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LIQUIDITY AND SIZE EFFECTS ON THE JSE

by

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ABSTRACT

This study tests the efficacy of the liquidity variables of Liu (2006) in determining the existence of a liquidity premium on the South African market and finds evidence of a significant liquidity effect. This factor is determined to be robust and to proxy for a different underlying effect than the Fama-French (1992) effects and the market risk premium. The analysis is performed through portfolio sorts and tests for difference of portfolio means, as well as both a univariate and multivariate regression analysis. The sample period covers 16 years from 2000 to 2015. The relationship between size and liquidity is clear, however liquidity is found to be separate from the size effect. This study recommends the use of a liquidity-augmented model for the analysis of asset returns in South Africa.

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1 INTRODUCTION

Much academic literature in the field of investments focuses on the driving factors that explain returns. Seminal papers such as the work done by Fama and French (1992) show that there are certain factors that can help explain the nature of the return-generating machine. The debate over which factors may explain these returns however is a complex and contested one. The paper by Fama and French (1992) created an entirely new framework for understanding returns through the examination of a three-factor model comprising of size, book-to-market and the previously used CAPM factor of beta as the explanatory variables.

Amihud and Mendelson (1986) analysed the effect of a new variable on asset pricing: the bid-ask spread. They found that the spread had a significant and consistent effect with the price of assets, thus laying the groundwork for a liquidity-adjusted asset pricing model. This was further reinforced by a later paper by Amihud (2002) where he finds that market illiquidity affects stock returns positively over time.

The question of whether liquidity has a significant effect on returns is also addressed by Liu (2006) who states that a liquidity measure is vital in understanding the cross-section of returns. The liquidity factor he uses accounts for various dimensions of liquidity and captures more facets of the liquidity effect than traditional measures such as turnover or bid-ask spread. This liquidity effect was also found by Liu (2006) to explain some variation in returns that was before attributed to the Fama-French (1992) effects (Size and book-to-market variables). It follows that there may be some correlation or co-dependence between liquidity and these variables, and if so this leaves the question of whether these variables are in fact capturing, for example, a size effect or if the size variable itself is simply an imperfect proxy for the underlying liquidity of the firm.

In emerging markets, some literature suggests that a liquidity effect may be persistently effective in describing the variation of equity returns (Bekaert, Harvey, & Lundblad, 2007). However, there are conflicting findings in this field as a paper by Rouwenhorst (1999) shows that although there is a correlation present between share turnover and return in emerging markets, the author states that this relationship does not sufficiently explain the movement of stock returns. Due to the uncertainty around this relationship there is a lot of space for research in emerging markets.

1.1 CORE RESEARCH QUESTION

There is much debate around the process driving security returns in both emerging and developed markets. The question has been examined in past literature (Fama & French, 1992) and several variables have been found to explain the variation in returns to some extent. Notable among these explanatory variables are the size and liquidity effects. However, the size and liquidity measures are often found to interact with one another suggesting that they may be accounting for similar effects. The contrasting arguments present an avenue for further research which this paper seeks to investigate.

1.2 RESEARCH OBJECTIVES

This study firstly seeks to investigate the validity and explanatory power of a liquidity effect in predicting stock returns. The efficacy of several measures used in past research by authors such as Amihud and Mendelson (1986) and Liu (2006) will be tested in order to unearth an appropriate proxy for liquidity on the emerging market of the Johannesburg Securities Exchange (JSE). This liquidity effect will be tested for significance and will then be compared to more traditional explanatory factors relating to stock returns, especially the size factor as outlined by Fama and French (1992).

The question addressed in the second instance will be whether this liquidity proxy is independent of the already well documented size effect or whether there is some overlap between the two with regards to explanatory power. This will provide an insight into the power of a liquidity-augmented model (Liu, 2006) within the context of an emerging market such as South Africa.

