.

We, also, constructed 10 liquidity-based sorted portfolios, ranking stocks with respect to the liquidity betas that they have in terms of the two liquidity factors. For the purpose of portfolio formation, we defined β^L_j as the coefficient on L_t (liquidity factor) in a regression that also includes the three factors of Fama and French (1992). We repeated it for the two liquidity factors we examined.

$$R_{j,t} = \beta_j^0 + \beta_j^l L_t + \beta_j^M MKT_t + \beta_j^S SMB_t + \beta_j^H HML_t + \varepsilon_{j,t} \tag{22}$$

where $R_{j,t}$ denotes asset’s j excess return, MKT denotes the excess return on a broad market index and SMB and HML are the factors of Fama and French constructed by sorting stocks according to market value and book-to-market ratio.

This definition of β_j^l captures the asset’s co-movement with aggregate liquidity that is distinct from it’s co-movement with other commonly used factors. At first we identified the stocks with at least 20 months of trading activity. For each of these stocks we estimated its historical liquidity beta β_j^l by running the above regression with 36 past (monthly) observations and stocks are then sorted by these historical betas into ten equal-weighted portfolios. The portfolios are rebalanced yearly. Analogous to our sort we obtained a January 1996 through December 2005 series of monthly returns on each portfolio by linking across years the post-ranking returns during the next 12 months.

It should be pointed out that ILLIQ1 presents stocks negatively sensitive to illiquidity in comparison to ILLIQ10 that contains stocks positively sensitive to illiquidity. On the other hand, OFL1 contains stocks negatively sensitive to liquidity to OFL10 that contains stocks positively sensitive to liquidity.

5.2.4 Asset pricing and systematic liquidity (time-series evidence)

In our research we employed four alternative pricing models: the traditional CAPM, the three-factor Fama and French model and the two CAPM liquidity-based models, in which we added the liquidity factor (either OFL or ILLQ) to the standard CAPM model. For each portfolio and for each asset pricing model we investigated whether the liquidity factors are priced.

In order to find if the liquidity risk factors we analyzed above are priced in the market we should find systematic differences in the risk-adjusted average returns of our liquidity-beta-sorted and size-sorted portfolios. More specifically, for a given asset pricing model, the risk-adjusted average return (alpha) of the OFL10 portfolio which is positively sensitive to market-wide liquidity should be significantly higher than the alpha for the OFL1 portfolio which is negatively sensitive to market-wide liquidity. On the other hand, given the way in which ILLIQ is defined, the opposite results should hold, the alpha of the ILLIQ10 portfolio which is positively sensitive to market-wide illiquidity should be significantly smaller than the alpha for the ILLIQ1 portfolio which is negatively sensitive to market-wide illiquidity.

6. Empirical Evidence

6.1 Empirical results on commonality in liquidity

We first examined if commonality in liquidity exists in the Greek stock market. We performed the regression Eq.(14). Specifically we regress the monthly percentage change in the quoted bid-ask spread for each of the stocks included in the sample, DSP_{jt}, on a cross-sectional equally weighted average of the same variable representing the market-wide quoted spread, DSP_{mt}. We considered stocks with more than 2500 observations during the whole period and at least five transactions on the month. The number of stocks included was 144. We examined percentage changes rather than levels for two reasons: first, our interest was fundamentally in discovering whether liquidity co-moves, and second, time series of liquidity levels are more likely to be plagued by econometric problems (e.g. non-stationarity)

The cross-sectional average of the 144 individual coefficients is reported in Table 1. The average sensitivity of changes in the bid-ask spread relative to changes in the aggregate measure of liquidity is a significant 0,716, as the t-statistic is 6,326. The cross-sectional t-statistic for the average β is calculated under the assumption that the estimation errors in β_j are independent across regressions. Also, it should be reported that most of the individual coefficients are positive and significantly different from zero. Specifically, 98,61% of the individual coefficients are positive and 94,44% are significantly different from zero at the 5% level. This indicates that individual liquidity co-moves with market liquidity and that commonality in liquidity exists in the Greek stock market.

Table 1
Market-wide commonality in liquidity 1993-2005

	Average alpha	Average beta	R^2	Adjusted R^2
Coefficient	4,741	0,716	0,215	0,210
t-statistic	(1,129)	(6,326)		
%Positive		98,61		
%+Significant		94,44		

$$\boxed{DSP_{jt} = a_j + \beta_j DSP_{mt} + \varepsilon_{jt}}$$

where DSP_{jt} is the percentage change from month t-1 to t in liquidity, as proxied by the relative spread of stock j, and DSP_{mt} is the concurrent change in a cross-sectional average of the same variable or the market-wide (equally weighted) relative spread. Average numbers reported are for 144 stocks.

Moreover, this test assumes independent estimation error across equations (Chordia, Roll & Subrahmanyam (2000)). The explanatory power of the typical individual regression is not very impressive as the average adjusted R^2 is 21%. Clearly, there is a large component of noise and other influences on daily changes in individual stock liquidity constructs. In the Appendix in Table 12 is reported the sensitivity of changes in the bid-ask spread relative to changes in the market-wide quoted spread, the t-statistic, the R^2 and the adjusted R^2 for each of the 144 stocks..

6.2 Preliminary empirical evidence

After having confirmed the commonality in liquidity that exists in the Greek stock market we calculated the two systematic liquidity risk factors we analyzed above. The monthly market-wide liquidity factors (ILLIQ and OFL) for the period January 1993 – December 2005 are reported in the Appendix in Tables 13 and 15, respectively. The Tables that contain the monthly liquidity factors for each stock were not possible to be reported in the Appendix because of their large size but they can be provided, if required.

Moreover, we calculated the usual descriptive statistics of the factors employed in the research. Table 2 reports the monthly average characteristics of the distribution of the market return factor (R_m), the Fama-French factors (SMB and HML) and the two liquidity-based systematic factors (ILLIQ and OFL).

In Panel A is reported the descriptive statistics. Specifically, all the factors have positive kurtosis and this indicates “peaked” distributions relative to a normal distribution. The OFL factor has rather large kurtosis, at least relative to the other factors and this means that tends to have a distinct peak near the mean, decline rather rapidly, and have heavy tails. On the other hand the other factors (R_m, SMB and ILLIQ) which have low kurtosis tend to have a flat top near the mean rather than a sharp peak. Also, all the factors have right-skewed distributions except for OFL which have left-skewed, as its value is negative. By skewed left, we mean that the left tail is long relative to the right tail. It should, also, pointed out that the mean and standard deviation of the three factors of Fama and French (R_m, SMB and HML) are very small.

In Panel B of Table 2 is reported the correlation coefficients of the alternative risk factors. As expected the market return is positively related to OFL and negatively related to ILLIQ. Given the way that these two liquidity factors are constructed and assuming that they correctly capture market-wide liquidity, low liquidity is denoted by a high value for ILLIQ and low values for OFL. For this reason we should expect a negative correlation between the two market-wide liquidity factors. But in our data set we found, although very small, a positive correlation between OFL and ILLIQ. It is important to report again that ILLIQ measures the illiquidity of a stock and OFL the liquidity of a stock.

Table 2
Summary statistics for risk factors Jan 1996-Dec 2005
Panel A. Descriptive Statistics

Risk Factor	Mean	Standard Deviation	Skewness	Kurtosis
Rm	0,00044	0,1196	0,375	0,622
SMB	0,0027	0,0801	0,702	1,862
HML	0,0031	0,0687	1,8229	6,603
ILLIQ	3,0723	2,6772	1,0867	1,424
OFL	-0,145	1,807	-0,567	18,488

Panel B. Correlation Coefficients

	Rm	SMB	HML	ILLIQ	OFL
Rm	1	0,552	0,3339	-0,2133	0,0326
SMB		1	0,1726	-0,2037	0,0141
HML			1	-0,3039	-0,088
ILLIQ				1	0,0459
OFL					1

The numbers represent the monthly mean, standard deviation, skewness, kurtosis and correlation coefficients of alternative risk factors : Rm is the equally-weighted market portfolio, SMB is the Fama-French size-related factor, HML is the Fama-French book-to-market related factor, ILLIQ is the monthly average across days and stocks of the ratio of absolute stock return to euro volume (multiplied by 10^6) and OFL is the liquidity factor based on the order flow, inducing greater return reversal when liquidity is lower. Data are monthly covering the period from January 1996 to December 2005.

Also, Figure 1 plots the time-series of the ILLIQ and OFL factors over the period 1996-2005[15]. Over this period, market-wide liquidity seems to reflect a much stronger response to national events rather than international. Specifically, at the half of 1996 there was a big decline in market liquidity which may be caused by political circumstances (e.g. IMIA and elections). Also, in 2004 we can observe a decline in market liquidity probably due to elections and the change of government. Moreover, events like the terrorist attack on 9/11/2001 do not seem to have influenced very much the liquidity of the Greek stock market, as the level of liquidity is low but not lower than that observed in any prior period. There may be also (positive/negative) movements in liquidity which do not correspond to macro events.

