ΟΙΚΟΝΟΜΙΚΟ ΠΑΝΕΠΙΣΤΗΜΙΟ ΑΘΗΝΩΝ

ΤΜΗΜΑ ΛΟΓΙΣΤΙΚΗΣ & ΧΡΗΜΑΤΟΟΙΚΟΝΟΜΙΚΗΣ

ΠΡΟΓΡΑΜΜΑ ΜΕΤΑΠΤΥΧΙΑΚΩΝ ΣΠΟΥΔΩΝ

"CAPM vs LIQUIDITY CAPM: THE CASE OF THE ATHENS STOCK EXCHANGE"

ΟΝΟΜΑΤΕΠΩΝΥΜΟ

ΑΓΓΕΛΟΣ ΝΙΚΗΤΑΚΗΣ

Εργασία υποβληθείσα στο

Τμήμα Λογιστικής & Χρηματοοικονομικής

του Οικονομικού Πανεπιστημίου Αθηνών

ως μέρος των απαιτήσεων για την απόκτηση

Μεταπτυχιακού Διπλώματος Ειδίκευσης

Αθήνα

{Οκτώβριος, 2009}

Εγκρίνουμε την εργασία του

ΝΙΚΗΤΑΚΗ ΑΓΓΕΛΟΥ

[ΟΝΟΜΑ ΕΠΙΒΛΕΠΟΝΤΟΣ ΚΑΘΗΓΗΤΗ] **[ΥΠΟΓΡΑΦΗ]**

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27/10/2009

ΒΕΒΑΙΩΣΗ ΕΚΠΟΝΗΣΗΣ ΔΙΠΛΩΜΑΤΙΚΗΣ ΕΡΓΑΣΙΑΣ

«Δηλώνω υπεύθυνα ότι η συγκεκριμένη πτυχιακή εργασία για τη λήψη του Μεταπτυχιακού Διπλώματος Ειδίκευσης στη Λογιστική και Χρηματοοικονομική έχει συγγραφεί από εμένα προσωπικά και δεν έχει υποβληθεί ούτε έχει εγκριθεί στο πλαίσιο κάποιου άλλου μεταπτυχιακού ή προπτυχιακού τίτλου σπουδών, στην Ελλάδα ή στο εξωτερικό. Η εργασία αυτή έχοντας εκπονηθεί από εμένα, αντιπροσωπεύει τις προσωπικές μου απόψεις επί του θέματος. Οι πηγές στις οποίες ανέτρεξα για την εκπόνηση της συγκεκριμένης διπλωματικής αναφέρονται στο σύνολό τους, δίνοντας πλήρεις αναφορές στους συγγραφείς, συμπεριλαμβανομένων και των πηγών που ενδεχομένως χρησιμοποιήθηκαν από το διαδίκτυο».

ΑΓΓΕΛΟΣ ΝΙΚΗΤΑΚΗΣ* ………………………………

*: Θα ήθελα να ευχαριστήσω τον επιβλέποντα καθηγητή μου κ. Κωνσταντίνο Δράκο για την ουσιαστική καθοδήγηση και συμπαράστασή του στο παρών έργο. Για τυχόν λάθη ή παραλείψεις είναι εξ’ ολοκλήρου υπεύθυνος ο συγγραφέας αυτής της Διπλωματικής εργασίας.

Table of Contents

Abstract

There is a consensus among economists that rational investors are concerned not only about systematic risk, but potential liquidity shortages as well. In other words, they require additional compensation for bearing liquidity risk, apart from systematic risk. This is translated into "liquidity premia" investors are willing to pay in order to obtain more liquid assets. This paper attempts to answer the question whether liquidity is priced in the Greek market. In order to capture liquidity, liquidity measures are estimated and inserted in the CAPM formula as an additional factor, apart from the beta. This study shows that the cross-section of stock returns in the Athens Stock Exchange reflects a negative tradeoff between average stock returns and liquidity, but this relation is extremely fragile. Therefore, this paper concludes that liquidity is not priced in the Athens Stock Exchange and it does not add any significant information to the original Market Model. As errors-in-the-variables effects and extremes have been taken into consideration, this might be due to sample anomalies generated by the recent major market crash.

1. Introduction

One of the fundamental questions that asset pricing attempts to address, is the exploitation and understanding of the factors that cause risk, as expressed by the risk premia that rational investors demand for investing in a risky asset, in an efficient (or at least semi-efficient) market. As soon as these factors are discovered and explained, the second issue that economists face is how this risk can be measured and modeled in a convenient way that will be easily calculated on the one hand, and precise and accurate on the other. The existence of such an accurate model would help investors price the risky assets objectively, and having such a precise benchmark they would be able to see if a security is underpriced or overpriced. Therefore it would be easier to predict in a way its potential future price movements. Although there are several different theoretical models that claim to solve the problem stated above, one is considered to be the most accurate and easy to apply contemporaneously. This is the Capital Asset Pricing Model (CAPM), according to which, stock returns are closely related to their systematic risk, expressed as the "beta" factor, and the return of the Market. Hence, knowing only the two above factors, one can price easily a particular stock and therefore predict potential future price movements. Another utility of the model is that investors knowing the systematic risk of each stock, which means knowing how a particular stock will "behave" relative to the market, can easily form various strategies. For example, if they expect a bull market, they can use high-beta stocks for speculative purposes. On the other hand, if a bear market is expected, low or negative-beta stocks can be used for hedging.

However, later studies have revealed that risk-averse and return-seeking agents are not the only types of rational investors existing in modern economies. The complexity of the financial environment, forces institutional, mainly, investors to be liquidity seekers too. The recent major market crash showed that even large financial institutions could be led to insolvency if they do not hold liquid assets to help them in times of serious liquidity shortage. In economic terms, this can be translated in the risk premia investors are willing to pay in order to obtain liquid assets, which can be used for future payments if needed. This approach has been strengthened during the recent years by several studies, most of which will be discussed later in this paper.

The general methodology in the literature for taking into account if and in what extent liquidity can be priced, is an extension of the CAPM testing, the model discussed earlier. The purpose of this paper is to investigate whether the liquidity–extended CAPM can indeed satisfactorily explain the Athens Stock Exchange stock returns. In other words, our goal is firstly to examine whether liquidity is priced in the Greek stock market. The second aspect of this research is to find out whether liquidity has an incremental effect on the original CAPM, which assumes that only systematic risk is priced in a competitive market. The analysis is done in such a way, that if the first holds, the second is also true. The methodology used mainly follows the papers of Fama & McBeth (1973) and Fama & French (1992). We use three liquidity measures as liquidity proxies, and test each one separately. The liquidity measures used are the daily trading volume of each stock, the proportion of zero daily returns, and the number each stock traded during the day.

We find that liquidity is not priced in the Greek market. One of the three measures used produces completely opposite results to the ones expected. The other two measures, although supportive to theory's predictions, completely fail to pass robustness checks and therefore cannot be used for theory's confirmation. More specifically, the proportion of zero returns measure produces results contrary to theory, while the trading volume and number of trades' measures perform poorly. Therefore, as far as the Athens Stock Exchange is concerned, it seems that investors do not require additional reward for bearing liquidity risk.

The present study is organised as follows. Section 2 presents a summary of the existing literature on the CAPM and the role of liquidity in asset pricing. Section 3 presents briefly the two models that will be used, CAPM and Liquidity-based CAPM. Section 4 shows the data used. Section 5 explains the methodology used and any theoretical predictions about the results. Section 6 exhibits the outcome of the research and its interpretation, and Section 7 concludes. Sections 8 and 9 display all tables and graphs respectively. The Appendix section presents results from slightly different methodologies used, so the reader can get a fuller picture of all the possible outcomes of the research.

2. Literature Review

2.1 Pre-CAPM period

Formulating a proper risk measure for speculative securities remains a fundamental issue in financial economics literature. Early in this debate, Markowitz (1952) proposed the variance of the return distribution, as a convenient, familiar and computationally efficient risk measure. According to his study, rational investors should choose their portfolios in such a way that they maximize their expected return on a given level of risk (variance), and minimize their risk on a given level of expected return. The combination of the above two assumptions forms the financial term that Markowitz proposed as "the efficient frontier". This is the geographical space in a return-variance plot drawn by a portfolio which consists of all the securities that offer maximum expected return for a given variance, and have the minimum variance for a given level of expected return.

2.2 Literature concerning CAPM

The Markowitz approach was the very first big step to model the behavior of the risky assets in terms of expected return and variance, and did so in a satisfactory level for that time. However, during the following years economists tried to improve this model in a way that it would be more simple, efficient and easy to calculate at the same time. In the mid 60's, Sharpe, Lintner and Mossin in 1964, 1965 and 1966 respectively, working independently came out with a new model, based on Markowitz's previous work, which is widely known as the Capital Asset Pricing Model (CAPM). The new model, as will be discussed further later in this paper, implies that the expected return of an asset is a positive and linear function of its systematic risk exposure, as expressed by its market "beta". The market model is much more simple and easier to calculate than the Markowitz approach, especially when it comes to situations in which the number of securities involved is very high.

CAPM quickly became the most popular pricing model and became the subject of extensive literature, both supportive and skeptical, throughout the decades. The earlier academic debate about the market model is generally in favor of it. In contrast, Douglas (1969) rejects the linearity assumption of the model. However, Friend and Blume (1970) and Black, Jensen and Scholes (1972) find that the beta factor can satisfactorily explain the cross-section of stock returns. Perhaps the most important paper in favor of the model is that of Fama and McBeth (1973), henceforth FM. Their results show strong evidence in favor of CAPM as they cannot reject the hypothesis that there is a positive tradeoff between average stock returns and beta. Additionally, they cannot reject the hypothesis that this relation is linear and that the beta factor is the only type of risk priced in the market.