1.3 IMPORTANCE AND BENEFITS OF THE PROPOSED STUDY

The purpose of this study is to further contribute to the vast array of literature regarding the determinants of stock returns, specifically relating to the validity of the size and liquidity effects. The value of understanding liquidity premiums within emerging markets cannot be emphasised enough as emerging markets are significantly different from developed markets in the manner in which they are run and regulated. Liquidity and size are closely intertwined and further research into extracting the dominant or separate effects of these two variables is invaluable in understanding financial markets such as the JSE.

The study follows the following structure: section 2 analyses the extant literature through a literature review; section 3 sets out the methodology to be used in the study and the details thereof; section 4 details the results of the analyses and is itself subdivided according to the structure of the methodology; section 5 analyses any possible limitations and bias to the study; and section 6 completes the study with a conclusion.

2 LITERATURE REVIEW

2.1 THE CROSS SECTION OF RETURNS

Literature in the field of investments and finance has extensively studied the cross-section of returns in differing markets. Academic literature has continuously attempted to ascertain the variables and effects that best predict and explain stock returns. The fundamental relationship between a stock's Beta and the expected return originated through the work of Sharpe (1964) and Lintner (1965) in the introduction of the Capital Asset Pricing Model (CAPM). This theory posits that Beta identifies the sensitivity of an asset's price to changes in the overall market, and that this factor adequately explains stock return movements. The CAPM has since formed the cornerstone of many analytical models since its inception, however the pure model itself falls victim to the restrictiveness of its assumptions and the efficiency of the market in question.

Since its inception, the validity of the pure CAPM has been analysed extensively, with a host of literature arising that proposes different explanatory variables in order to more accurately explain stock return variation. This analysis has led to the introduction of asset-specific fundamental variables such as the earnings/price ratio being included in the asset-pricing models (Ball, 1978). Further variables have been tested with varying results over the years with multiple additions being made to the traditional CAPM (Basu, 1983).

The analysis conducted by Stattman (1980) in the US found that the book-to-market ratio provided significant explanatory power on the cross section of returns. This well-documented effect is intuitively explained as the difference between value (High B/M) and glamour (Low B/M) stocks.

The imperfect relationship between stock returns and Beta was addressed by Fama and French (1992) in their seminal paper which introduced a 3-factor model. This model expanded on the CAPM framework by including two commonly observed anomalies: the size and value effects. Fama and French (1992) analysed the effectiveness of two proxies for these effects (the High-minus-Low book to market ratio variable and the Small-minus-Big variable) and found that the inclusion of these factors with CAPM greatly enhanced the explanatory power of the model. Although this helped in predicting the return-generating process somewhat, there is much debate on the effects that these variables capture. This plethora of explanatory factors reverts to the central problem in isolating the factors explaining stock returns.

This relationship was further ratified through a number of studies, Gomes, Kogan and Zhang (2002) being among them. This study, however, found that the Fama-French characteristic factors subsist when controlling for the CAPM relationship and thus they may not be totally inconsistent with one another, thus adding a new dimension to the overall debate.

Although the Fama-French model proves promising for explaining the return-generating process, there are challenges to the efficacy of this model as well. Barbee et al. (1996) find that a sales-price ratio and debt-equity ratio had greater explanatory power than the Fama-French effects of size and book-to-market. They posit that the sale-price ratio is a more reliable explanatory factor than the model of Fama and French (1992).

Daniel and Titman (1997) provide an analysis on the Fama-French (1993) effects and posit that the model holds not due to the covariance of the returns but rather due to the correlation of the characteristics, stating that the distress risk is not a factor itself but that the relationship arises merely due to the similarity in the characteristics of the companies.

Other popular views have also been adopted in contrast to the seminal models such as the CAPM and Fama-French 3-factor model. Factors such as investor sentiment can also play an important role in defining asset returns. Research on the topic indicates that contrarian strategies can yield excess returns and that higher returns follow a lower investor sentiment, and *vice versa* (Baker & Wurgler, 2003). The analysis of Lakonishok, Shleifer and Vishny (1994) proposes that the Fama-French value effect is not in fact a systematic exposure to an underlying risk factor but rather that the return to a value strategy is as a result of the inefficient actions of investor behaviour. These behavioural factors provide a different perspective with which to view the cross section of returns and should be kept in mind when dealing with the prediction of asset returns.