15. Given the definitions of ILLIQ and OFL, it is important to note that the two liquidity factors must appear adverse.

FIGURE 1
Systematic Liquidity Factors: ILLIQ vs. OFL: 1996 - 2005

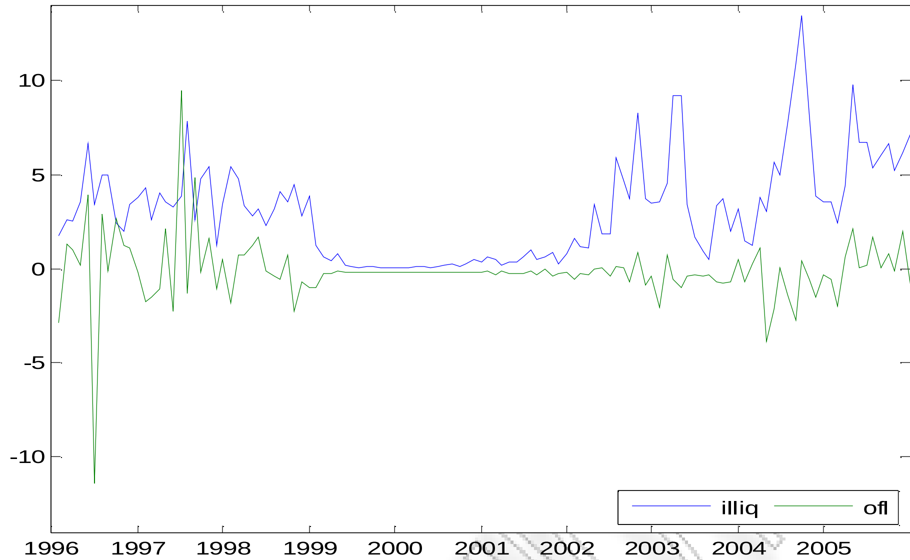

Figure 1: It plots the two systematic liquidity factors we examine in the paper from January 1993 to December 2005. ILLIQ is the monthly average across days and stocks of the ratio of absolute stock return to euro volume (multiplied by 10^6) and OFL is the liquidity factor based on the order flow, inducing greater return reversal when liquidity is lower.

We constructed 10 liquidity-based sorted portfolios, ranking stocks with respect to the liquidity betas they have in terms of both the ILLIQ and OFL factors. For each stock, we estimated its historical liquidity beta by running the regression in Eq. (22) using the most recent three years of monthly data. The historical liquidity beta ($\beta^L{}_j$) was defined as the coefficient on the L_t (liquidity factor) in a regression that also includes the three factors of Fama and French. Portfolios are rebalanced yearly. Analogous to our sort we obtained a January 1996 through December 2005 series of monthly returns on each portfolio by linking across years the post-ranking returns during the next 12 months. Also, it should be pointed out that ILLIQ1 includes stocks negatively sensitive to market-wide illiquidity, ILLIQ10 stocks positively sensitive to market-wide illiquidity, OFL1 represent stocks negatively sensitive to market-wide liquidity and OFL10 stocks positively sensitive to market-wide liquidity.

In Table 3 is reported the summary statistics for the ILLIQ portfolios (January 1996-December 2005). Panel A. presents the average returns and liquidity betas of each portfolio. Contrary to the findings of Martinez, Nieto, Rubio & Tapia ILLIQ1 has smaller average return than ILLIQ10 and the liquidity based betas follow in some way the pattern expected given the ranking of the individual stocks. But, it should be pointed out that all the illiquidity betas are insignificant at the 5% level which shows that these betas are actually equal to zero. The "10-1" spread has an overall-period liquidity beta of 0,00087, with a t-statistic of 0,179. Also, the equal-weighted average size in portfolio ILLIQ1 is

€172,14 million, as compared to €303,32 million in ILLIQ10 (averaged over time). Judging from this we could say that ILLIQ1 contains stocks with smaller market value but substantially the smaller stocks have been dispersed in all the portfolios as the market value of the stocks included in the ILLIQ10 is not too high. Panel B of Table 3 reports the portfolios’ betas with respect to the Fama-French factors. The Fama-French betas are estimated by regressing equal-weighted portfolios’ excess returns on the three factors. From the results we may observe that for each portfolio the three factors are statistically significant at the 5% level which means that these factors are capturing much of the common variation in portfolio returns. Additionally, in the “10-1” spread, which goes long the portfolio 10 (stocks with high sensitivity to illiquidity) and short the portfolio 1 (stocks with low sensitivity to illiquidity) for the factors of Fama and French we can observe a lack of statistical significance at the 5% or the 10% level.

Table 4 reports the summary statistics for the OFL portfolios (Jan 1996-Dec 2005). Specifically, contrary to the findings of Pastor & Stambaugh (2003), we found that OFL1 (highly negatively sensitive stocks) have a much larger average return than OFL10 (highly positively sensitive stocks). Moreover, OFL1 contains stocks of somewhat smaller firms with an equal-weighted average size €220,17 as compared to €333,94 for OFL10. This indicates that, as observed to the portfolios sorted according to the illiquidity betas, the small stocks have been dispersed to all the portfolios. Also, the liquidity betas increase across portfolios, consistent with the objective of the sorting procedure but we could notice a general lack of statistical significance at the 5% level. So, as expected the “10-1” spread is 0,0031 with a t-statistic of 0,947 (insignificant). Panel B reports some additional properties of the portfolios sorted by historical liquidity betas. The Fama-French betas are estimated by regressing equal-weighted portfolios’ excess returns on the three factors. We may also observe that the betas of the MKT and SMB for each portfolio and the half of the betas of HML are significant but the “10-1” spreads are insignificant at the 5% or 10% level.

Apart from the liquidity-based portfolios we constructed 10 size-sorted portfolios according to the market value of each security at the end of each year, named MV1 (smallest portfolio) to MV10 (largest portfolio). Table 5 reports the summary statistics for the MV portfolios. As expected, smaller stocks tend to have higher average returns to larger stocks. Thus, stock expected returns are negatively related to size which is consistent with it being a proxy for liquidity. The pattern in OFL liquidity betas is fairly flat across all ten portfolios but in ILLIQ liquidity betas the MV1 tends to have low sensitivity to that factor and MV10 high illiquidity sensitivity. But it should be pointed out that we may observe a general lack of significance at the 5% (and 10%) level, which means that these factors shouldn’t be included to the model. Also, we may notice that when we sort stocks according to their market values the betas of the factors of Fama and French and the “10-1” spreads are statistically significant. To be more specific, the “10-1” spread in the size-sorted portfolios of the MKT beta is significant at the 10% level and of the SMB and HML betas is significant negative at the 5% level. The SMB betas confirm the pattern in average capitalizations and the HML betas indicate that the “10-1” spread has a tilt toward growth stocks.

Table 3
Summary statistics for ILLIQ portfolios Jan 1996 - Dec 2005

	ILLIQ1	ILLIQ2	ILLIQ3	ILLIQ4	ILLIQ5	ILLIQ6	ILLIQ7	ILLIQ8	ILLIQ9	ILLIQ10	ILLIQ(10-1)
Panel A. Average returns and Liquidity betas (ILLIQ)											
Average return	-0,0143	-0,0013	0,0047	0,0066	-0,0045	-0,0086	0,0007	0,0014	-0,003	0,0077	
Market value	172,143	328,238	390,678	296,479	333,171	257,313	337,5558	371,8105	229,801	303,324	
ILLIQ beta	-0,0055	0,00028	0,00013	-0,00058	0,0064**	0,0016	0,0022	-0,0009	-0,0056	-0,0046	0,00087
t-statistic	(-1,592)	(0,151)	(0,0642)	(-0,2806)	(1,773)	(0,6689)	(0,832)	(-0,5714)	(-1,1415)	(-1,3752)	(0,1794)
Panel B. Additional properties											
MKT beta	1,0026*	0,9995*	0,9986*	1,00009*	1,0014*	1,00087*	1,0011*	0,999*	0,995*	0,9998*	-0,0027
t-statistic	(447,029)	(844,04)	(771,41)	(751,104)	(425,45)	(628,43)	(592,25)	(958,98)	(313,606)	(458,235)	(-0,868)
SMB beta	0,7161*	0,6024*	0,4871*	0,751*	0,723*	0,4789*	0,496*	0,414*	0,3994*	0,5627*	-0,1533
t-statistic	(6,4018)	(10,2001)	(7,544)	(11,309)	(6,1606)	(6,0297)	(5,8834)	(7,969)	(2,524)	(5,171)	(-0,982)
HML beta	0,2059	0,2231*	0,2275*	0,1922*	-0,0129	0,1266	0,3846*	0,2466*	0,4214*	0,244**	0,0385
t-statistic	(1,604)	(3,291)	(3,0691)	(2,5208)	(-0,0964)	(1,389)	(3,9738)	(4,1341)	(2,32)	(1,9567)	(0,2147)