However, in later studies economists started to test whether there are other firm characteristics, apart from systematic risk, that might incrementally explain stock returns. Ross (1976) proposed that the risk should be measured by many factors, both macroeconomic and microeconomic, contrary to the one–beta factor that the CAPM implies, initiating the Arbitrage Pricing Theory. Moreover, Roll (1977) shows in his study that a general index of all the securities in a stock market, as it is commonly used in the CAPM, is not a suitable proxy of the market portfolio, and it is extremely difficult, if not impossible, to construct one. The reason is that the Market does not consist only of the registered equities in a stock market. Bhanz (1981), Basu (1983) and Bhandari (1989) find that market equity, book-to-market equity and leverage respectively, have an incremental explanatory power on average stock returns. Furthermore, De Bondt and Thaler (1985) show that there might be a “reversal” pattern according to which stocks with low long-term returns tend to experience higher returns in the near future. In the early 90’s, Fama and French (1992), henceforth FF, find serious evidence concerning the significance of two other factors apart from the beta. They show that stocks with small capitalization and high book–to–market ratio experience higher excess returns than the market as a whole. Thus, they expand the original CAPM, transforming it from a one-factor model to a three-factor model, adding the risk measures SMB (Small minus Big capitalization) and HML (High minus Low book-to-price ratio). They find statistical significance of the excess returns, not only of small-cap over big-cap stocks, but also of value stocks over growth stocks. Other economists[1] find that there might be excess risk premia for "downside" betas as they can be used for hedging in cases of a bear market.

2. 3. Liquidity-based Pricing Model

An innovative approach about a new risk measure, which also relates to this study, made its appearance in 1986 when Amihud and Mendelson showed that illiquid assets with high transaction costs require higher returns, or "liquidity premia". Holmstrom and Tirole (1996) showed that firms and banks usually hold liquid assets for future payments that will help them against liquidity shocks, and they have to pay "liquidity premia" in order to obtain them. During the following years, the issue of liquidity and how it affects asset pricing has been widely examined in the economic literature. Later studies[2] revealed that liquidity risk does not appear to be idiosyncratic but systematic. Although most economists agree that liquidity plays a significant role in asset pricing, the liquidity measures proposed vary. Brennan and Subrahmanyam (1995) use trading volume as a liquidity determinant, showing that the greater the trading volume, the greater the market depth is. Furthermore, Chordia, Tarun, Subrahmanyam and Anshuman (2000) discover that liquidity, as measured by trading volume, is a robust and negative factor for risk-adjusted stock returns. In the following year, they show in another paper that trading volume as a liquidity proxy has high cross-sectional relationship with other liquidity measures like bid–ask spread, and it can capture forms of liquidity that bid-ask spread cannot. Bekaert, Harvey and Lunbland (2003) use the proportion of zero daily returns as a liquidity proxy, and they find that it has significant power in predicting future returns, whereas other measures of liquidity such as turnover do not.

The most important recent studies in the field of asset pricing employing liquidity is the work of Choe and Yang (2007), henceforth CY, and Korajckyk and Sadka (2008). The first compare various liquidity measures in order to see which ones have the strongest correlation with the stock returns of the U.S. and Korean stock markets. Among other liquidity proxies, they find that the trading volume, number of trades

[1] Hogan and Warren (1974), Bawa and Lindenberg (1977)
[2] Huberman, G., and Halka, D. (2001)

and the proportion of zero daily returns show robust explanatory power for the future stock returns. The later study attempts to examine whether the commonality across various liquidity determinants can be priced. Korajckyk and Sadka formulate an across-measure liquidity factor, which is tested for explanatory significance over the future stock returns. The liquidity measures used are price impact measures along with the Amihud (2002) measure, turnover and quoted and effective spread. They find robustness on the across-measure liquidity factor, strengthening the evidence, along with all the previous relative studies, that liquidity has a significant explanatory power on stock returns and it can be used for forecasting future returns.

3. Theoretical Background

3.1 Efficient set theorem

As argued before, in the early 50's Markowitz proposed his revolutionary theory about portfolio selection, according to which investors try to hold efficient portfolios with minimum variance and maximum expected return contemporaneously. All those possible portfolios form the so-called "efficient frontier", which is illustrated on the plot below. E[R] and σ stand for expected return and standard deviation respectively.

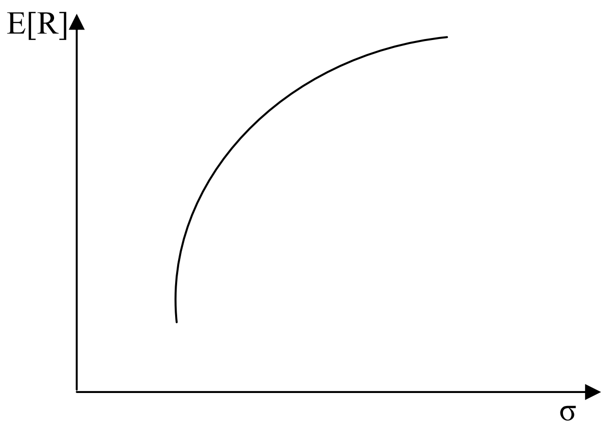


Figure 1: Efficient frontier

Mathematically, in order to determine the efficient frontier, the estimation of the expected return $E[R_p]$ and the variance (σ_p^2) of the portfolio are needed. Given a portfolio consisted of risky securities x and y, the equations of the above are:

$E[R_P] = w_x E[R_x] + w_y E[R_y]$ (1)

$\sigma_p^2 = w_x^2 \sigma_x^2 + w_y^2 \sigma_y^2 + 2 w_x w_y \sigma_{xy}$, (2)

where w_x, w_y represent the proportion of wealth invested in each security, and σ_{xy} the covariance of the two securities.

This leads to a large number of calculations when there are many risky assets involved.

3.2 Capital Asset Pricing Model

The problem mentioned above is reduced dramatically with the implication of the Capital Asset Pricing Model, proposed by Sharpe, Lintner and Mossin in the mid-60's. According to CAPM, the expected return of a risky security is related linearly with its Market risk. The model implies that a risky asset bears two forms of risk. The first one, the so-called "idiosyncratic" or non-systematic risk, is related to the individual characteristics of the asset. This form of risk can be "diversified away"[3] by holding an efficient portfolio with many risky assets[4]. The second form of risk is the systematic risk or "beta", which comes out of the Market variance and the covariance of the individual security with the Market. The variance of the market expresses the overall systematic risk, and the covariance is the contribution of the particular stock to the overall risk. Mathematically, the beta factor of a stock i is:

$$\beta_i = \frac{\sigma_{i,M}}{\sigma_M^2} \quad (3)$$

where $\sigma_{i,M}$, σ_M^2 are the covariance of stock i and the Market, and the Market variance respectively.

The Market Model states that in equilibrium the following equation holds:

$$E[R_p] = R_f + \frac{(E[R_M] - R_f)\sigma_p}{\sigma_M} \quad (4)$$

where $E[R_p]$ is the expected return of the selected efficient portfolio, R_f is the risk free interest rate, $E[R_M]$ is the expected return of the Market portfolio, and σ_M and σ_p stand for the standard deviation of the market and portfolio returns respectively. Graphically, the above equation is a straight line (called Capital Market Line[5]) tangent to the efficient frontier as shown in figure 2. In equilibrium, all investors hold portfolios on the CML. However, each investor has a different risk profile[6] and will hold portfolios on different areas on the CML. The letter M stands for the Market portfolio. Let's assume two rational investors, A and B, with the first one having greater risk aversion than the second. Investor A will choose to lend money and earn

[3] Mathematically, if σ^2_{ep} is the idiosyncratic risk of the portfolio, and n the number of risky assets, $\sigma^2_{ep} = \sum_{i=1}^{n} w_i^2 = \sum_{i=1}^{n} (\frac{1}{n})^2 \sigma^2_{ep} = (\frac{1}{n})^2 \sum_{i=1}^{n} (\frac{1}{n}) \sigma^2_{ep}$, which means as n rises, idiosyncratic variance decreases.

[4] with correlation $\neq 1$.

[5] Henceforth CML

[6] Expressed by indifference curves

the risk-free return (R_f), while investor B will choose to borrow money under the R_f. This approach sources from the Separation Theorem[7], which states that optimal combination of risky assets is formed without knowing the investor's risk/return preferences. In equilibrium, they will hold portfolios on the CML as shown on the plot. As investor A chooses to lend money, his investment position will be somewhere between the risk free asset (R_f) and the Market portfolio (M). Respectively, investor B who invests "on margin", will move from the Market portfolio spot to the northeastern area depending on the size of borrowing.

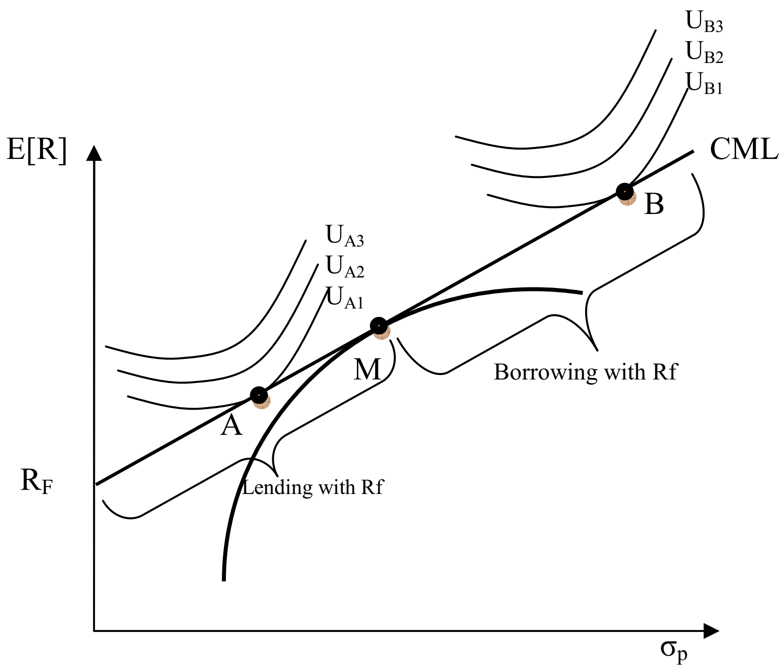


Figure 2: Capital Market Line

The Capital Market Line and equation (4) show the equilibrium relationship between the expected return and risk, in terms of standard deviation, of efficient portfolios. Thus, in order to see the relation between the expected return and risk of individual securities, adjustments to equation (4) need to be made. Substituting the portfolio risk σ_p with the contribution of the individual security to the market risk, expressed as the fragment of the covariance of the security i with the market M[8] and the standard deviation of the security i, we come up with a new form of the equation (4).