The process of predicting the future cross section of stock returns is not a perfectly accurate process by any means. Even though models such as that of Fama and French (1992) have gained traction internationally in providing significant explanatory power on the cross section of returns, the process remains more of an art than a science. The power of these models in predicting asset returns is limited, as the expectations drawn from the priced risk of the variables may be too extreme. La Porta (1996) shows that portfolios formed on low growth

according to analyst expectations outperform their expected high growth portfolio counterparts, this is further ratified by Dechow and Sloan (1997). Diether, Mallow and Scherbina (2002) take a fundamentally different approach to the cross section of stock returns and find that stocks with a higher dispersion of forecasts by analysts earn lower future returns. Thus, their model is based off of the difference in opinions of analysts rather than any stock-specific factors. More recent research by Fama and French has expanded on their original 3-factor model and includes the additional factors of profitability and investment, thereby incorporating a 5-factor model which is found to better capture asset returns than the original model (Fama & French, 2015).

It is clear from the above that the return-generating process is a puzzle with many complex interactions, and that the predictability of returns must be constantly assessed.

2.2 LIQUIDITY AS AN EXPLANATORY FACTOR

Liquidity is important to investment planning as in the financial industry asset managers must construct a suitable portfolio that is in line with their investor's liquidity preferences and time horizon (Amihud & Mendelson, 1986). As such, in order for investors to consider investing in illiquid securities, they must be compensated through a premium on their expected returns (liquidity premium). Amihud and Mendelson (1986) were among the pioneers in arriving at a suitable proxy for capturing this liquidity premium, by using the bid-ask spread as an explanatory factor for asset returns. The measure they used specifically captured a dimension of liquidity known as trading cost (Liu, 2006). The bid-ask spread provides an intuitive representation of a cost for illiquidity, and literature on the topic suggests that the CAPM captures systematic exposure of net returns (after taking into account the bid-ask spread) as opposed to asset returns in general (Jacoby, Fowler, & Gottesman, 2000). The study by Jacoby et al. (2000) finds the same positive relationship between returns and the bid-ask spread as Amihud and Mendelson (1986), however their relationship is convex rather than concave.

Alternative measures utilised in related research likewise capture differing dimensions of liquidity, such as trading quantity (Datar, Naik, & Radcliffe, 1998) and price impact (Amihud, 2002). A fourth dimension of liquidity (trading speed) was introduced by Liu (2006) in order to further elaborate on the composition of an all-encompassing liquidity measure.

Liu (2006) reinforces the interpretation that there are four dimensions of liquidity. First is Trading Cost, which refers to the extra cost incurred in buying (or selling) a security due to the illiquidity of the market. If the security has few sell orders open at fair price it may cost more for the buyer to complete their trade (normally measured through bid-ask spread). Second is Trading Quantity, reflecting the amount of securities traded in a certain time, thus a higher amount of trades being executed results in a higher liquidity. This is normally measured through variables such as turnover. Thirdly there is Price Impact, which pertains to the effect of executing trades on the price of the security. Buying a large amount of securities in a small company will result in the price increasing and larger costs arising with the purchases (measured through a return to volume variable). Lastly there is Trading Speed, which refers to the degree of ease in which a security can be quickly sold or bought. If a security has a high trading speed it will be easier to sell it off quickly and as soon as possible when required (can be measured in accordance with the methodology of Liu (2006)).

As liquidity is multidimensional, Liu (2006) constructed a liquidity measure that accounted for multiple dimensions of the liquidity effect with a focus on the trading speed dimension. This measure will be referred to often in this study and will form a core focus of the analysis.
The issue in the literature is clearly differentiating between the different anomalies such as size, book-to-market and liquidity and to observe whether one effective measure subsumes another. This pattern of analysis is further focused in this paper to ascertain whether size and liquidity in fact proxy for the same underlying effect.