At each year-end between 1996 and 2005, stocks are sorted into 10 portfolios according to historical liquidity betas. The betas are estimated as the slope coefficients on the aggregate liquidity factor in regressions of excess stock returns on that liquidity factor (ILLIQ) and the three Fama-French factors. The regressions are estimated using the most recent three years of data. The portfolio returns for the 12 post-ranking months are linked across years to form one series of post-ranking returns for each portfolio. Panel A reports the decile's portfolios' average returns and liquidity betas, estimated by regressing equal-weighted portfolio excess returns on the liquidity factor and the Fama-French factors. Panel B reports the betas with respect to the Fama-French factors, estimated by regressing equal-weighted portfolio excess returns on the three factors. The t-statistics are in parentheses. ILLIQ1 includes stocks negatively sensitive to market-wide illiquidity and ILLIQ10 stocks positively sensitive to market-wide illiquidity.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

Table 4
Summary statistics for OFL portfolios

	OFL1	OFL2	OFL3	OFL4	OFL5	OFL6	OFL7	OFL8	OFL9	OFL10	OFL(10-1)
					Panel A. Liquidity betas (OFL)						
Average return	0,0007	-0,0052	-0,0045	-0,0046	0,0077	-0,0148	-0,0017	-0,0105	0,0054	-0,0042	
Market value	220,1768	267,781	467,5907	279,481	332,83	389,688	284,69	829,682	201,234	333,947	
OFL beta	-0,0039**	-0,0052	-0,0016	-0,0017	-0,0036	-0,0062	-0,0039	-0,0019	-0,001	-0,00089	0,00306
t-statistic	(-1,724)	(-1,577)	(-0,565)	(-0,5634)	(-0,837)	(-1,333)	(-1,072)	(-0,537)	(-0,3179)	(-0,39)	(0,947)
					Panel B. Additional properties Jan 1996 - Dec 2005						
MKT beta	1,0012*	0,999*	0,999*	1,0007*	1,0015*	0,9988*	1,0038*	1,0003*	0,999*	0,999*	-0,0013
t-statistic	(932,349)	(644,47)	(728,86)	(688,25)	(491,15)	(461,25)	(587,01)	(588,39)	(661,14)	(947,43)	(-0,85)
SMB beta	0,399*	0,4028*	0,42*	0,4635*	0,492*	0,1756	0,62*	0,563*	0,3417*	0,427*	0,027
t-statistic	(7,461)	(5,2068)	(6,146)	(6,392)	(4,841)	(1,625)	(7,269)	(6,6389)	(4,532)	(8,112)	(0,3651)
HML beta	0,217*	0,0507	0,0426	0,009	0,424*	0,307*	-0,073	-0,0003	0,2787*	0,1738*	-0,0437
t-statistic	(3,5383)	(0,572)	(0,543)	(0,1082)	(3,635)	(2,4775)	(-0,746)	(-0,0029)	(3,22)	(2,876)	(-0,507)

At each year-end between 1996 and 2005, stocks are sorted into 10 portfolios according to historical liquidity betas. The betas are estimated as the slope coefficients on the aggregate liquidity factor in regressions of excess stock returns on that liquidity factor (OFL) and the three Fama-French factors. The regressions are estimated using the most recent three years of data. The portfolio returns for the 12 post-ranking months are linked across years to form one series of post-ranking returns for each portfolio. Panel A reports the decile's portfolios' average returns and liquidity betas, estimated by regressing equal-weighted portfolio excess returns on the liquidity factor and the Fama-French factors. Panel B reports the betas with respect to the Fama-French factors, estimated by regressing equal-weighted portfolio excess returns on the three factors. The t-statistics are in parentheses. OFL1 includes stocks negatively sensitive to market-wide liquidity and OFL10 stocks positively sensitive to market-wide liquidity.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

Table 5
Summary statistics for MV portfolios

	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10	MV(10-1)
					Panel A. Market value and Average Returns						
Market value	2,3618	9,69	22,526	35,517	63,45	93,327	149,63	278,38	597,798	2865,26	
Average return	0,0219	0,0138	0,0181	0,0111	-0,0018	-0,0023	-0,0006	0,0003	0,005	0,0051	
					Panel B. Liquidity betas						
ILLIQ beta	-0,0055	-0,0073*	-0,0022	-0,0014	-0,0004	0,0018	0,0019	0,0024	0,0023	0,0004	0,0059
t-statistic	(-1,438)	(-2,7119)	(-0,595)	(-1,016)	(-0,27)	(1,146)	(1,169)	(1,544)	(1,656)	(0,369)	(1,484)
OFL beta	-0,0016	-0,0024	0,0011	-0,0006	-0,0018	-0,002	0,0004	-0,0013	0,0006	-0,0018	-0,0002
t-statistic	(-0,3027)	(-0,6205)	(0,2141)	(-0,3559)	(-0,9113)	(-0,91)	(0,1766)	(-0,6029)	(0,328)	(-0,9507)	(-0,038)
					Panel B. Additional properties Jan 1996 - Dec 2005						
MKT beta	0,9964*	0,999*	0,9995*	1,000*	1,000*	1,0011*	1,0006*	1,0005*	0,999*	1,0009*	0,0045**
t-statistic	(405,554)	(560,236)	(428,28)	(1240,59)	(1077,82)	(967,43)	(958,796)	(1004,03)	(1111,505)	(1252,54)	(1,754)
SMB beta	0,3917*	0,6342*	0,6753*	0,7879*	0,6915*	0,6986*	0,491*	0,311*	0,1516*	-0,239*	-0,6307*
t-statistic	(3,1969)	(7,1312)	(5,8017)	(15,388)	(14,94)	(13,537)	(9,4337)	(6,258)	(3,3828)	(-7,119)	(-4,964)
HML beta	0,6088*	0,4602*	1,0436*	0,2374*	0,1076*	-0,0286	-0,0697	-0,0426	-0,1288*	-0,0985*	-0,7073*
t-statistic	(4,3278)	(4,5078)	(7,81)	(4,174)	(2,026)	(-0,482)	(-1,166)	(-0,747)	(-2,502)	(-2,56)	(-4,849)

At each year-end between 1996 and 2005, stocks are sorted into 10 portfolios according to their market values. The portfolio returns for the 12 post-ranking months are linked across years to form one series of post-ranking returns for each portfolio. Panel A reports the time-series averages of the deciles portfolios' market value and returns, obtained as equal-weighted averages of the corresponding measures across the stocks within each portfolio. Panel B reports the liquidity betas, estimated by regressing equal-weighted portfolio excess returns on the liquidity factor (ILLIQ or OFL) and the Fama-French factors. Panel C reports the betas with respect to the Fama-French factors, estimated by regressing equal-weighted portfolio excess returns on the three factors. The t-statistics are in parentheses. MV1 has small market value stocks and MV10 has large market value stocks. All statistics are calculated over the period January 1996 through December 2005.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

6.3 Asset pricing and systematic liquidity: the empirical evidence

After having sorted stocks in 10 liquidity-based portfolios with respect to the liquidity betas that they had in terms of the two liquidity factors we examined and 10 size-sorted portfolios according to the market value of each stock at the end of each year, we examined if our risk factors are priced in the market. Analogous to our sort we obtained a January 1996 through December 2005 series of monthly returns on each portfolio by linking across years the post-ranking returns. These are the returns we used in the asset pricing models.

In our research we employed four alternative pricing models: the traditional CAPM, the three-factor Fama and French model and the two CAPM liquidity-based models, in which we added the liquidity factor (either OFL or ILLQ) to the standard CAPM model. For each portfolio and for each asset pricing model we investigated whether the liquidity factors are priced.

CAPM: $R_{jt} = a_j + \beta_{jm} R_{mt} + \varepsilon_{jt}$ (23)

Fama-French: $R_{jt} = a_j + \beta_{jm} R_{mt} + \beta_{jsmb} SMB_t + \beta_{jhml} HML_t + \varepsilon_{jt}$ (24)

CAPM+ILLIQ: $R_{jt} = a_j + \beta_{jm} R_{mt} + \beta_{jilliq} ILLIQ + \varepsilon_{jt}$ (25)

CAPM+OFL: $R_{jt} = a_j + \beta_{jm} R_{mt} + \beta_{jofl} OFL + \varepsilon_{jt}$ (26)

where R_{jt} is the excess return on the portfolio j, R_{mt} the excess return on the market portfolio, SMB_t the size factor, HML_t the book-to-market factor, ILLIQ and OFL are the liquidity factors, a_j the intercept of portfolio j and β_{jm}, β_{jsmb}, β_{jhml}, β_{jilliq} and β_{jofl} are the sensitivities to the risk factors.

It is important to note that if the liquidity risk factors are priced in the market, we should find systematic differences in the risk-adjusted average returns (alphas) of our liquidity-beta-sorted portfolios. In other words, for a given asset pricing model, the risk-adjusted average return (alpha) of the OFL10 portfolio should be significantly higher than the alpha for the OFL1 portfolio as long as the market prices market-wide liquidity risk. On the other hand, given the way in which ILLIQ is defined, the opposite results should hold. If there is a significant liquidity premium associated with aggregate liquidity risk, the difference in average market risk-adjusted returns between ILLIQ10 and ILLIQ1 should be significantly negative. This is the approach followed by Pastor & Stambaugh (2003) to test alternative asset pricing models. They found that average risk-adjusted returns of stocks with high sensitivity to liquidity exceed those for stocks with low sensitivity by 7,5% on an annual basis when a four factor asset pricing model is employed in the estimation (the three Fama-French factors plus a momentum factor). Pastor & Stambaugh interpret the result as the average liquidity premium existing in the U.S. market between 1966 and 1999.