[7] Tobin, James, ("Liquidity Preference as Behaviour Toward Risk," Review of Economic Studies, I958).
[8] The tangent portfolio M represents the Market portfolio

$E[R_i] = R_f + [\frac{(E[R_M]- R_f)}{\sigma_M}] \frac{\sigma_{i,M}}{\sigma_M} \Rightarrow E[R_i] = Rf + \frac{(E[R_M]- R_f)\sigma_{i,M}}{\sigma_M^2} \overset{(3)}{\Longrightarrow}$

$\Rightarrow E[R_i] = R_f + (E[R_M] - R_f)\beta_i$ (5)

Equation (5) is the most important equation of the CAPM, showing that the return of any individual security depends only on the return of the market and its systematic risk, and this relation is linear[9]. Considering the above transformation, a new plot can be drawn representing the beta factor[10] on the horizontal axis, instead of the portfolio standard deviation. The new line formed below is called Security Market Line (SML).

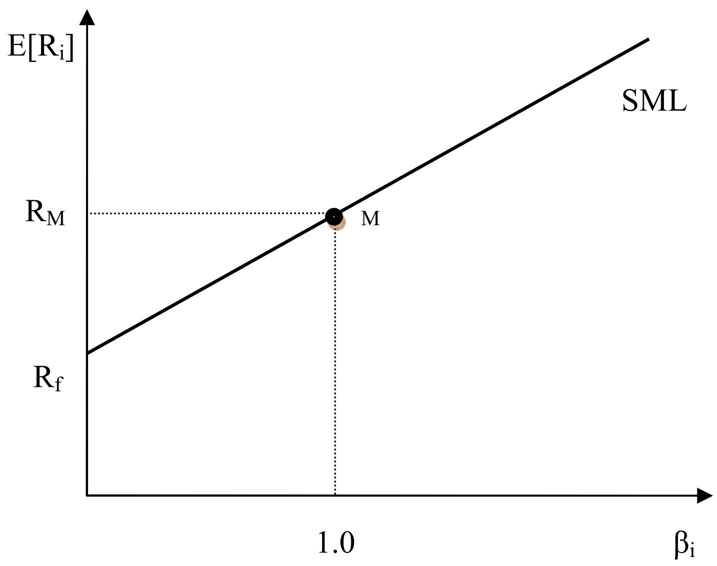


Figure 3: Security Market Line

SML is the graphical presentation of the central meaning of CAPM. It represents the actual tradeoff between the systematic risk and the expected return of every stock. The slope of the SML is upward and it's actually the market excess return. The upward sloping makes sense as the higher the systematic risk, the higher the premia investors demand from their investments. In equilibrium, all securities are supposed to plot on the SML, on different points depending on their risk–return characteristics. In real world, they plot above or below the Line.

[9] The above equation can also take the form of "excess returns". More specifically: $E[R_i] = R_f + (E[R_M] - R_f)\beta_i \Rightarrow E[R_i] - R_f = (E[R_M] - R_f)\beta_i$ or $E[\tilde{R}_i] = E[\tilde{R}_M]\ \beta_i$, where ~ denote excess returns.
[10] Another form is with the covariance of security I with the market instead of the beta.

However, in order for all of the above to hold, the Capital Asset Pricing Model depends on several simplifying assumptions:

1. All investors are rational and risk averse, i.e. between two portfolios with the same returns they will choose the one with lower risk.
2. Investors evaluate portfolios based on risk return characteristics, and they have the same period horizon.
3. Investors seek to maximise economic utility.
4. All investors can borrow or lend money unlimitedly at the same risk rate.
5. There are no taxes, transaction costs or inflation.
6. There are many investors and all of them are equally informed.
7. Assets are infinitely divisible into tiny portions.
8. All assets are tradable on the market.
9. All investors have the same expectations in terms of mean, variance and covariance.
10. There are perfectly competitive markets.

Taking the above into consideration, it goes without saying that most, if not all, of these assumptions do not appeal in the real world. However, despite the critique showed earlier, the model is still considered satisfactory.

3.3 Liquidity CAPM (LAPM)

As discussed before, although the one factor of the market model is considered to have some explanatory power on the future returns, there could be other factors that may have additional explanatory power. One of the most widely known empirical researches about that issue is the one of FF. Using a 37-year data sample of NYSE stocks, they come to the conclusion that there are two more factors, apart from the beta, that show serious additive explanatory power over stock returns. As seen before, the first one was the SMB factor and the other was the HML. The mathematical expression of the FF model is:

$$E\left[\widetilde{R_\iota}\right] = E\left[\widetilde{R_M}\right]b_i + SMB\gamma_i + HLM\eta_i, \text{ where}$$

- SMB is the difference between small and big capitalisation (Small minus Big)
- HML is the difference between high and low book to value ratio (High minus Low)
- b_i is the beta factor of the market Model.
- γ_i, η_i are the sensitivity factors of the two extra measures.

During the recent years, though, many economists believe that apart from systematic risk and capitalization, liquidity also plays a major role influencing stock returns. Empirically, this approach has been supported by several studies as discussed before. The new model, which controls for liquidity, was first named "LAPM" by Holstrom and Tirole (2001),[11] in a relative study. The general idea of the model is to combine the CAPM beta factor with one or more liquidity factors, in the way the FF model does. Hence, the new expression of the market model is supposed to have greater explanatory power on the stock returns, as it controls not only for systematic risk but also for liquidity, which is believed to be priced. The general expression of the liquidity-based CAPM is the following

$$E\left[\widetilde{R_\iota}\right] = E\left[\widetilde{R_M}\right]b_i + LM\gamma_i,$$

[11] Holmstrom,B., and Tirole, J., 2001, "LAPM: A Liquidity-Based Asset Pricing Model".

Where: LM is the liquidity measure
γ_i is the liquidity factor
b_i is the systematic risk factor
$E[\widetilde{R_i}]$ is the expected excess stock return of stock i
$E[\widetilde{R_M}]$ is the expected excess stock return of the market index

We argued earlier that the CY study is perhaps the most integrated one. CY test 13 liquidity measures, as proposed by various related papers. First of all they categorise all liquidity measures into four categories:

Liquidity as a concept of: a) trading quantity b) price impact c) trading cost d) trading speed.
More specifically, each category consists of the following liquidity measures:

A) Trading quantity: 1) Trading Volume
2) Turnover
3) Number of Trades

B) Price Impact: 4) Amivest Measure
5) Amihud's Illiquidity Measure
6) Kyle's Lambda
7) Reversal Measure of Pastor and Stambaugh

C) Trading Cost: 8) Bid-Ask Spread
9) Roll's Spread
10) Amortized Spread

D) Trading Speed (Time): 11) Proportion of Zero Daily Return
12) Lesmond, Ogden, and Trzcinka (LOT) Measure
13) Liu Measure
14) Modified Amihud Measure

This study focuses on the trading volume, number of trades and zero proportion as proxies for the liquidity factor. Trading volume is the size of each trade investors make. Thus, the bigger the trading volume, the more "liquid" the asset is, in the concept of trading quantity. Many studies[12] about volume conclude that it is a considerable liquidity proxy and it demonstrates a strong cross-sectional relationship with stock returns. The number of trades is how many times in a day a share is traded. It makes sense that a "liquid" stock should be traded multiple times. Last but not least, the proportion of zero daily returns has the opposite effect as a liquidity measure, as it actually measures "illiquidity". That's because as this proportion rises (more zero returns) the asset is considered less liquid.

[12] In the "Literature Review" Section.

4. Data Set

Our data originate from the Athens Stock Exchange Data Dissemination Service. The raw data used in this study are daily volume, number of trades and closing prices for all of the 586 stocks of the Athens Stock Exchange (ATHEX in Datastream) in an eight–year period, from 2001 till 2008. The daily closing prices of the Athens Stock Exchange General Index and the yearly Treasury bill rates[13] for the same time period are also included in the initial data. The General Index is used as the market portfolio proxy. It is consisted of the 60 biggest blue chips in the Athens Stock Exchange, weighted by capitalization with base equal to 100 and base date 31 December, 1980[14]. It is assumed to be a suitable market determinant as it contains approximately 78% of the total market capitalization. However, it may not capture any excess return and volatility generated by potential value stocks. The main statistical-econometric programming software used in this study was Stata 10. Also, EViews 6.0 and Microsoft Excel 2007 were used in a much lower degree relative to Stata 10, mostly for presentation purposes.

The raw data need to be transformed in order to be useful in the process. As will be discussed later in the methodology section, several major measures need to be computed. Among these are the daily stock and index (market) returns, the daily excess stock and market returns, as well as the liquidity measures. The daily continuous compounded returns for both individual stocks and market index are computed using the following expression:

$Return_t = \ln(clprice_t / clprice_{t-1}) = \ln(clprice_t) - \ln(clprice_{t-1})$, where clprice is the closing price of either the stock or market index, and t stands for the time period (here is days).

However, apart from the daily returns, the daily excess returns must also be calculated, by subtracting the daily risk free interest rate[15] for each daily return, for both the stocks and the market.

[13] Used for risk free interest proxy.
[14] As only closing prices where available, we did not compute potential dividend reinvestments.
[15] It is firstly divided by 252 as it is on a yearly basis.

4.1 Constructing the Liquidity Measures

The raw data from which the liquidity measures will be derived are the daily return, number of trades and trading volume of each stock. As we argued earlier, the zero proportion is the number of zero daily returns of each stock. To obtain this number, we construct a dummy variable which takes the number 1 each day the stock experienced zero return, and 0 if not. This dummy will help us count how many times a particular stock had zero returns during the month. To do so, a second variable is constructed to count all the ones during the month. Then, this number is divided by the number of observations during the month[16]. The number-of-trades measure is constructed more simply. Firstly, to simplify the sample, number of trades is divided by 1000 to obtain the number of trades in thousands. Then, a variable is constructed to count all the trades for each stock during the month. Finally the total number of trades is divided by the number of observations during the month. The trading volume liquidity measure is constructed in the exact same way as the number-of-trades measure.

4.2 Descriptive Statistics

Plot 1 in the Graphs section represents descriptive statistics, after winsorisation, of daily stock returns as well as a histogram of the distribution.

…………………………………Insert Plot 1 here…………………………………….

Plot 2, 3 and 4 also show descriptive statistics of daily market returns, daily excess stock returns and daily excess market returns.

………………………………...Insert Plots 2,3,4 here………………………………....