In a fairly recent study, Ibbotson, Chen, Kim and Hu (2013) offer that liquidity performs well as an investment style and reinforce that it is a separate effect from momentum and other styles. This analysis found that liquidity presents an intuitive, understandable premium to investors and that this premium can be traded on like any other investment style. These findings are pertinent to this study as it validates the findings of Liu (2006) and further reinforces the power of the liquidity premium in explaining/predicting stock returns. The literature on liquidity strategies follows that these strategies should provide excess returns for those investors with a long horizon for investment that are willing to shoulder liquidity risk.

2.3 EMPIRICAL EVIDENCE

2.3.1 Global Research and Findings

Much research has been done into the explanatory factors of asset returns, with multiple studies yielding conflicting results. The basic framework posited by Sharpe (1964) and Lintner (1965) and expanded upon by Fama and French (1992) has been tested extensively in past literature with varying results. The existence of a size effect has been found to be present for a significant length of time, in that firms with a lower market value exhibit higher returns. Literature suggests that such a relationship is not simply a linear function of size but rather a characteristic of small firms that becomes less apparent when examining differences of size in larger firms (Banz, 1981). Fama and French (1992) themselves found that a combination of their size and value (book-to-market) factors explain the variation of stock returns on average, finding also that the Beta variable implied by Sharpe (1964) and Lintner (1965) has a "flat" relationship with average returns even in the absence of their two factors.

The subsequent studies using and adapting this framework yield differing results with regards to the explanatory power of the generic Fama-French model (Liu, 2006). Various methodologies have been used in testing factors akin to the size and value variables used in Fama and French (1992), but the consensus (at least in developed markets such as the US) is that these two anomalies exist and are best accounted for with the Fama and French factors (Fama & French, 1992). The Fama-French factors are ratified through an analysis on the efficiency of the market which finds that the price of stocks explained by their cash flow betas, exhibits a relationship with value and growth stocks that is consistent with the seminal theory (Cohen, Polk, & Vuolteenaho, 2009). The study in question proposes the use of cash flow betas as an effective measure, or indeed the traditional CAPM beta if measuring over a long-term horizon. The Fama-French factor effects seem to be a global phenomenon as the study by Bauman, Conover and Miller (1994) suggests. Their study shows that value strategies outperform growth strategies on a global scale, as their analysis covers a wide array of countries and markets[1]. They also find that the size effect is strong and significant.

However, liquidity has also been found as a significant factor in explaining average returns (Amihud & Mendelson, 1986) and so a puzzle arises in that there are many "suitable" variables

[1] The study by Bauman et al. (1994) covers 21 countries, namely all 20 constituents of the MSCI Europe/Australasia/Far East Index and Canada.

to utilise but they are all interrelated to one another. This paper examines this relationship specifically with regard to liquidity and the Fama-French factors.

Amihud and Mendelson (1986) show that liquidity in the form of a bid-ask spread proxy variable is vital in determining asset returns and that the factor must not be ignored in modelling said returns. Likewise, in a later study by Amihud (2002), it was found that expected market illiquidity positively affects stock returns and that there is evidence of an illiquidity premium. This relationship is further linked to the original Fama-French model as small stocks are found to be more seriously affected by illiquidity (Amihud, 2002). This view is corroborated in additional studies that further reinforce the importance of a liquidity factor and illuminate the shortcomings of the traditional Fama-French three-factor model (Pastor & Stambaugh, 2003). Pedersen (2005) shows that in a simplistic model, the inclusion of a liquidity factor in addition to the standard CAPM model improves the explanatory power of the model and enhances predictability.

A study by Lustig (2001) finds that there is a liquidity risk involved in investor asset pricing. The findings of this paper show that there is an excess return required by investors on stocks relative to their illiquidity, and that this excess return is due to the costs incurred in holding illiquid stocks during a recession, where they cannot be easily disposed of. Therefore, the sensitivity of an asset to liquidity will result in a higher expected return.