We followed the same testing strategy and we reported the equal-weighted portfolios' alphas estimated under four different factor specifications. The CAPM alpha is computed with respect to MKT, the Fama-French alpha with respect to the Fama-French factors, the CAPM+ILLIQ alpha with respect to MKT and ILLIQ factor and the CAPM+OFL alpha with respect to MKT and OFL factor. We found the differences in alphas between January 1996 and December 2005 on an annual basis (Annual alphas are computed as 12 times the monthly estimates). Unfortunately, our results are dramatically different as reported in Table 6, 7 and 8. None of the models seems to indicate that there exists a liquidity premium.

Specifically, in Table 6 is reported the estimated alphas of the equal-weighted portfolios sorted on historical liquidity betas according to the ILLIQ factor. All four alphas of the “10-1” spread are insignificantly positive: CAPM alpha is 9,99% per year (t = 0,311), the Fama-French alpha is 5,84% per year (t = 0,208), the CAPM+ILLIQ alpha is 4,21% per year (t = 0,107) and the CAPM+OFL alpha is 15,87% per year (t = 0,493). As observed, none of the differences is significantly different from zero, so it is not really important that the differences have the wrong sign, as the alphas are equal to zero. The evidence strongly supports the hypothesis that ILLIQ risk factor is not priced in the Greek market. Also, it is important to notice that CAPM alphas and CAPM+OFL alphas for the half of the portfolios are significant but the alphas of the extreme portfolios (ILLIQ1 and ILLIQ10) are insignificant.

In Table 7 is reported the alphas of the equal-weighted portfolios sorted on historical liquidity betas according to the OFL factor. All four alphas of the “10-1” spread are insignificantly negative: CAPM alpha is -16,9% per year (t = -0,977), the Fama-French alpha is -15,78% per year (t = -1,169), the CAPM+ILLIQ alpha is -15,1% per year (t = -0,716) and the CAPM+OFL alpha is -15,439% per year (t =-0,888). It is relevant to point out that adding the OFL or the ILLIQ factor to the CAPM does not seem to have significant effects on the results. There, also, may be noticed that for more than half of the portfolios CAPM alphas and CAPM+OFL alphas are significant but the “10-1” spreads have the wrong sign and are insignificant. These results support the hypothesis that neither OFL liquidity factor is priced in the Greek market.

Finally, in Table 8 is reported the alphas of the equal-weighted portfolios sorted on market value. Regardless of which asset pricing model is considered, we did not find significant differences for the size-sorted portfolios. This suggests that there was not a size-related premium in the Greek stock market for the period January 1996 through December 2005 despite some of the portfolio’s alphas are statistically significant.

We also test the models using OLS system-based method. We observed the standard zero intercept restriction that constitutes the null hypothesis: Ho: $a_j=0$ where j= 1,2,….,10 using the Wald test asymptotically distributed as a chi-square statistic with degrees of freedom equal to the number of restrictions under the null hypothesis. Specifically, it analyzes whether portfolio intercepts are jointly equal to zero. It shows whether the models completely capture average returns when used as asset pricing models. For the equal-weighted ILLIQ portfolios and for all the four models, the hypothesis is not rejected neither at the 5% nor the 10% level. This evidence strongly supports the hypothesis that this liquidity factor (ILLIQ) is not priced.

Moreover, for the equal-weighted OFL portfolios and for all asset models considered except the illiquidity-based CAPM the Wald test rejects the null hypothesis with a significance level of 5%. But, as we noted earlier the premium should be positive and in our analysis has the wrong sign and is insignificant (10-1 spread). So it appears

Table 6
Alphas of Equal-Weighted Portfolios Sorted on Historical Liquidity Betas
Jan 1996-Dec 2005

	ILLIQ1	ILLIQ2	ILLIQ3	ILLIQ4	ILLIQ5	ILLIQ6	ILLIQ7	ILLIQ8	ILLIQ9	ILLIQ10	ILLIQ(10-1)	Wald test
CAPM alpha	-32,0036	-37,01*	-33,178*	-27,267	-30,647	-32,487**	-18,127	-31,997*	-66,487*	-22,007	9,9961	X^2=3,477
	(-1,36)	(-2,438)	(-2,262)	(-1,54)	(-1,28)	(-1,987)	(-0,989)	(-2,59)	(-2,253)	(-1,006)	(0,357)	(0,967)
Fama-French alpha	-16,626	-24,59*	-23,623*	-10,89	-12,83	-22,088	-9,9799	-24,426*	-61,084*	-10,777	5,848	X^2=3,381
	(-0,827)	(-2,3168)	(-2,0359)	(-0,913)	(-0,608)	(-1,547)	(-0,658)	(-2,616)	(-2,1479)	(-0,551)	0,276	(0,971)
CAPM+ILLIQ alpha	15,193	-15,145	-13,365	0,518	-39,246	-22,75	-0,498	-9,018	-18,56	19,406	4,213	X^2=0,44
	(0,533)	(-0,808)	(-0,736)	(0,024)	(-1,312)	(-1,113)	(-0,0218)	(-0,598)	(-0,512)	(0,727)	(0,194)	(1)
CAPM+OFL alpha	-36,806	-39,98*	-34,1*	-27,519	-34,45	-32,97*	-19,119	-33,055*	-68,039*	-20,929	15,877	X^2=4,98E+00
	(-1,57)	(-2,642)	(-2,304)	(-1,54)	(-1,441)	(-1,997)	(-1,034)	(-2,655)	(-2,284)	(-0,947)	(-0,627)	(0,892)

This table reports the portfolios' alphas in percent per year (each estimated intercept (alpha) from the regression using monthly returns over the whole period is multiplied by 1200 (by 12 to make it “per year” rather than monthly and by 100 to make it “percent”). It also reports the differences in percent per year between estimated alphas based on four asset pricing models: CAPM, Fama-French, and the two liquidity based asset pricing model alphas. The portfolios sorted according to the sensitivity of returns to monthly average across days of the absolute percentage price change per euro of trading volume (ILLIQ). ILLIQ1 includes stocks negatively sensitive to market-wide illiquidity and ILLIQ10 includes stocks positively sensitive to market-wide illiquidity. The last column reports the Wald test that analyzes whether alpha coefficients are jointly equal to zero. Data are from January 1996 to December 2005.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

Table 7
Alphas of Equal-Weighted Portfolios Sorted on Historical Liquidity Betas
Jan 1996-Dec 2005

	OFL1	OFL2	OFL3	OFL4	OFL5	OFL6	OFL7	OFL8	OFL9	OFL10	OFL(10-1)	Wald test
CAPM alpha	-16,08	-36,336*	-34,96*	-29,42**	-6,359	-45,92*	-6,823	-42,39*	-21,949	-32,99*	-16,904	X^2=38,336
	(-1,312)	(-2,38)	(-2,501)	(-1,97)	(-0,302)	(-2,31)	(-0,37)	(-2,409)	(-1,44)	(-2,7)	(-1,392)	(0*)
Fama-French alpha	-8,567	-27,01**	-25,12*	-18,18	1,286	-44,81*	9,093	-28,629**	-16,479	-24,349*	-15,78	X^2=28,015
	(-0,89)	(-1,943)	(-2,044)	(-1,39)	(0,07)	(-2,308)	(0,593)	(-1,878)	(-1,216)	(-2,57)	(-1,684)	(0,002*)
CAPM+ILLIQ alpha	6,331	-15,429	-20,6	-15,79	1,712	-34,614	-3,493	-37,416**	-5,335	-8,773	-15,104	X^2=8,253
	(0,422)	(-0,819)	(-1,18)	(-0,849)	(0,065)	(-1,394)	(-0,154)	(-1,696)	(-0,28)	(-0,591)	(-1,013)	(0,604)
CAPM+OFL alpha	-18,217	-38,807*	-35,79*	-30,24*	-8,675	-49,21*	-8,521	-43,3*	-22,839	-33,65*	-15,439	X^2=41,285
	(-1,48)	(-2,54)	(-2,536)	(-2,009)	(-0,409)	(-2,477)	(-0,467)	(-2,437)	(-1,483)	(-2,732)	(-1,247)	(0*)

This table reports the portfolios' alphas in percent per year (each estimated intercept (alpha) from the regression using monthly returns over the whole period is multiplied by 1200 (by 12 to make it “per year” rather than monthly and by 100 to make it “percent”). It also reports the differences in percent per year between estimated alphas based on four asset pricing models: CAPM, Fama-French, and the two liquidity based asset pricing model alphas. The portfolios sorted according to the sensitivities of returns to fluctuations in aggregate liquidity, as measured by order flow inducing greater return reversals when liquidity is lower (OFL). OFL1 represents stocks negatively sensitive to market-wide liquidity and OFL10 represents stocks positively sensitive to market-wide liquidity. The last column reports the Wald test that analyzes whether alpha coefficients are jointly equal to zero. Data are from January 1996 to December 2005.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