The horizontal axis of each plot represents returns and the vertical axis represents the number of observations. The most important issue here concerns the abnormal skewness and kurtosis of the sample. Jarque-Bera statistic is very high with a p-value equal to zero, implying the serious non-normality of the sample. As expected, Jarque-Bera statistic of stock returns is higher relative to the one of market returns, confirming the common sense assumption that individual stocks experience more

[16] For statistical reasons, we construct the measure only if observations are at least 15 during the month.

abnormal returns than the market as a whole. Although the non-normal sample violates one of the major assumptions for running a correct regression, which is sample normality, there is not much concern about it in the economic literature when it comes to testing a model. To get a better view of the sample structure, summary statistics are represented for each year, too. Panel A and B of Table 1 presents summary statistics of the daily stock and market returns respectively, across the whole sample for each year period.

……………………………………Insert Table 1 here……………………………………

In that way, one can discern the impact each year had on the mean returns of the whole sample. As expected, the year 2008, when the notorious economic crisis began, is the year with the lowest returns for both individual stocks as well as the market. It should be stated here that such an enormously bear market might lead to a significant alteration of any "normal" results that this study might have produced. However, a serious study should try to produce "real" than "normal" results and, as financial crises are part of the global financial market system, it is positive that such a market crash exists in the sample.

Apart from simple returns, excess stock and market returns are also presented in Panels A and B of Table 2 respectively.

……………………………………Insert Table 2 here……………………………………

As far as the liquidity measures are concerned, summary statistics are presented in Table 2 Panel C and D, showing the mean, standard deviation and highest and lowest values of each measure, as well as the correlations between them.

……………………………………Insert Table 2 Panel C, D here………………………

As expected, the zero proportion measure has negative correlation with the other two measures. That is because it measures *illiquidity*, while the other two measure *liquidity*. What is more interesting about these measures is their peculiar, non-normal distribution. Plots 5, 6 and 7 represent the Kernel density function of each measure.

…………………………….…...Insert Plot 5, 6, 7 here………………………………..

Attempting to classify their distribution into one of the standard ones[17], it could be said that they resemble mostly the log-normal probability distribution or the chi-square one.

[17] Apart from the zero proportion measure which seems completely abnormal.

Finally, extreme observations are removed from the 1st and 99th quintile of the distribution through the winsorisation process[18]. This procedure is applied to the stock and market returns as well as all liquidity measures.

[18] The same analysis has been done also with completely deleting the outliers. Results do not differ much. See Appendix.

5. Econometric Methodology

The present study implements the procedure of FM(1973) and FF(1992) with some variations, for the Greek stock market. Also, the CY study is mostly used for comparison purposes, as it is related to this study and also based on the work of FM and FF. Compared to CY, our sample period is slightly shorter. They use a 12-year period[19] while we use an 8-year period[20]. However, it is considered as a satisfactorily long period, as stated in the previous section. FF and FM use a far larger sample period[21].

5.1 First Pass Regressions

The first step of the procedure is to estimate, using monthly returns[22] for the whole eight-year period, the realised risk and liquidity factors for individual equities: the beta factor (β), the zero proportion factor (β_{zero}), the number of trades factor (β_{trade}), and the volume factor (β_{vol}). The mathematical expression of the beta, as we discussed earlier, is the following.

$$\beta_i = \frac{Cov(r_i, r_M)}{Var(r_M)}$$

In order to obtain the beta estimator $\widehat{\beta_i}$ for each stock, as well as the liquidity factor's estimators, $\hat{\beta}zero, \hat{\beta}trade$ and $\hat{\beta}vol$, we run time series regressions over the pooled data[23]. More specifically, the first regression we run, which derives from the mathematical expression of the CAPM, is the following:

$R_{it} - R_f = \hat{\alpha}_{it} + (R_{M,t} - R_f)\beta_{it} + e_{it}$, or $\tilde{R}_{it} = \hat{\alpha}_{it} + (\tilde{R}_{Mt})\hat{\beta}_{it} + e_{it}$ (i) where:

- $\tilde{R}_{it}$, $\tilde{R}_{Mt}$ stand for the excess return of stock i at time t[24] and the excess return of the market at time t respectively.
- $\hat{\beta}_{it}$ is the beta estimator of stock i for the time period 1 to t

19 1993-2004
20 2001-2008
21 The FF sample range is 1941-1990 while the FM one is 1935-1968
22 We collapse the whole daily sample into monthly returns to avoid the volatility clustering effect or any "noise" effect.
23 They are also usually called "first pass regressions" in the literature.
24 Time period is month.

- $\hat{\alpha}_{it}$ is the intercept estimator. It is expected to be zero ($E[\hat{\alpha}_{it}]=0$), as the model implies that the beta factor explains totally and exclusively the excess stock returns. Hence, if $\hat{\alpha}_{it}$ is not zero, there are other factors apart from beta that may add information about the excess stock returns, such as liquidity, leverage and capitalization.
- e_i is the residual of the regression for stock i, and it has an expected value of zero. ($E[e_i] = 0$).

As mentioned earlier, the above time series regression will give us the beta estimator of each stock, throughout our eight-year sample. Apart from the CAPM factor, we need to compute any potential liquidity factors that may have additive explanatory power in the CAPM formula. The typical econometric methodology implies to run a regression similar to the above, but also adding the liquidity measure. This is translated in the equation below, where $\hat{\beta}_L$ is the liquidity sensitivity factor, LM is the liquidity measure and $\hat{\beta}_{capm,i,t}$ is the beta factor[25]:

$\tilde{R}_{it} = \hat{\alpha}_{it} + (\tilde{R}_{Mt})\hat{\beta}_{capm,i,t} + \hat{\beta}_L(LM) + e_i$ (ii)

However, in order to isolate the liquidity factor to test the robustness of its contribution to the returns' explanation, we use the FF methodology. Following their work, $\hat{\beta}_L$ is regressed over the *risk adjusted* excess stock returns. Mathematically, equation (i) is transformed as illustrated below:

$\tilde{R}_{it} = \hat{\alpha}_{it} + (\tilde{R}_{Mt})\hat{\beta}_{it} + e_{it} \Longrightarrow \tilde{R}_{it} - (\tilde{R}_{Mt})\hat{\beta}_{it} = \hat{\alpha}_{it} + e_{it} \Longrightarrow \hat{R}_{adj,i,t} = \hat{\alpha}_{it} + e_{it}$ (iii), where $\hat{R}_{adj,i,t}$ is the risk adjusted excess return of stock i in time t. Then, equation (ii) due to (iii) becomes:

$\hat{R}_{adj,i,t} = \hat{\alpha}_{it} + \hat{\beta}_L(LM) + e_{it}$ (iv)

In that way, the liquidity factor becomes the only sensitivity factor in the regression, and it is easier to test. The paper of CY is slightly different to ours in that, although they also use risk adjusted excess returns in their methodology, they use more than one liquidity measure in the regression[26]. However, we do not do that in order to avoid multicolinearity in the regression, as all measures provide theoretically the same information. The three first-pass regressions for each liquidity measure are presented below:

[25] $\hat{\beta}_{capm}$ is slightly different than $\hat{\beta}$.

[26] They use mostly one measure from each group from the ones stated in the Theoretical Background section.

$\hat{R}_{adj,i,t} = \hat{\alpha}_{it} + \hat{\beta}_{zero,i,t}(ZERO_{i,t}) + e_{it}$ (v)

$\hat{R}_{adj,i,t} = \hat{\alpha}_{it} + \hat{\beta}_{trade,i,t}(NTRADES_{i,t}) + e_{it}$ (vi)

$\hat{R}_{adj,i,t} = \hat{\alpha}_{it} + \hat{\beta}_{vol,i,t}(VOL_{i,t}) + e_{it}$ (vii)

Where ZERO is the average proportion of zero daily returns of stock i for month t, NTRADES is the monthly average amount of daily trades stock i had in month t, and VOL is the monthly average daily trading volume of stock i for month t. From the above three regressions we obtain the risk factor roadings for each liquidity measure.

5.2 Fama McBeth Regressions

However, although the above analysis will provide some evidence on the relationship between β_{zero}, β_{trade} and β_{vol} risk loadings and the average returns, we need to test formally whether liquidity is priced in the cross section of the Greek stock returns. To do so, we apply the FM(1973) methodology, which implies running cross sectional regressions[27] of the average risk adjusted returns of each stock, on the realised liquidity loadings, in a yearly basis. These regressions are illustrated below:

$\bar{R}_{adj,it} = \gamma_0 + \gamma_1\hat{\beta}_{zero,i,t} + u_{it}$ (viii)

$\bar{R}_{adj,it} = \gamma_0 + \gamma_1\hat{\beta}_{trade,i,t} + u_{it}$ (ix)

$\bar{R}_{adj,it} = \gamma_0 + \gamma_1\hat{\beta}_{vol,i,t} + u_{it}$ (x), where

$\bar{R}_{adj,it}$ are the yearly averaged risk adjusted returns.

γ_0 is the intercept of the regression and has an expected value of zero.

γ_1 shows the correlation of the liquidity factor to the risk adjusted stock returns[28]. In other words it expresses risk premiums (or discounts if negative).

u_{it} stands for the residual of the regression. It has an expected value of zero.

Although the above is the general idea of the FM regressions, there have been many earlier reports in the economic literature[29] about the errors-in-the-variables problem.

[27] These regressions are also called Fama-McBeth or second-pass.

[28] $\gamma_{1i} = \frac{\partial \hat{R}adj,i,}{\partial \beta i}$

[29] Blume (1970), Friend and Blume (1970), Black Jensen and Scholes (1972). Also FM (1973) & FF (1992) themselves state the problem and use portfolio sorting for solution. Nevertheless, we also run the cross sectional regressions without portfolio formations. The results appear in the Appendix section.