It is suggested by Liu (2006) that a liquidity factor can more accurately capture the distress risk of a security than the traditional Fama-French factors. Liu (2006) proposes a measure that is used in this study as a multidimensional proxy for liquidity. He introduces this measure in order to account for liquidity risk that he suggests is imperfectly captured by the Fama-French factors used in the existing literature. It is found that the introduction of such a measure into the base model has significant effects on the explanatory power of the variables as well as the power of the model itself (Liu, 2006). The multi-dimensional nature of the liquidity variable makes the analysis robust in finding that liquidity is a significant factor in explaining stock returns. The author proposes a two-factor model of liquidity that consists solely of beta and the liquidity factor discussed above. This model is found to be more powerful than the original Fama-French model and the liquidity factor is found to be separate from the size and value variables used in the Fama-French model as a proxy for liquidity.

Pastor and Stambaugh (2003) show that smaller stocks are less liquid and thus imply that there is a link between the original Fama-French (1992) factors and a liquidity state variable. The same study also finds that their liquidity measure accounts for a significant portion of the returns to a momentum strategy, thus raising more questions to the validity of proxies for existing anomalies. Lastly, Pastor and Stambaugh (2003) reiterate the persistent power of the liquidity measure as a priced state variable and show that the sensitivity of a stocks return to liquidity is strongly related to size.

2.3.2 South African Research and Findings

Care must be taken not to blindly apply the findings of seminal papers discussing the cross-section of returns to developing markets as the dynamics of the exchange and securities market can differ vastly. This may be due to any number of factors such as regulatory deficiency, market inefficiency or liquidity. This study will primarily concern itself with the latter, as the dynamics of the South African market may cause a liquidity-based model to be more appropriate than a traditional Fama-French or CAPM model.

The analysis of risk premiums in emerging markets has shown a significant difference in results to analyses in developed markets. Literature on the topic shows that applying the same single-factor and multi-factor models to emerging markets creates substantial errors (Harvey, 1995). Harvey (1995, p. 812) stated that "local information" was the most important factor when considering emerging market returns and that this is due to a level of segmentation between emerging and world markets. This study uses a more recent sample size, and thus could implicitly analyse the effect of globalisation on the efficacy of multi-factor models in emerging markets.

The application of Fama-French and arbitrage pricing theory to the South African market has yielded slightly different results than the US market (van Rensburg & Robertson, 2003). One particularly startling anomaly that was observed was a significant positive relationship between size and beta, strongly contradicting the international evidence and the research of Fama and French (1992). Van Rensburg and Robertson (2003, p. 9) posit that this anomaly could have arisen due to "thin-trading effects" thus stocks that are traded sporadically and intermittently have a bias to have lower betas than is truly reflective of the security. Another reason could be that the JSE is very divided in terms of weighting and size, with the top five securities

comprising half the market cap of the JSE in total at the time of the study conducted (van Rensburg & Robertson, 2003). The conclusion of the van Rensburg and Robertson (2003) paper reveals that the beta variable is far less powerful in the South African market than in the US and that there is in fact, shockingly, an inverse relationship between beta and returns on the JSE. They also find that size together with a price-to-earnings variable could constitute an agreeable predictive model to use on South African data.

Research by Auret and Sinclaire (2006) and Basiewicz and Auret (2009) corroborate the general proposition that the South African market exhibits a return-generating process that differs to that of developed markets and thus follows a different asset-pricing model. The authors do find evidence of a value effect proxied for by a book-to-market variable but as with van Rensburg and Robertson (2003), they find that the original Fama-French model is not as powerful as other factors (such as P/E ratios) in South African markets. It should also be noted that liquidity was accounted for in these studies using a liquidity filter in order to isolate value and size effects.

A variety of factors are comprehensively addressed in the paper by Ward and Muller (2013) where significant results are found for a large array of "styles" or market factors. The authors reiterate the significance of the illiquidity premium and find liquidity to have a significant effect. The strategy that they posit, however, consists of "momentum, return on capital (ROC), cash flow-to-price and earnings yield" (p. 14) thus adding further questions to the validity of a two/three-factor model in a South African context. Ward and Muller (2013) also find that there is no small size effect, which is in stark contrast to the conclusions drawn from the majority of the literature, however they did make use of a size filter in their sampling which could have had some effect on this finding.