Table 8
Alphas of Equal-Weighted Portfolios Sorted on Market Value
Jan 1996-Dec 2005

	MV1	MV2	MV3	MV4	MV5	MV6	MV7	MV8	MV9	MV10	MV(10-1)	Wald test
CAPM alpha	-24,62	-22,346	-10,284	-29,536*	-37,176*	-30,072*	-26,843*	-21,358*	-22,76*	4,863	29,483	X^2=34,323
	(-1,0007)	(-1,083)	(-0,356)	(-2,016)	(-2,583)	(-2,048)	(-2,204)	(-2,112)	(-2,716)	(0,62)	(1,622)	(0*)
Fama-French alpha	-21,343	-11,603	-4,574	-14,31*	-21,383*	-12,69	-14,117	-13,312	-17,72*	-3,006	18,336	X^2=23,464
	(-0,969)	(-0,726)	(-0,218)	(-1,974)	(-2,57)	(-1,368)	(-1,509)	(-1,49)	(-2,199)	(-0,476)	(0,493)	(0,009*)
CAPM+ILLIQ alpha	29,463	39,534	53,659	15,703	-14,75	-21,48	-25,05	-24,88*	-33,06	-6,29	-35,754	X^2=25,939
	(0,992)	(1,643)	(1,538)	(0,862)	(-0,832)	(-1,169)	(-1,64)	(-1,96)	(-3,182)	(-0,639)	(-1,63)	(0,004*)
CAPM+OFL alpha	-26,26	-24,12	-11,343	-30,18*	-38,17*	-30,96*	-26,56*	-21,889*	-22,28*	3,867	30,127	X^2=34,494
	(-1,057)	(-1,16)	(-0,388)	(-2,04)	(-2,628)	(-2,09)	(-2,159)	(-2,144)	(-2,634)	(0,486)	(1,54)	(0*)

This table reports the decile portfolios' alphas in percent per year (each estimated intercept (alpha) from the regression using monthly returns over the whole period is multiplied by 1200 (by 12 to make it "per year" rather than monthly and by 100 to make it "percent"). It also reports the differences in percent per year between estimated alphas based on four asset pricing models: CAPM, Fama-French, and the two liquidity based asset pricing model alphas (CAPM +ILLIQ and CAPM+OFL). The portfolios sorted according to the market value of the stocks (MV). MV1 contains stocks with small market value and MV10 contains stocks with big market value. The last column reports the Wald test that analyzes whether alpha coefficients are jointly equal to zero. Data are from January 1996 to December 2005.
* Statistically significant at 5% level.
** Statistically significant at 10% level.

that for some portfolios the liquidity factor plays an important role in explaining the average returns but not for the extreme portfolios. Finally, for the portfolios sorted according to the market value of each stock the Wald test rejects the null hypothesis at the 5% level for all asset models examined. But, we also noted that the 10-1 spreads are insignificant, so there is either a size related premium.

The results found in Tables 6, 7 and 8 are consistent with the results already reported in Tables 3, 4 and 5. We could conclude that our empirical results show that neither of these proxies for systematic liquidity risk carries a premium in the Greek stock market for the period January 1996 through December 2005. There is a general lack of statistical significance. This may indicate that the two liquidity factors we analyzed may be weak proxies for liquidity in the Greek stock market.

7. Conclusions

In this paper, we examined the asset pricing role of liquidity, proxied by Amihud's ratio and Pastor & Stambaugh's liquidity factor, in the context of four asset pricing models: the standard CAPM, the Fama and French three factor model and the two liquidity based asset pricing models, in which we added a liquidity factor (ILLIQ or OFL) to the standard CAPM. The motivation for our study was provided by the growing interest in liquidity that has emerged in the asset pricing literature over recent years.

Evidence found with U.S and Spanish market data confirms that market-wide liquidity should be a key ingredient of asset pricing models. It seems reasonable that many investors might require higher expected returns on assets whose returns have higher sensitivities to aggregate liquidity. A pervasive drop in liquidity is undesirable for investors, so that investors demand compensation for holding stocks with greater exposure to this liquidity risk. From our empirical results it seems possible to conclude that individual liquidity co-moves with market liquidity and thus commonality in liquidity exists in the Greek stock market. Also, we examined whether market-wide liquidity is priced, measuring liquidity with two different liquidity factors, the ILLIQ ratio of Amihud and the OFL factor of Pastor & Stambaugh. We concluded that none of the liquidity factors analyzed in the paper seems to be priced in the Greek market. Thus, in our database, expected stock returns are not related to betas of returns to aggregate liquidity. This may indicate that the two liquidity factors we analyzed may be weak proxies for liquidity in the Greek stock market.

Of course, the results should be interpreted with care given the short period of time covered by this research. Given the design employed in any asset pricing work, where the key parameters are estimated with relatively long series of past data, we are forced to use monthly data only from 1996 to 2005 in our tests of the asset pricing models. This may be considered to be short for a paper of these characteristics but it wasn't feasible to find data for a longer period. On the other hand, testing models like the one proposed by Amihud with an alternative database and making comparisons with competing liquidity factors seems to be a crucial step in this type of research.

The empirical results of this paper are suggestive of further empirical work. In particular, it would be of interest to explain time series and cross-sectional the asset pricing role of liquidity employing a longer series of data and alternative measures of aggregate liquidity.

8. APPENDIX

Table 9
MKT factor of Fama-French Jan1993-Dec 2005

month	MKT	month	MKT	month	MKT	month	MKT	month	MKT	month	MKT
1	-22,44	**27**	-16,73	**53**	-9,62	**79**	-8,867	**105**	-3,768	**131**	-2,34
2	-22,43	**28**	-16,48	**54**	-9,47	**80**	-8,701	**106**	-3,599	**132**	-2,364
3	-22,39	**29**	-16,001	**55**	-9,67	**81**	-8,413	**107**	-3,051	**133**	-2,17
4	-22,3	**30**	-15,67	**56**	-9,47	**82**	-9,048	**108**	-3,226	**134**	-2,09
5	-21,74	**31**	-15,3	**57**	-9,53	**83**	-8,811	**109**	-3,51	**135**	-2,065
6	-21,31	**32**	-14,69	**58**	-11,15	**84**	-8,274	**110**	-3,57	**136**	-2,19
7	-20,71	**33**	-14,238	**59**	-11,34	**85**	-7,423	**111**	-3,885	**137**	-2,24
8	-20,13	**34**	-13,99	**60**	-11,37	**86**	-6,939	**112**	-3,897	**138**	-2,44
9	-20,26	**35**	-13,9	**61**	-12,41	**87**	-6,689	**113**	-4,003	**139**	-2,39
10	-20,26	**36**	-14,22	**62**	-12,75	**88**	-6,508	**114**	-3,842	**140**	-2,309
11	-20,26	**37**	-13,78	**63**	-10,76	**89**	-6,629	**115**	-3,679	**141**	-2,379
12	-20,18	**38**	-13,31	**64**	-10,78	**90**	-6,307	**116**	-3,491	**142**	-2,319
13	-19,67	**39**	-13,28	**65**	-11,023	**91**	-6,501	**117**	-3,252	**143**	-2,265
14	-18,89	**40**	-13,32	**66**	-11,68	**92**	-6,281	**118**	-3,269	**144**	-2,237
15	-18,5	**41**	-13,38	**67**	-11,529	**93**	-6,009	**119**	-3,041	**145**	-2,253
16	-18,56	**42**	-13,28	**68**	-13,07	**94**	-5,489	**120**	-2,79	**146**	-2,269
17	-18,52	**43**	-12,80	**69**	-11,85	**95**	-5,505	**121**	-2,908	**147**	-2,278
18	-25,6	**44**	-12,73	**70**	-11,019	**96**	-5,015	**122**	-2,5754	**148**	-2,348
19	-20,04	**45**	-12,64	**71**	-10,4	**97**	-4,58	**123**	-2,395	**149**	-2,199
20	-19,96	**46**	-12,27	**72**	-10,21	**98**	-4,657	**124**	-2,517	**150**	-2,064
21	-20,01	**47**	-11,52	**73**	-9,397	**99**	-4,47	**125**	-2,116	**151**	-2,149
22	-19,003	**48**	-11,22	**74**	-8,98	**100**	-4,477	**126**	-1,99	**152**	-2,145
23	-18,29	**49**	-10,89	**75**	-8,72	**101**	-4,45	**127**	-1,98	**153**	-2,207
24	-17,47	**50**	-10,31	**76**	-8,81	**102**	-4,402	**128**	-2,132	**154**	-2,365
25	-17,457	**51**	-10,25	**77**	-8,504	**103**	-4,413	**129**	-2,27	**155**	-2,7
26	-17,07	**52**	-10,18	**78**	-8,58	**104**	-4,09	**130**	-2,367	**156**	-2,74

This table contains the MKT factor (R_m-R_f) calculated following the Fama & French methodology.