The problem is about abnormal results derived from cross-sectional regressions that are run over pooled data. Blume (1970), Friend and Blume (1970) Black Jensen and Scholes (1972) suggest constructing portfolios equally weighted by the number of stocks[30] for each time period. These portfolios contain all the stocks sorted with respect to their risk factor. Hence, the first portfolio for example, contains the lowest risk factor for every period. Analogically, the last portfolio contains the highest risk factor for the same periods. In this study we use the following procedure for portfolio sorting. At first, we sort the sample by year and then by the liquidity factor[31]. Then, for each year, we break the sample into 10 quintiles and form a portfolio for each quintile, so that each portfolio contains the 10% of the sample in that particular year. Hence, ten portfolios from 1 to 10 are constructed for each year. Portfolio 1 contains the stocks with the lowest liquidity factors while portfolio 10 the stocks with the highest ones. After portfolio formation, the previous regressions (viii), (ix) and (x) take the following form:

$$\bar{R}_{adj,pt} = \gamma_0 + \gamma_{1zero}\hat{\beta}_{zero,p,t} + u_{pt} \qquad \text{(VIII)}$$

$$\bar{R}_{adj,pt} = \gamma_0 + \gamma_{1trade}\hat{\beta}_{trade,p,t} + u_{pt} \qquad \text{(IX)}$$

$$\bar{R}_{adj,pt} = \gamma_0 + \gamma_{1vol}\hat{\beta}_{vol,p,t} + u_{pt} \qquad \text{(X)}$$

, where the subscript p stands for portfolio instead of individual stock i.

5.3 Final step - Testing if Liquidity is Priced

Previously we argued that the sensitivity factor γ_1 measures the correlation of the liquidity factor and the average risk adjusted stock (portfolio) returns. If liquidity is priced, this factor should be positive for the illiquidity measures[32] and negative for the liquidity measures (number of trades and trading volume). That is because there is supposed to be a compensation for bearing illiquidity risk, while a premium should be paid for enjoying liquidity stability. In any case, γ_1 factor should be statistical significant in order to be sure that liquidity is priced. The standard econometrical procedure is to use the classical t-test, with the null hypothesis that the mean estimator for all years $\hat{\gamma}_1$ is zero. If the null hypothesis is rejected, there is a high possibility that

[30] FF use cap weights.
[31] The same procedure is done for each liquidity factor $\hat{\beta}_{zero}$, $\hat{\beta}_{trade}$ and $\hat{\beta}_{vol}$
[32] here zero proportion.

liquidity is priced. However, with the current sample, there is an estimation bias. More specifically, to perform the test, we need to calculate the t-statistic, which is: $t(\hat{\gamma}_1) = \frac{\hat{\gamma}1}{\sigma(\hat{\gamma}1)/\sqrt{n}}$[33], where $\sigma(\hat{\gamma}1)$ is the standard deviation of $\hat{\gamma}_1$ and n is the number of observations. In the current sample, n = 80 as there are 10 portfolios which contain 8 observations, one for each year. Earlier, we took the mean of each portfolio so for the eight-year period there are now ten identical observations. Put more simply, there are ten different $\hat{\gamma}_1$ coefficients related to 80 different risk-adjusted returns. This leads to an overestimation of the factor's significance, as there are 79[34] degrees of freedom for 10 different observations. In order to have an accurate test, we need to average the sample by year, so that the number n decreases to eight, corresponding to one observation for each year. We use a confidence level of 95%.

[33] This equation can also take the standard error form: $t(\hat{\gamma}_1) = \frac{\hat{\gamma}1}{se(\hat{\gamma}1)}$

[34] 80 – 1, as there is an one-factor model.

6. Empirical Results and Interpretation

6.1 Results from First Pass Regressions

Table 3 Panel A shows the average of the risk loadings for each measure obtained from the first pass regression, as well as their standard errors and t-statistics.

…………………………………..Insert Table 3 Panel A here…………………………

All risk coefficients are statistically significant in 5% significance level. In addition, all liquidity risk factors are negative on average whilst CAPM beta is the only positive one. The market model factor is the most robust one (t = 191.2), followed by the volume risk (t=-10.7).

The correlations between the risk factors are presented in Panel B of Table 3.

…………………………………..Insert Table 3 Panel B here…………………………

As shown in the table, there is a high correlation between the zero proportion factor and the β_{trade}. This is consistent with the CY, who also find high correlations between the two measures. Serious correlations also exist between the number of trades' factor and beta, as well as the β_{zero} and β_{vol}. Previously, we argued that all the liquidity factors are negative in general, as an average of the whole sample. Nevertheless, taking a closer look by breaking the results into years, one can see that although the averages are negative, some years experience positive liquidity factors. This is shown in Panel C of Table 3, where all the factors are represented for each year along with their t-statistics.

………………………………..Insert Table 3 Panel C here……………………………

As far as the β_{zero} illiquidity factor is concerned, it is negative monotonically for years 2001 to 2007. Apart from years 2002 and 2004, the negativity is significant, and only in 2008 the factor turns to a positive ground. The other two factors are negative for the first half of the sample and positive for the other half. However, they are mostly significantly negative rather than positive, which is confirmed by their overall negative mean.

Concerning the distribution form of the factors, is demonstrated on Kernel density function graphs. More specifically Plot 3 a, b, and c represent the distribution of β_{zero} β_{vol} and β_{trade} respectively.

………………………………… Insert Plot 1 a, b, c here ……………………………..

Looking at the plots it seems that the coefficients' distributions are generally normal ("bell"- shaped), but with long and fat tails. This might be due to extreme observations, although we cut down most of them through the winsorisation process.

6.2 Portfolio Sorts

Before proceeding to the cross-sectional regression analysis, the sample is sorted to equally-weighted quintile portfolios with respect to each liquidity factor. Table 4 demonstrates the portfolios created by all the realized factor loadings, along with these average factor loadings, and average stock and market excess returns. Panels A, B C and D represent portfolios sorted by the CAPM beta, trading volume, number of trades and zero proportion sensitivity factor, respectively. Also, the last row of each panel shows the difference between the measures of the last portfolio minus the first.

…………………………………… Insert Table 4 here ………………………………..

In Panel A we can see a negative relationship between the CAPM beta factor and all the liquidity factors. This was expected considering the table with the factors' correlations. Considering the relationship between the beta factor and the stock excess returns one can see that from portfolio 2 to 9 the excess returns rise in most cases. In contrast, however, the high-beta portfolio experiences lower returns and the low-beta one shows higher returns. This might be due to the fact that these portfolios are "extreme" and might contain more outliers[35]. In the portfolio in Panel B, the stocks sorted where based on trading volume. It seems, not clearly though as there is some fluctuation, that as the volume factor in absolute terms decreases, the stock excess returns become less negative. This is consistent with the theory, which assumes that the compensation should be lower for holding liquid assets, as expressed with high trading volume. A similar pattern seems to exist also with the number of trades' liquidity factor, as from portfolios low to high in Panel C, stock excess returns

[35] Although outliers have been "trimmed" through the winsorisation process, they still exist but have less effect on the results.

(losses) tend to increase (decrease). Panel D which shows the stocks' sorting based on the zero proportion illiquidity factor, confirms our earlier statement about the weakness of the measure's explanatory power. It seems that as the factor loadings increase from low β_{zero}'s to high ones, the stock excess returns fluctuate in a completely random manner. Hence, there seems to be no pattern that connects the number of zero daily returns and the stock returns. Nevertheless, the results from the second pass regressions will help us deal with this controversy.

6.3 Cross Sectional Regressions

Revising the Methodology section, it is obvious that the patterns discovered above will be of least importance if they fail to explain the cross-section of the risk-adjusted excess returns of the sample. If liquidity is priced in the Greek market, there should be a negative tradeoff between the liquidity measure and stock returns. Put more simply, the estimators from the second pass regression $\hat{\gamma}_{1trade}$ $\hat{\gamma}_{1vol}$ should be negative, and $\hat{\gamma}_{1zero}$ should be positive. Table 5 shows the results from the second-pass regressions for each liquidity measure. The intercept, standard error and t statistics for each regression are also presented in the table.

…………………………… Insert Table 5 Panel A and B here ………………………..

Taking a close look at the results, liquidity seems to be priced in the Greek market as measured by the daily number of trades for each stock and its daily trading volume. Zero proportion, as expected from the results from the first pass regression, does not seem to be an accurate measure of liquidity for the stocks in Athens Stock Exchange. In Panel A, more specifically, $\hat{\gamma}_{1zero}$ estimator is negative for years 2001-2003 and 2005-2008, contrary to the theory. What is more, it is robustly negative in year 2008. Number of trades presents far more "better" results. Although it is negative for only three years out of eight, it shows a negative correlation of liquidity and stock returns on average, as theory suggests. As far as trading volume is concerned, $\hat{\gamma}_{1vol}$ is robust and negative for the first two years. It flips sign in year 2003 and it turns negative again in 2004 but loses its significance this time. In 2005 it turns to positive ground where it stays till 2008. However, its negative loadings seem stronger, as its average shown in Panel B is negative. Although $\hat{\gamma}_{1vol}$ and $\hat{\gamma}_{1trade}$ express a discount, as theory predicts, it would be of minor importance if they fail to pass the robustness t test.

Panel B also shows the results from the t-test for the yearly sample. The t values for all γ_1 coefficients are very low and they fail to pass the 5% significance level. Moreover, $\hat{\gamma}_{1vol}$ and $\hat{\gamma}_{1trade}$ stay insignificant at 10% level, too. All in all, although liquidity as measured with trading volume and stock's number of trades seems to be related to a discount with the cross section of average stock excess returns, this relation is too fragile to be taken seriously into account. The proportion of zero daily returns as an illiquidity measure contradicts theory as it expresses a negative tradeoff between average stock returns and illiquidity, but this relation is also weak.

In the end, one last measure in the results that cannot be ignored is the unexpected robustness of the intercept in the cross section of the risk-adjusted average excess stock returns. Intuitively, it could be said that the significant intercepts imply that both the CAPM beta factor and the liquidity coefficients still do not explain fully the average stock returns in Athens Stock Exchange, and other measures such as the FF measures for example, should be considered.

Taking the outcome of the analysis into consideration, we can say that liquidity, measured by stock trading volume, number of stock trades, and proportion of zero returns, is not priced in the Greek Stock Exchange and therefore it does not add explanatory information to the Market Model[36] . These findings are inconsistent with the results of CY, who argue that liquidity is priced in the US and Korean market, and the above measures perform generally well.

[36] However, results seem to be highly sensitive the errors-in-the-variables effect. Using different treatment of this factor we take completely different results. The findings are presented in the Appendix section.

7. Conclusion

This study tests whether liquidity is priced in the Greek market. Theory predicts that assets bearing high liquidity risk offer higher average returns in order to entice investors to buy them. In contrast, investors are expected to demand lower returns for liquid assets as a payoff for avoiding liquidity risk exposure.