Table 10
SMB factor of Fama-French   Jan1993-Dec 2005

month	SMB	month	SMB	month	SMB	month	SMB	month	SMB	month	SMB
1	0,050	**27**	0,001	**53**	-0,006	**79**	0,150	**105**	0,037	**131**	0,027
2	0,034	**28**	-0,011	**54**	-0,003	**80**	0,067	**106**	-0,055	**132**	-0,049
3	-0,056	**29**	-0,037	**55**	0,049	**81**	0,191	**107**	-0,032	**133**	-0,054
4	0,004	**30**	-0,050	**56**	0,037	**82**	0,114	**108**	0,124	**134**	-0,009
5	-0,042	**31**	-0,058	**57**	0,007	**83**	0,144	**109**	-0,048	**135**	-0,053
6	0,040	**32**	-0,004	**58**	0,073	**84**	0,110	**110**	0,050	**136**	-0,040
7	0,033	**33**	0,006	**59**	0,039	**85**	-0,152	**111**	0,015	**137**	-0,052
8	0,025	**34**	0,037	**60**	-0,003	**86**	0,312	**112**	-0,046	**138**	0,022
9	0,033	**35**	0,062	**61**	-0,016	**87**	-0,195	**113**	-0,019	**139**	-0,111
10	-0,022	**36**	0,001	**62**	0,100	**88**	-0,186	**114**	-0,022	**140**	0,010
11	0,021	**37**	0,006	**63**	0,025	**89**	0,009	**115**	-0,034	**141**	-0,024
12	0,131	**38**	-0,023	**64**	-0,177	**90**	0,102	**116**	-0,029	**142**	-0,069
13	0,139	**39**	-0,058	**65**	-0,051	**91**	-0,043	**117**	0,013	**143**	-0,038
14	-0,049	**40**	-0,001	**66**	0,227	**92**	-0,092	**118**	-0,072	**144**	-0,028
15	-0,008	**41**	-0,027	**67**	0,082	**93**	-0,097	**119**	0,006	**145**	-0,044
16	0,073	**42**	0,006	**68**	0,013	**94**	0,110	**120**	0,066	**146**	0,006
17	-0,011	**43**	-0,002	**69**	0,068	**95**	-0,115	**121**	-0,118	**147**	-0,043
18	0,010	**44**	0,013	**70**	-0,018	**96**	0,002	**122**	-0,025	**148**	0,000
19	-0,031	**45**	-0,007	**71**	-0,028	**97**	-0,046	**123**	-0,039	**149**	-0,005
20	0,021	**46**	-0,035	**72**	-0,016	**98**	-0,115	**124**	0,004	**150**	-0,037
21	0,001	**47**	-0,012	**73**	-0,084	**99**	0,187	**125**	0,090	**151**	-0,036
22	0,003	**48**	0,010	**74**	0,083	**100**	0,124	**126**	0,033	**152**	-0,016
23	-0,037	**49**	-0,014	**75**	0,141	**101**	-0,074	**127**	0,001	**153**	-0,035
24	0,006	**50**	-0,077	**76**	0,090	**102**	-0,062	**128**	0,037	**154**	0,013
25	0,005	**51**	0,027	**77**	0,085	**103**	-0,040	**129**	-0,050	**155**	0,046
26	-0,021	**52**	-0,039	**78**	0,152	**104**	0,077	**130**	-0,048	**156**	-0,014

This table contains the SMB factor (small minus big ME) calculated following the Fama & French methodology

Table 11
HML factor of Fama-French Jan1993-Dec 2005

month	HML	month	HML	month	HML	month	HML	month	HML	month	HML
1	0,023	**27**	-0,018	**53**	-0,044	**79**	0,108	**105**	-0,034	**131**	0,102
2	-0,024	**28**	-0,030	**54**	-0,037	**80**	0,225	**106**	0,012	**132**	-0,029
3	0,036	**29**	-0,014	**55**	-0,040	**81**	0,102	**107**	-0,019	**133**	-0,029
4	-0,059	**30**	-0,014	**56**	0,046	**82**	-0,069	**108**	0,058	**134**	-0,027
5	0,051	**31**	0,005	**57**	-0,033	**83**	-0,011	**109**	-0,047	**135**	-0,032
6	-0,094	**32**	-0,024	**58**	-0,048	**84**	0,015	**110**	-0,003	**136**	-0,065
7	-0,016	**33**	-0,034	**59**	0,105	**85**	0,039	**111**	-0,035	**137**	-0,018
8	-0,040	**34**	-0,083	**60**	-0,009	**86**	-0,142	**112**	-0,012	**138**	0,018
9	0,005	**35**	0,035	**61**	0,018	**87**	0,045	**113**	0,006	**139**	-0,009
10	-0,001	**36**	0,058	**62**	-0,131	**88**	0,025	**114**	0,056	**140**	0,004
11	-0,025	**37**	-0,002	**63**	-0,057	**89**	0,041	**115**	0,001	**141**	-0,017
12	0,009	**38**	-0,035	**64**	-0,053	**90**	-0,045	**116**	-0,031	**142**	0,004
13	-0,215	**39**	-0,026	**65**	-0,069	**91**	-0,017	**117**	0,003	**143**	-0,015
14	-0,035	**40**	-0,025	**66**	-0,058	**92**	0,006	**118**	-0,055	**144**	0,033
15	-0,018	**41**	-0,072	**67**	0,019	**93**	0,035	**119**	-0,019	**145**	-0,082
16	0,033	**42**	0,040	**68**	-0,014	**94**	0,363	**120**	-0,005	**146**	0,090
17	0,029	**43**	-0,045	**69**	0,024	**95**	0,024	**121**	-0,082	**147**	-0,069
18	-0,006	**44**	-0,045	**70**	0,010	**96**	0,078	**122**	-0,055	**148**	-0,074
19	-0,016	**45**	0,071	**71**	-0,006	**97**	-0,016	**123**	-0,026	**149**	-0,038
20	-0,004	**46**	0,020	**72**	-0,007	**98**	0,038	**124**	-0,024	**150**	0,018
21	0,021	**47**	-0,018	**73**	0,043	**99**	-0,063	**125**	0,063	**151**	-0,002
22	0,033	**48**	0,053	**74**	0,001	**100**	-0,034	**126**	0,039	**152**	0,080
23	0,015	**49**	-0,034	**75**	0,127	**101**	-0,016	**127**	0,075	**153**	0,043
24	-0,024	**50**	-0,079	**76**	-0,003	**102**	-0,046	**128**	0,177	**154**	0,022
25	-0,016	**51**	-0,064	**77**	0,112	**103**	-0,033	**129**	0,007	**155**	0,044
26	0,049	**52**	-0,066	**78**	0,216	**104**	0,053	**130**	-0,083	**156**	-0,034

This table contains the HML factor (high minus low B/M) calculated following the Fama & French methodology

Table 12
Market-wide commonality in liquidity 1993-2005

Stocks	Alpha	t-statistic	Beta	t-statistic	R^2	Adjusted R^2
1	6,141	1,619	0,606	5,655	0,174	0,168
2	0,205	0,059	0,950	9,672	0,381	0,377
3	3,299	0,860	0,420	3,879	0,090	0,084
4	5,737	0,973	1,136	6,817	0,234	0,229
5	4,571	1,010	0,682	5,335	0,158	0,152
6	4,527	1,277	0,621	6,201	0,202	0,197
7	4,785	0,884	1,219	7,974	0,295	0,290
8	4,986	1,302	0,575	5,310	0,156	0,151
9	3,428	1,061	0,635	6,955	0,241	0,236
10	6,847	1,715	0,622	5,513	0,167	0,161
11	4,933	1,402	0,665	6,691	0,228	0,222
12	6,634	1,533	0,718	5,869	0,185	0,179
13	4,226	1,464	0,499	6,112	0,197	0,192
14	4,615	1,135	0,726	6,320	0,208	0,203
15	1,318	0,454	0,653	7,971	0,295	0,290
16	4,977	1,204	1,086	9,297	0,362	0,358
17	38,832	1,116	4,753	4,833	0,133	0,127
18	3,152	0,844	0,702	6,653	0,226	0,220
19	5,425	1,338	0,710	6,195	0,202	0,196
20	3,533	0,938	0,571	5,365	0,159	0,154
21	7,686	1,333	1,183	7,262	0,258	0,253
22	0,951	0,316	0,629	7,387	0,264	0,259
23	4,272	1,128	0,788	7,359	0,263	0,258
24	1,721	0,547	0,643	7,226	0,256	0,251
25	6,416	1,545	0,488	4,159	0,102	0,096
26	3,254	0,975	0,507	5,378	0,160	0,154
27	-51,675	-0,891	-5,455	-3,329	0,068	0,062
28	-0,818	-0,312	0,568	7,671	0,279	0,274
29	5,772	1,012	1,108	6,877	0,237	0,232
30	3,408	1,036	0,502	5,405	0,161	0,156
31	4,552	1,327	0,502	5,175	0,150	0,144
32	2,578	0,678	0,373	3,473	0,074	0,067
33	7,506	1,936	0,743	6,777	0,232	0,227
34	-0,877	-0,079	0,184	0,588	0,002	-0,004
35	7,089	1,839	1,027	9,425	0,369	0,365
36	4,972	1,404	0,684	6,837	0,235	0,230
37	6,964	1,180	1,040	6,239	0,204	0,199
38	1,903	0,718	0,563	7,511	0,271	0,266
39	5,738	1,136	0,942	6,604	0,223	0,218
40	7,057	1,298	0,787	5,121	0,147	0,142
41	2,660	0,852	0,535	6,068	0,195	0,190
42	6,090	1,631	0,770	7,294	0,259	0,254
43	5,816	1,567	0,507	4,837	0,133	0,128
44	5,517	1,438	0,803	7,408	0,265	0,260
45	-0,494	-0,150	0,573	6,155	0,200	0,194
46	12,027	2,396	0,189	1,335	0,012	0,005
47	3,441	1,015	0,674	7,040	0,246	0,241
48	4,332	1,235	0,675	6,807	0,234	0,229
49	4,130	0,933	0,604	4,829	0,133	0,127
50	-0,415	-0,129	0,604	6,395	0,212	0,207