Three measures are used to capture liquidity risk. These measures are the trading volume, number of trades and the proportion of zero returns for each stock. By using portfolio sorts and outliers' winsorisation, the study attempts to eliminate any potential abnormalities in the data. Then, time series regressions are used to estimate the realised risk loadings for each factor. Liquidity risk estimators are then sorted into portfolios and second pass regressions are carried out to check if these factors indeed explain the cross section of average stock returns.

In general, results contradict theory's predictions. One of the three measures used exhibits totally opposite results to the expected ones. More specifically, the zero-return proportion measure reveals a negative tradeoff between liquidity risk and stock returns. In other words it counter-intuitively shows that investors do not require additional compensation for bearing liquidity risk but, in opposite, they pay for it. The other two measures perform slightly better, as they show that there might be a pattern that connects liquidity risk with higher stock returns. However, this pattern seems to be almost flat and it cannot be taken into serious consideration. Therefore, we come to the conclusion that liquidity is not priced in the Greek market and hence it does not add any serious information to the original Market Model.

Finally, among the results of this analysis, are the highly significant intercepts. It might be an indication that other factors might fit in the model apart from the regular systematic risk factor and the one controlling for liquidity.

8. Tables

Table 1: Summary Statistics of Returns

Panel A: Stock Returns

Year	Observations	Mean	Std Dev	Min	Max
2001	61208	.0014659	.0275059	-.08187	.0890796
2002	60590	-.001784	.0228979	-.08178	.0890796
2003	55843	.0001057	.0256322	-.08186	.0889475
2004	54716	-.000606	.0211702	-.08183	.0890796
2005	45187	.0005656	.0201888	-.08178	.0890518
2006	50368	.0013615	.02368	-.08183	.0890796
2007	55761	.0005485	.0221174	-.08187	.0890796
2008	42998	-.002503	.0260488	-.08186	.0890317

Panel B: Market Returns

Year	Observations	Mean	Std Dev	Min	Max
2001	250	.0013301	.0163674	-.08058	.0674543
2002	247	-.001242	.0101246	-.028426	.0402093
2003	247	.0011708	.0110259	-.02636	.0410047
2004	253	.001249	.0084243	-.02486	.0233908
2005	250	.0013345	.0081041	-.02457	.0250902
2006	249	.0015589	.0108211	-.03275	.049736
2007	252	.0010687	.0100218	-.04134	.0336828
2008	249	-.004906	.0208491	-.07295	.0769339

Table 2: Summary Statistics of Excess Returns & Liquidity Measures

Panel A: Stock Excess Returns

year	observations	Mean	Std Dev	Min	Max
2001	61208	-.01472	.0276398	-.09981	.0755942
2002	60590	-.00124	.0101246	-.02842	.0402093
2003	55843	-.00911	.0256784	-.09254	.0805772
2004	54716	-.00962	.0211734	-.09115	.0803788
2005	45187	-.00871	.0201893	-.09212	.0806141
2006	50368	-.01232	.0237439	-.09738	.0778495
2007	55761	-.01714	.0221445	-.10017	.0721836
2008	42998	-.02176	.0262169	-.10292	.075257

Panel B: Excess Market Returns

year	observations	Mean	Std Dev	Min	Max
2001	250	-.01486	.0165619	-.095545	.0493194
2002	247	-.015124	.0101631	-.042910	.0277887
2003	247	-.00805	.0111064	-.035925	.0327507
2004	253	-.007769	.0084428	-.033040	.0141447
2005	250	-.007948	.0081575	-.03386	.0164791
2006	249	-.012131	.0109267	-.045887	.0362043
2007	252	-.016626	.0100268	-.057572	.0151511
2008	249	-.024168	.0210886	-.093823	.0590767

Panel C: Liquidity Measures

measure	observations	Mean	Std Dev	Min	Max
trading volume	426671	1.409971	2.870691	0	113.07
number of trades	426671	.1017257	.6123687	0	1,60
zero proportion	296099	.1641681	.1674036	0	1

Panel D: Correlations of Liquidity Measures

	number of trades	trading volume	zero proportion
number of trades	1.00		
trading volume	0.6871	1.00	
zero proportion	-0.2476	-0.1226	1.00

Table 3: Descriptive Statistics & Correlations of Risk Factors

Panel A: Descriptive Statistics*

Variable	Obs	Mean	Std. Dev.	Min	Max	t stat 95%
beta	27758	**.8796643**	.7663227	-1.39	2.85	191,2491
se(beta)	27139	.5754801	.3554485	.0518306	4,984460	
β_{trade}	27045	**-.0001456**	.0031305	-.0325279	.0226429	-7,6496
se(β_{trade})	27045	.0026924	.0019481	.000443	.049448	
β_{zero}	16026	**-.0023613**	.0278617	-.3291152	.4335819	-8,3133
se(β_{zero})	16026	.0213628	.028669	.0005973	1,0306250	
β_{vol}	27057	**-.0000148**	.0002937	-.0058377	.0026989	-10,729
se(β_{vol})	27057	.0002331	.000186	.0000402	.0062071	

*Note: Numbers in bold denote significance at the 5% level

Panel B: Correlations of sensitivity factors

	beta	β_{zero}	β_{trade}	β_{vol}
beta	1.00			
β_{zero}	-0.0295	1.00		
β_{trade}	-0.0595	-0.0733	1.00	
β_{vol}	-0.0376	-0.0493	0.3267	1.00

(Table 3: Continued)

Panel C: Summary Statistics of Risk Factors by Year

eta	β_{zero}		β_{trade}		β_{vol}	
tstat	mean	tstat	mean	tstat	mean	tstat
118.726	-.0015637	-1.4729	-.0006867	-13.9681	-.0000694	-17.4
95.3422	-.0019692	-3.251	-.0014404	-37.473	-.0001251	-37.444
80.3355	-.0058118	-12.313	-.0003335	-6.4960	-.0000311	-6.9014
59.9304	-.0004317	-1.0491	-.0005334	-12.7677	-.0000486	-13.272
41.51690	-.0042873	-10.5326	.000906	15.459	.0000535	6.2979
66.37420	-.003558	-7.58750	.0009105	17.2317	.0000765	16.0271
51.04240	-.0029376	-4.7093	.000249	5.509	.0000315	8.294
62.73270	.0038377	5.9000	.0003796	4.5435	.0000462	6.3611

Table 4: Portfolio Sorts

Panel A: CAPM Beta

portfolio	beta	β_{zero}	β_{vol}	β_{trade}	$\widetilde{R}_i$	$\widetilde{R}_M$
low β	-0.3650675	-0,002407	0.0000318	0.0005254	-0.0133313	-0.013533
2	.1871756	-.002764	-.0000199	-.0002129	-.013184	-.0132437
3	.4192	.000584	-0.000611	-.0000537	-.0134219	-.0132776
4	.5948076	-.0019933	-.0000212	-.0002171	-.013537	-.0132873
5	.7539782	-.0040335	-.000029	-.0002635	-.0137183	-.0132607
6	.9157535	-.0009917	-.0000219	-.0001921	-.0137746	-.013287
7	1.078548	-.0001175	-.0000201	-.0001872	-.0137258	-.0132721
8	1.297720	-.0025127	-.0000132	-.000273	-.013864	-.0132284
9	1.581712	-.0043156	-.0000333	-.0003814	-.0140066	-.0133263
high β	2.310119	-0.006836	-0.000013	-0.000199	-0.0143415	-0.013232
HIGH-LOW	2.6751865	-0.004428	-0.000045	-0.0007244	-0.0010102	0.0003009

Panel B: Volume Measure

portfolio	beta	β_{zero}	β_{vol}	β_{trade}	$\widetilde{R}_i$	$\widetilde{R}_M$
low β	.9547945	-.004727	-.000489	-.0052271	-.0147782	-.013279
2	.9167266	-.0044114	-.0002433	-.0026665	-.0141903	-.0132506
3	.8180664	-.0028979	-.0001529	-.0016844	-.013555	-.0132813
4	.8129591	-.0012306	-.0000952	-.0010352	-.0137498	-.0133051
5	.810171	-.0012412	-.0000422	-.0004234	-.0135298	-.013227
6	.821201	-.003665	.0000132	.000152	-.0134218	-.0133473
7	.7749416	-.0029052	.0000641	.0007045	-.013273	-.0128327
8	.8885633	-.0013001	.0001329	.0015281	-.0134923	-.0133
9	.8067188	-.000114	.000211	.0021902	-.0133615	-.0133188
high β	.7488364	-.001398	.0004325	.0048179	-.0131475	-.013727
HIGH-LOW	-.2059581	.0033291	.0009216	.010045	.0016307	-.000448

(Table 4: Continued)

Panel C: Number of Trades Measure

portfolio	beta	β_{zero}	β_{vol}	β_{trade}	$\widetilde{R}_i$	$\widetilde{R}_M$
low β	.9700762	-.0044049	-.000472	-.005528	-.0147893	-0,013269
2	.9216971	-.0037439	-.0002377	-.002762	-.0141919	-.013257
3	.7834748	-.0032539	-.0001529	-.0017169	-.0136495	-.0132912
4	.8110258	-.0027912	-.0000939	-.0010603	-.0137397	-.0132998
5	.8045129	-.0004763	-.0000383	-.0004426	-.0136357	-.0132511
6	.7839451	-.0024984	.0000111	.0001624	-.0134908	-.0133488
7	.7962347	-.0046073	.0000626	.0007575	-.0131201	-.012813
8	.9244323	-.000906	.0001323	.0015243	-.0133828	-.0133067
9	.8041486	.0017636	.0002105	.0024437	-.0133769	-.013301
high β	0.7509413	-.0025329	0.0004108	.004955	-.01314	-.0137422
HIGH-LOW	-.2191349	.001872	.0008831	.0104832	.0016493	-.0004732