Table 12 (continue)
Market-wide commonality in liquidity 1993-2005

Stocks	Alpha	t-statistic	Beta	t-statistic	R^2	Adjusted R^2
51	5,083	1,243	0,802	6,688	0,227	0,222
53	2,355	0,703	0,718	7,313	0,260	0,255
54	2,625	0,841	0,614	6,966	0,242	0,237
55	3,086	1,008	0,657	7,599	0,275	0,271
56	3,259	1,027	0,854	9,529	0,374	0,370
57	3,471	1,045	0,623	6,636	0,225	0,220
58	3,722	1,135	0,549	5,924	0,188	0,182
59	2,990	0,860	0,533	5,430	0,162	0,157
60	2,861	0,979	0,560	6,785	0,232	0,227
61	9,604	1,749	0,774	4,988	0,141	0,135
62	6,993	1,748	0,420	3,712	0,083	0,077
63	11,206	1,490	0,353	1,663	0,018	0,011
64	17,152	2,450	0,840	4,247	0,106	0,100
65	1,108	0,261	0,554	4,616	0,123	0,117
66	3,008	0,864	0,515	5,231	0,153	0,147
67	6,452	1,611	0,837	7,400	0,265	0,260
68	2,446	0,845	0,684	8,359	0,315	0,310
69	0,388	0,143	0,605	7,910	0,292	0,287
70	2,261	0,765	0,525	6,295	0,207	0,202
71	2,380	0,717	0,609	6,488	0,217	0,212
72	3,242	1,038	0,686	7,773	0,284	0,280
73	6,600	1,581	0,852	7,227	0,256	0,251
74	9,334	1,757	0,544	3,623	0,080	0,073
75	13,868	2,345	0,329	1,968	0,025	0,018
76	6,570	1,493	0,775	6,235	0,204	0,198
77	6,415	1,566	0,904	7,806	0,286	0,281
78	2,806	0,836	0,597	6,289	0,206	0,201
79	5,227	1,615	0,789	8,623	0,328	0,324
80	4,375	1,025	0,906	7,512	0,271	0,266
81	5,909	1,706	0,525	5,361	0,159	0,153
82	0,521	0,183	0,641	7,977	0,295	0,290
83	5,447	1,170	0,848	6,446	0,215	0,210
84	8,061	1,754	1,081	8,326	0,313	0,309
85	7,966	1,990	0,972	8,594	0,327	0,323
86	4,561	1,199	0,637	5,925	0,188	0,182
87	3,277	1,038	0,446	5,004	0,141	0,136
88	5,211	1,315	0,592	5,287	0,155	0,150
89	4,011	1,129	0,486	4,845	0,134	0,128
90	4,789	1,321	0,575	5,617	0,172	0,166
91	4,658	1,434	0,631	6,870	0,237	0,232
92	7,501	1,587	0,595	4,457	0,116	0,110
93	3,970	1,322	0,564	6,651	0,225	0,220
94	2,290	0,769	0,480	5,702	0,176	0,171
95	3,465	0,934	0,559	5,329	0,157	0,152
96	3,261	0,943	0,602	6,161	0,200	0,195
97	3,417	1,006	0,561	5,845	0,184	0,178
98	12,347	2,689	0,222	1,707	0,019	0,012
99	2,831	1,023	0,517	6,618	0,224	0,219
100	11,882	1,366	1,076	4,379	0,112	0,106
101	0,302	0,112	0,583	7,633	0,277	0,272
102	4,040	1,146	0,761	7,635	0,277	0,272
103	2,459	0,664	0,870	8,315	0,313	0,308
104	2,832	1,056	0,541	7,140	0,251	0,246
105	2,844	0,971	0,380	4,596	0,122	0,116

Table 12 (continue)
Market-wide commonality in liquidity 1993-2005

Stocks	Alpha	t-statistic	Beta	t-statistic	R^2	Adjusted R^2
106	10,995	1,719	1,279	6,816	0,234	0,229
107	3,528	1,477	0,496	7,076	0,248	0,243
108	5,988	0,938	0,393	2,098	0,028	0,022
109	29,382	1,011	4,246	4,979	0,140	0,135
110	17,261	1,935	-0,098	-0,391	0,001	-0,006
111	1,179	0,414	0,814	10,108	0,402	0,398
112	0,460	0,133	0,749	7,677	0,279	0,275
113	6,666	1,165	0,754	4,665	0,125	0,120
114	2,808	0,915	0,421	4,855	0,134	0,129
115	1,060	0,384	0,927	11,878	0,481	0,478
116	12,106	1,804	1,598	8,427	0,318	0,314
117	10,134	2,213	0,890	6,878	0,237	0,232
118	1,926	0,649	0,598	7,136	0,251	0,246
119	-1,097	-0,348	0,520	5,840	0,183	0,178
120	3,979	1,558	0,118	1,631	0,017	0,011
121	1,505	0,471	0,441	4,891	0,136	0,130
122	3,786	1,168	0,601	6,567	0,221	0,216
123	4,112	1,199	0,538	5,555	0,169	0,163
124	2,337	0,799	0,629	7,607	0,276	0,271
125	3,261	0,984	0,801	8,555	0,325	0,321
126	3,018	0,908	0,806	8,586	0,327	0,322
127	3,079	0,984	0,804	9,093	0,352	0,348
128	1,716	0,579	0,567	6,778	0,232	0,227
129	5,189	1,008	0,545	3,746	0,085	0,078
130	3,861	1,104	0,580	5,866	0,185	0,179
131	2,336	0,753	0,831	9,478	0,371	0,367
132	3,287	0,888	0,706	6,752	0,231	0,226
133	5,638	1,549	0,813	7,906	0,291	0,287
134	1,290	0,467	0,568	7,274	0,258	0,253
135	2,447	0,757	0,650	7,116	0,250	0,245
136	3,331	0,912	0,768	7,449	0,267	0,263
137	4,126	1,167	0,645	6,454	0,215	0,210
138	5,620	1,666	0,806	8,451	0,320	0,315
139	2,246	0,874	0,508	6,988	0,243	0,238
140	7,602	1,676	0,805	6,283	0,206	0,201
141	7,590	1,513	0,654	4,613	0,123	0,117
142	5,614	1,227	0,542	4,188	0,103	0,098
143	7,546	2,036	0,668	6,376	0,211	0,206
144	3,718	1,029	0,751	7,354	0,262	0,258
Average	**4,645**	**1,099**	**0,677**	**6,199**	**0,209**	**0,204**
%Positive			**98,61**			
%+Significant			**94,44**			

$$\boxed{DSP_{jt} = a_j + \beta_j DSP_{mt} + \varepsilon_{jt}}$$

where DSP_{jt} is the percentage change from month t-1 to t in liquidity, as proxied by the relative spread of stock j, and DSP_{mt} is the concurrent change in a cross-sectional average of the same variable or the market-wide (equally weighted) relative spread. Average numbers reported are for 144 stocks.