Panel D: Zero Proportion Measure

portfolio	beta	β_{zero}	β_{vol}	β_{trade}	$\widetilde{R}_i$	$\widetilde{R}_M$
low β	0,982752	-0,0460028	-.000482	-0.0006955	-0.0128706	-0.0128532
2	.8957395	-.0220587	-.00074	-.0001	-.0127659	-.012793
3	.7782267	-.0135854	-.0000248	-.0001662	-.0127718	-.0129204
4	.7820853	-.0081905	-.0000441	-.000483	-.0128849	-.012887
5	.8734821	-.0045049	-.000034	-.0003194	-.013519	-.0132868
6	.6555512	-.0012114	-.0000037	-.0000387	-.0130066	-.0127412
7	.787971	.0031481	.00000649	.0000606	-.0133272	-.0129687
8	.8109648	.0078371	.000037	.0003307	-.0134791	-.0126625
9	.8425338	.0146248	.00000331	.0003052	-.0134741	-.0128811
high β	0.95	0.0392226	-0.000004	-0.000092	-0.013335	-0.0125992
HIGH-LOW	-0.033788	0.08523	0.0000445	0.00060350	-0.0004644	0.000254

Table 5: Fama McBeth Regressions

Panel A: Descriptive statistics for each period*

γ_{1trade}	se_{trade}	γ_{0vol}	γ_{1vol}	se_{vol}	γ_{0zero}	γ_{1zero}	se_{zero}
-.230691	.1457593	**-.0012484**	**-3,815652**	1.499518	-.0008029	-.01740	.0123652
[-1.58]		[-3.40]	[-2.54]		[-1.79]	[-1.41]	
-.444502	.2378426	-.0010034	**-4,674974**	1.581383	-.0001657	-.074985	.0345557
[-1.87]		[-1.40]	[2,48]		[-0.23]	[-2.17]	
.011091	.0968505	**-.001162**	.3097882	1.2934080	**-.000960**	-.007645	.0184399
[0.11]		[-3.48]	[0.24]		[-2.45]	[-0.41]	
-.123001	.2073229	**-.0030541**	-1,72995	1.6613340	**-.0021643**	.0163458	.0186933
[-0.59]		[-8.96]	[-1.04]		[-7.30]	[0.87]	
.159344	.1258251	**-.0047177**	1,0766140	.6758364	**-.0047103**	-.051460	.0266326
[1.27]		[-24.80]	[1.59]		[-11.14]	[-1.93]	
.0317223	.1714942	**-.0017887**	.0733534	1.89391100	-.0016264	.010929	.0495063
[0.18]		[-3.51]	[0.04]		[-1.76]	[0.22]	
.2448198	.4547098	**-.0047718**	3,840947	1.6390472	**-.004422**	-.002543	.0349653
[0.54]		[-4.37]	[0.77]		[-5.55]	[-0.07]	
.3003979	.1236382	**-.0070164**	3,7735040	1,626518	**-.0061568**	**-.051786**	.021036
[2.43]		[-13.77]	[2.32]		[-12.17]	[-2.46]	

atistics are in parentheses. Values in bold denote significance at the 5% level.

(Table5: Continued)

Panel B: Summary statistics of FM coefficients

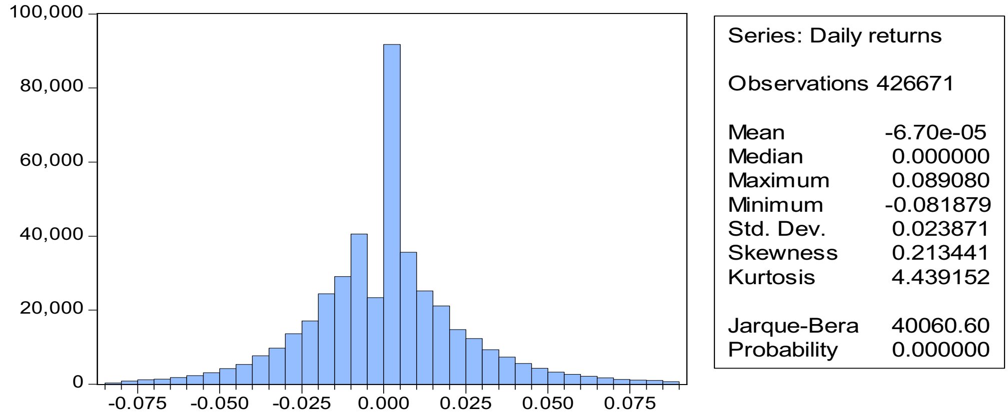
Coefficients	Intercept	Mean	T-stat*	p-value*	T-stat**	P-value**
γ1trade	-.002957	-.006352	-0.2501	0,405	-0.0715	0.9350
γ1vol	-.0029536	-.143296	-0.88	0.337	-0.1286	0.8913
γ1zero	-.0026825	-.022318	-2.27	0.026	-19.006	0.0991

*n = 80

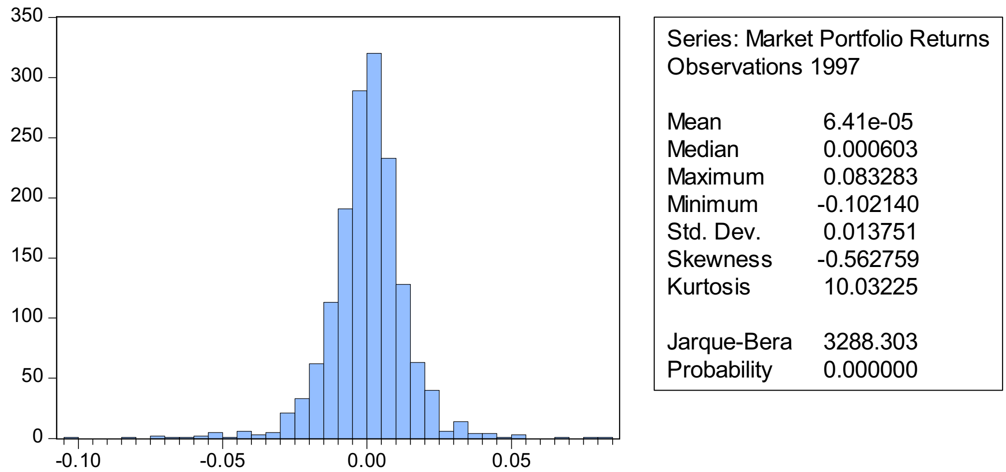
**n = 8

9. Graphs

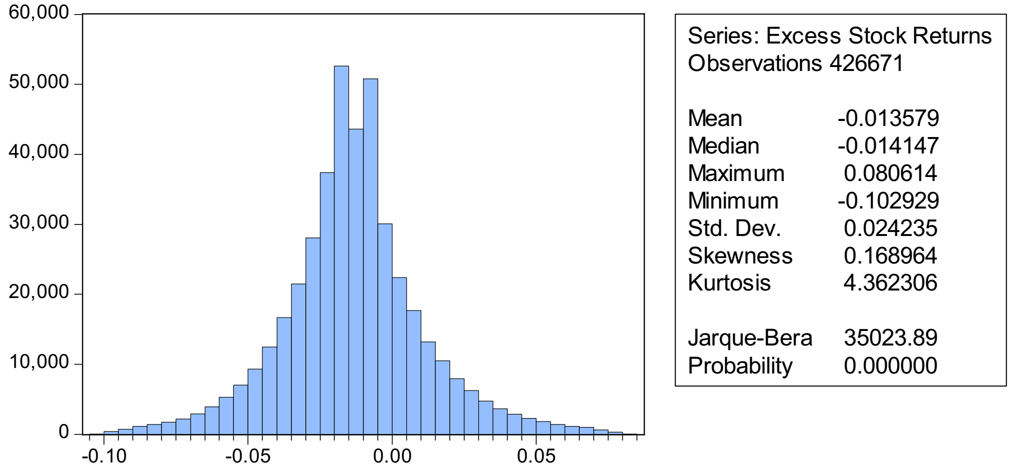
Plot 1a: Distribution & Descriptive statistics of Daily Stock Returns



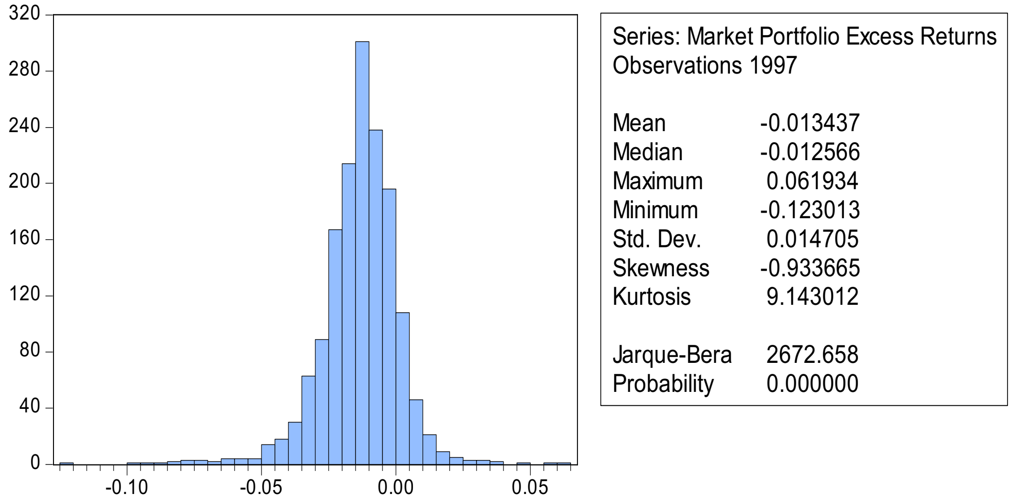
Plot 1b: Distribution & Descriptive statistics of Daily Market Returns



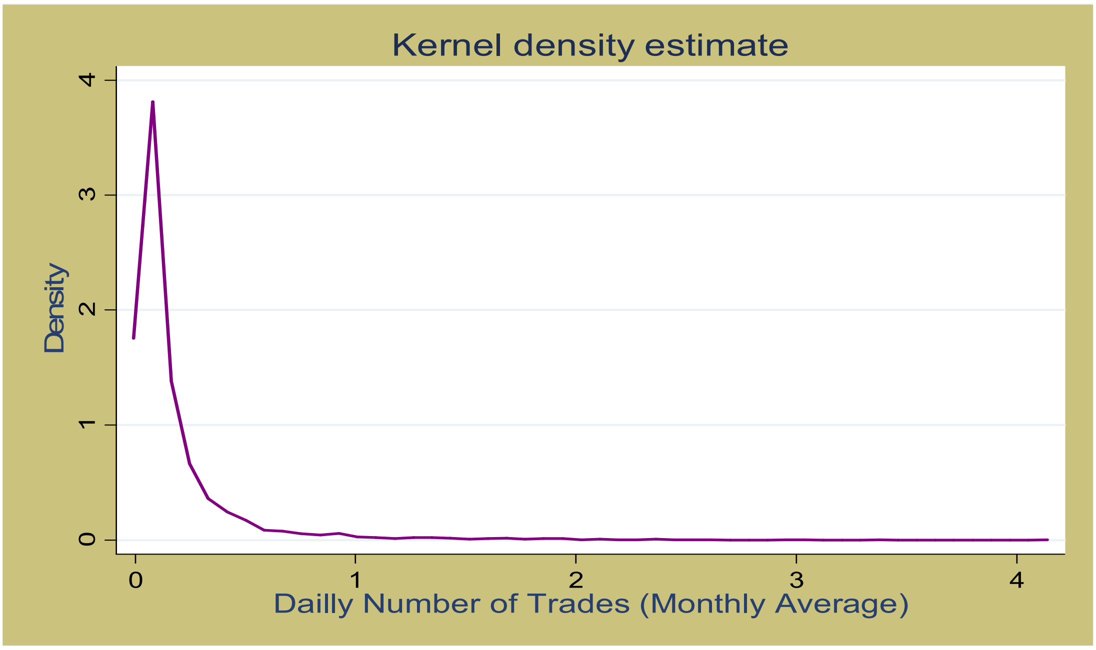
Plot 1c: Distribution & Descriptive statistics of Daily Excess Stock Returns



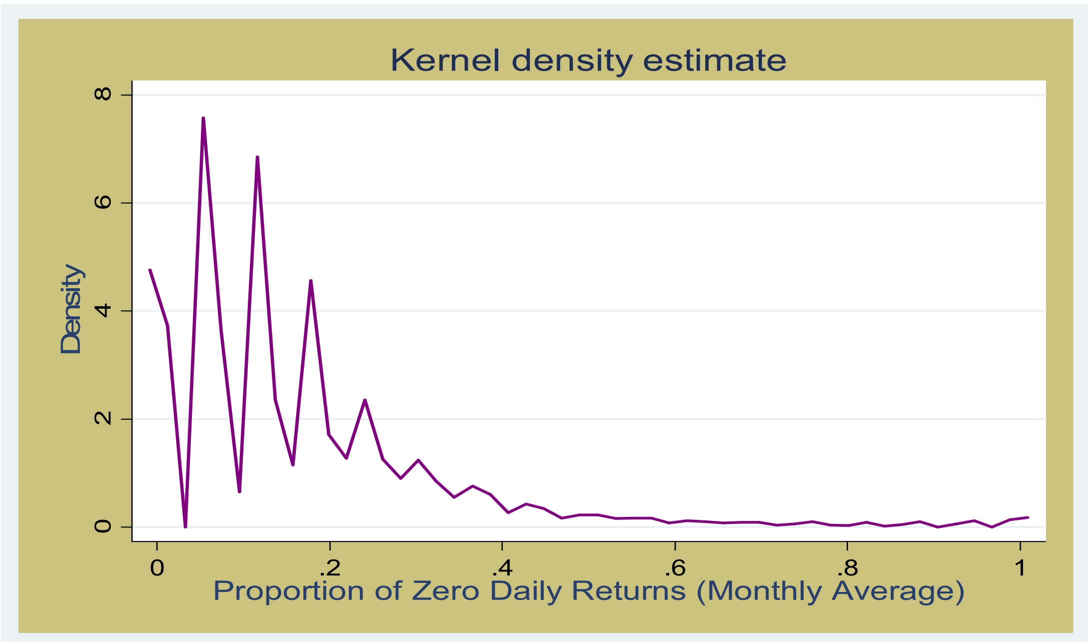
Plot 1c: Distribution & Descriptive statistics of Daily Excess Stock Returns



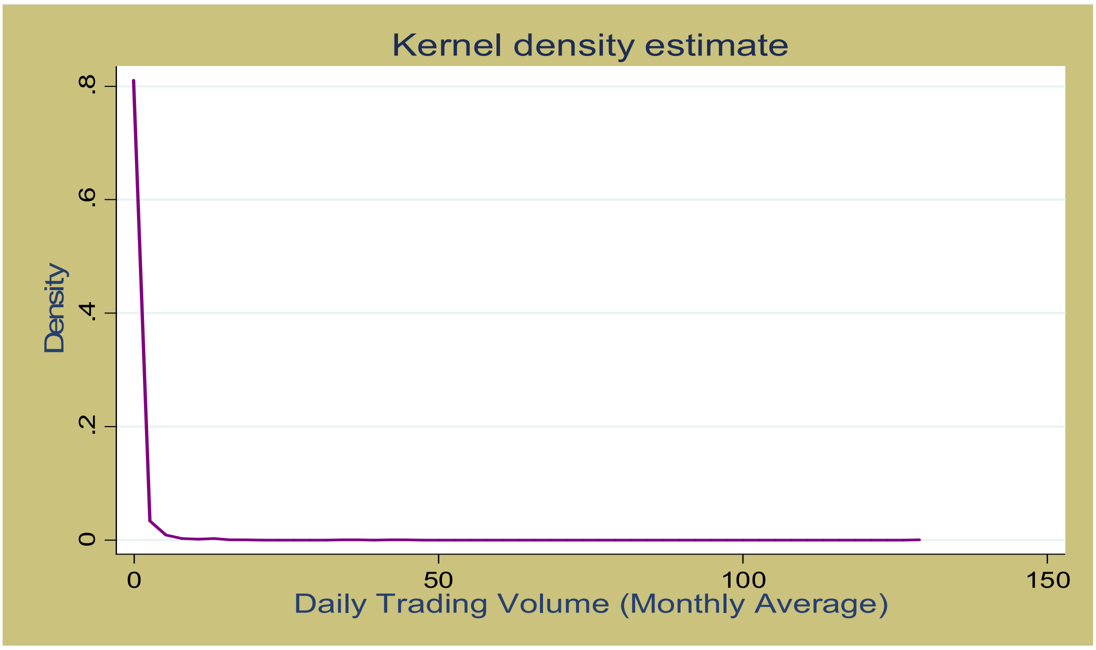
Plot 2a: Number of Trades Distribution



Plot 2b: Zero Proportion Distribution



Plot 2c: Trading Volume Distribution



APPENDIX

A. Introduction

In the main part of this paper, the analysis presented was done following the most popular methodology proposed in the economic literature. There are, nonetheless, other slightly different ways in which this study could be carried out, and two of them are presented here. The first one follows the methodology of the CY paper presented before, according to which the liquidity factors are not sorted into portfolios this time but are regressed on the pooled sample. The second attempts to examine whether different treatment of outliers can alter significantly the outcome of the study. More specifically, extreme values are not moved towards the center of the distribution as before this time, but completely deleted. Then, cross sectional regressions are run with and without portfolio sorting. Therefore, in total, there are three additional slightly different methodologies presented here. To save space, the results presented are only summary statistics of the cross sectional regressions.

B. Regressions with winsorisation but without portfolio sorts

So far we have seen the results from the most commonly used methodology in the literature. According to that, liquidity factors are sorted into portfolios, to avoid the errors-in-the-variables effect. However, it is interesting to see any potential results without using portfolio sorts. The summary statistics of $\gamma 1$ values are presented on Table 3 Panel A.

……………………………..Insert Table 6 Panel A here………………………………

It is obvious that these results differ significantly from the previous ones. The correlations of trading volume and number of trades with stock returns have not only opposite signage but robustness too. The zero proportion measure continues to be negative but its statistical significance rises. Hence, all measures totally contradict theory if study is carried through in this way.

C. Regressions with outliers' deletion and without portfolio sorts

Attempting to change now the way the effects of extreme values are reduced, we completely delete the outliers that lie before and after the 1st and 99th percentile of each important measure's distribution. More specifically, extreme stock returns, market returns and liquidity coefficients are reduced to the first and last percentage of their previous distribution. In that way, we take more "aggressive" measures against extreme values. Then, if we compute the robustness factors in the cross section without using portfolios, we have the results shown in Panel B of Table 6.

……………………………Insert Table 6 Panel B here……………………………….

The results are totally opposite than the previous ones concerning the γ_{1trade} and γ_{2vol} coefficients. They are negative and robust this time supporting the theory's assumption that there should be a premium for obtaining liquid assets. More specifically, t-statistics for the number of trades and the volume measure soared to 42.87 and 28.27 respectively. The proportion of zero returns measure still contradicts theory as it counter-intuitively shows that illiquidity is connected with lower returns. However, these results might be spurious as the errors-in-the-variables problem may exist.

D. Regressions with outliers' deletion and portfolio sorts

There is only one minor change in the data left to examine every possible outcome of the analysis[37]. We refer to using the same treatment on the data as before but using portfolio sorts instead. The correlation factors from the cross sectional regressions are exhibited in Table 6 Panel C.

………………………………Insert Table 6 Panel C here……………………………..

[37] Major potential alterations in the methodology still exist, for example using "panel" regressions instead of first and second pass regressions, but further analysis is beyond the scope of this study.

The results this time are similar to the ones presented in the main body of this paper. More specifically, $\hat{\gamma}_{1\mathrm{vol}}$ and $\hat{\gamma}_{1\mathrm{trade}}$ weakly support theory's predictions concerning the negative correlation between liquidity and average stock returns. The zero proportion measure continues to present negative signage, opposing theory.

E. Appendix Graphs

Table 6: Cross Sectional Regressions

Panel A: Winsorisation – No Portfolio sorts

Coefficient	Mean	p-value	t-stat
γ_{1trade}	.0387258	0	10,52010
γ_{1vol}	.4422119	0	9,2031
γ_{1zero}	-.0133007	0	-20,0208

Panel B: Outliers' Deletion – Portfolio sorts

Coefficient	Mean	p-value	t-stat
γ_{1trade}	-.001724	0.6600	-0.4592
γ_{1vol}	-.0021158	0.4982	-0.7143
γ_{1zero}	-.0356403	0.2792	-1,17300

Panel C: Outliers' Deletion – No Portfolios sorts

Coefficient	Mean	p-value	t-stat
γ_{1trade}	-.0013145	0.0000	-43
γ_{1vol}	-.003995	0.0000	-28
γ_{1zero}	-.0149174	0.0000	-225.354

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