Table13
Illiquidity Ratio Jan1993-Dec 2005

months	illiq	months	illiq	months	illiq	months	illiq	months	illiq	months	illiq
1	14,755	**27**	4,093	**53**	3,237	**79**	0,055	**105**	0,655	**131**	2,007
2	30,889	**28**	3,533	**54**	3,859	**80**	0,141	**106**	0,832	**132**	3,201
3	10,560	**29**	4,259	**55**	7,787	**81**	0,128	**107**	0,233	**133**	1,456
4	10,791	**30**	5,859	**56**	2,610	**82**	0,045	**108**	0,785	**134**	1,237
5	14,135	**31**	4,783	**57**	4,773	**83**	0,022	**109**	1,626	**135**	3,807
6	6,536	**32**	5,074	**58**	5,426	**84**	0,073	**110**	1,130	**136**	3,047
7	19,499	**33**	4,084	**59**	1,249	**85**	0,057	**111**	1,122	**137**	5,618
8	6,360	**34**	4,362	**60**	3,372	**86**	0,051	**112**	3,412	**138**	4,980
9	7,777	**35**	3,503	**61**	5,438	**87**	0,116	**113**	1,804	**139**	7,709
10	7,789	**36**	2,663	**62**	4,738	**88**	0,122	**114**	1,820	**140**	10,880
11	9,100	**37**	1,728	**63**	3,318	**89**	0,072	**115**	5,879	**141**	13,475
12	5,740	**38**	2,571	**64**	2,807	**90**	0,097	**116**	4,685	**142**	8,097
13	5,618	**39**	2,471	**65**	3,179	**91**	0,152	**117**	3,741	**143**	3,851
14	7,949	**40**	3,580	**66**	2,264	**92**	0,240	**118**	8,266	**144**	3,582
15	4,205	**41**	6,629	**67**	3,216	**93**	0,144	**119**	3,719	**145**	3,564
16	7,624	**42**	3,400	**68**	4,078	**94**	0,243	**120**	3,472	**146**	2,452
17	7,232	**43**	4,951	**69**	3,564	**95**	0,500	**121**	3,548	**147**	4,353
18	7,869	**44**	4,971	**70**	4,471	**96**	0,373	**122**	4,506	**148**	9,777
19	7,193	**45**	2,422	**71**	2,771	**97**	0,663	**123**	9,161	**149**	6,711
20	6,393	**46**	2,016	**72**	3,885	**98**	0,508	**124**	9,135	**150**	6,666
21	6,503	**47**	3,405	**73**	1,260	**99**	0,194	**125**	3,382	**151**	5,360
22	5,499	**48**	3,798	**74**	0,600	**100**	0,317	**126**	1,695	**152**	6,046
23	5,271	**49**	4,278	**75**	0,410	**101**	0,333	**127**	0,901	**153**	6,595
24	4,441	**50**	2,612	**76**	0,799	**102**	0,654	**128**	0,457	**154**	5,201
25	6,402	**51**	4,022	**77**	0,166	**103**	0,990	**129**	3,349	**155**	6,183
26	3,964	**52**	3,589	**78**	0,086	**104**	0,498	**130**	3,735	**156**	7,184

This table contains the monthly market-wide liquidity risk factor proposed by Amihud (2002) and is measured for a given stock on a given day as the ratio of absolute percentage price change per euro of daily trading volume. Data are from January 1993 to December 2005

Table 14
Pastor & Stambaugh Liquidity Factor (γ_t)   Jan1993-Dec 2005

months	γ_t	months	γ_t	months	γ_t	months	γ_t	months	γ_t	months	γ_t
1	777,546	**27**	5,222	**53**	44,620	**79**	-1,375	**105**	16,977	**131**	-53,381
2	-83,462	**28**	14,068	**54**	209,455	**80**	1,003	**106**	-12,457	**132**	79,785
3	-145,650	**29**	-84,411	**55**	45,143	**81**	0,831	**107**	-14,598	**133**	-24,565
4	-237,137	**30**	45,051	**56**	106,548	**82**	0,380	**108**	1,178	**134**	21,527
5	875,584	**31**	-132,797	**57**	-33,173	**83**	-0,444	**109**	-43,875	**135**	163,961
6	-310,247	**32**	-87,466	**58**	53,854	**84**	1,361	**110**	-17,112	**136**	-377,235
7	-285,821	**33**	111,076	**59**	-72,638	**85**	0,033	**111**	-4,878	**137**	-218,593
8	-188,206	**34**	22,779	**60**	44,308	**86**	-0,442	**112**	24,753	**138**	13,688
9	-21,697	**35**	-73,887	**61**	37,522	**87**	1,554	**113**	32,089	**139**	-64,089
10	112,829	**36**	-10,263	**62**	69,478	**88**	1,427	**114**	-26,253	**140**	-309,751
11	-404,524	**37**	17,764	**63**	55,102	**89**	2,148	**115**	15,949	**141**	-53,599
12	-109,518	**38**	-2,260	**64**	50,185	**90**	1,650	**116**	38,051	**142**	173,117
13	175,449	**39**	68,995	**65**	221,402	**91**	1,565	**117**	-44,620	**143**	-136,951
14	-379,659	**40**	-4,142	**66**	-0,250	**92**	-3,869	**118**	65,675	**144**	-74,665
15	18,832	**41**	-0,734	**67**	-57,895	**93**	-3,979	**119**	-21,368	**145**	-37,770
16	49,812	**42**	-130,255	**68**	-40,831	**94**	5,202	**120**	-45,868	**146**	-236,220
17	-146,540	**43**	-15,388	**69**	29,571	**95**	9,338	**121**	-162,656	**147**	54,023
18	-143,078	**44**	151,430	**70**	-117,283	**96**	-0,723	**122**	24,673	**148**	251,892
19	-114,181	**45**	-0,321	**71**	-175,793	**97**	6,243	**123**	37,816	**149**	177,325
20	75,504	**46**	14,106	**72**	-39,844	**98**	-19,370	**124**	-33,263	**150**	9,457
21	258,701	**47**	6,566	**73**	-24,831	**99**	8,486	**125**	-55,810	**151**	209,648
22	135,960	**48**	65,239	**74**	-1,685	**100**	1,946	**126**	-20,231	**152**	68,320
23	50,730	**49**	-126,949	**75**	5,025	**101**	-15,670	**127**	-4,208	**153**	108,507
24	-32,721	**50**	60,552	**76**	10,469	**102**	-18,837	**128**	-5,273	**154**	4,172
25	13,447	**51**	-20,432	**77**	-2,575	**103**	12,132	**129**	-60,877	**155**	335,353
26	-138,999	**52**	94,585	**78**	0,861	**104**	-8,808	**130**	-78,934	**156**	-20,500

This table contains the γ_t of the liquidity risk factor proposed by Pastor & Stambaugh (2003) and is measured by performing an OLS regression using daily data. Data are from January 1993 to December 2005

Table 15
Pastor & Stambaugh Liquidity Factor (OFL) Jan1993-Dec 2005

month	ofl	month	ofl	month	ofl	month	ofl	month	ofl	month	ofl
1	NaN	**27**	2,503	**53**	-2,306	**79**	-0,211	**105**	-0,032	**131**	-0,707
2	0,517	**28**	-3,865	**54**	9,434	**80**	-0,191	**106**	-0,407	**132**	0,451
3	12,312	**29**	-3,809	**55**	-1,290	**81**	-0,198	**107**	-0,247	**133**	-0,748
4	17,407	**30**	-6,971	**56**	4,806	**82**	-0,197	**108**	-0,199	**134**	0,252
5	67,387	**31**	-2,363	**57**	-0,154	**83**	-0,199	**109**	-0,572	**135**	1,067
6	4,589	**32**	-6,606	**58**	1,577	**84**	-0,194	**110**	-0,226	**136**	-3,844
7	8,208	**33**	5,116	**59**	-1,063	**85**	-0,200	**111**	-0,306	**137**	-2,145
8	-23,871	**34**	-6,930	**60**	0,457	**86**	-0,199	**112**	-0,008	**138**	0,061
9	-7,783	**35**	2,781	**61**	-1,849	**87**	-0,192	**113**	0,007	**139**	-1,408
10	9,522	**36**	-0,880	**62**	0,742	**88**	-0,195	**114**	-0,419	**140**	-2,751
11	-1,019	**37**	-2,913	**63**	0,735	**89**	-0,189	**115**	0,108	**141**	0,400
12	-26,328	**38**	1,292	**64**	1,256	**90**	-0,191	**116**	0,038	**142**	-0,545
13	6,654	**39**	1,040	**65**	1,697	**91**	-0,191	**117**	-0,699	**143**	-1,530
14	-12,785	**40**	0,163	**66**	-0,111	**92**	-0,217	**118**	0,871	**144**	-0,346
15	-4,456	**41**	3,930	**67**	-0,376	**93**	-0,210	**119**	-0,865	**145**	-0,555
16	0,703	**42**	-11,402	**68**	-0,585	**94**	-0,180	**120**	-0,408	**146**	-1,973
17	-9,065	**43**	2,898	**69**	0,740	**95**	-0,166	**121**	-2,064	**147**	0,646
18	0,613	**44**	-0,148	**70**	-2,287	**96**	-0,217	**122**	0,725	**148**	2,157
19	-10,441	**45**	2,664	**71**	-0,741	**97**	-0,145	**123**	-0,534	**149**	0,070
20	3,724	**46**	1,231	**72**	-1,034	**98**	-0,334	**124**	-1,015	**150**	0,197
21	-4,343	**47**	1,064	**73**	-1,043	**99**	-0,101	**125**	-0,430	**151**	1,704
22	5,727	**48**	-0,171	**74**	-0,292	**100**	-0,239	**126**	-0,368	**152**	0,017
23	5,288	**49**	-1,783	**75**	-0,241	**101**	-0,275	**127**	-0,439	**153**	0,770
24	2,342	**50**	-1,531	**76**	-0,127	**102**	-0,278	**128**	-0,311	**154**	-0,096
25	-2,230	**51**	-1,068	**77**	-0,213	**103**	-0,092	**129**	-0,737	**155**	1,977
26	-4,245	**52**	2,164	**78**	-0,170	**104**	-0,331	**130**	-0,771	**156**	-0,873

This table contains the market-wide liquidity risk factor proposed by Pastor & Stambaugh (2003) and is measured by order flow inducing greater return reversal when liquidity is lower. Data are from January 1993 to December 2005.

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