Auret and Cline (2015) found that, over two separate periods, size and value effects were not present on the JSE, further reinforcing the difference in the South African market to developed markets. Related South African research has found evidence of significant momentum and value premiums on the JSE, with the persistence of the value effect being largely affected by transaction costs (Page, Britten, & Auret, 2016).

It is obvious that there are clear differences between South African and US studies with regard to the findings that have arisen. Clearly there is no true global model that spans both developed and emerging markets, rather a variety of different local factors must be considered. The challenge in distinguishing which variables proxy for specific effects is a difficult one as discussed above.

Liu (2006) finds that the "liquidity-augmented" model accounts for various anomalies that the Fama-French or CAPM models cannot explain. This analysis is treated as the cornerstone of this study. As the power of the liquidity-augmented model was tested in developed markets from 1963-2003, this study seeks to conduct an analysis in a similar vein in order to highlight any differences due to the sample consisting of the developing South African market in the 21st century.

This study seeks to understand the liquidity premium in a South African context through the methodology utilised by Liu (2006) in conjunction with a regression analysis. This differs to the usual practice which consists of either introducing a liquidity filter rather than a variable, or to use a simple one-dimensional variable of liquidity. This will provide an interesting expansion upon international methodology within emerging markets in order to test the effectiveness of a liquidity-based model. There have not been many studies that have included this liquidity variable within this context and certainly not within emerging markets. The study also seeks to test the robustness of the liquidity effect in the 21st century by covering a sample period of 2000-2015. This research seeks to realign international asset-pricing and liquidity theory with emerging markets and to observe the efficacy of this theory-based model in explaining stock returns on the JSE in the 21st century.

3 METHODOLOGY

3.1 SAMPLING AND DATA COLLECTION

3.1.1 Sample

The sample consists of main board listed stocks covering the 16-year period from 2000 to 2015 (inclusive), including delisted firms. The total variables collected per share are monthly data points with the exception of volume, which is a daily measure that is used to calculate the liquidity measure in accordance with the methodology of Liu (2006).

The variables collected are namely:

- Volume (daily)
- Number of outstanding shares
- Closing price
- Market capitalisation
- Book/market ratio
- Cash flow/price ratio
- Earnings/price ratio

The three ratios are calculated using monthly variables and in accordance with the methodology of Liu (2006). All monthly and daily data is collected via the iNet BFA database for all shares listed on the main board of the JSE from 2000 to 2015. All returns analysed in the study are computed arithmetically using monthly closing prices retrieved from the iNet BFA database (which are adjusted for corporate actions).

In determining the market proxy for use in the CAPM formula and determination of Beta, this study makes use of the JSE All Share Index (J203) as retrieved from the iNet BFA database for the entire sample period under study. The use of the J203 is consistent with the past literature in the South African context, such as the study of Auret and Sinclaire (2006) and van Rensburg and Robertson (2003). This benchmark provides an accurate representation of the overall market's movement and tracks the value-weighted average return of all shares listed on the JSE. The other integral variable in the CAPM methodology is the risk-free rate. For the purposes of this study, the risk-free rate is drawn from the 91-day treasury bill rate retrieved from the South African Reserve Bank database for the entire sample period. The use of the 91-day risk free rate is due to the monthly holding periods employed within this study, as the extant literature suggests the use of proxies that align with the investment horizon (Nel, 2011). Following the prior research in South Africa referenced above, the author believes these proxies to be the most applicable for the purposes of the study in the context of the South African market.

As prior data of up to a year is required, the data collected for this study extends as far back as January 1999. This is considered to be a robust data set in terms of the period covered as the sample period provides a view of both before and after the global financial crisis. The sample is therefore not static and incorporates all shares that have been listed on the JSE during the sample period, save for those listed below. This mitigates survivorship bias and allows the sample size to change over the period as shares list and delist from the main board of the JSE.

3.1.2 Exclusions and Adjustments

Only firms that have been listed for the entirety of one 12-month analysis period are considered for the purposes of this study, hence firms that have been listed for less than a year are excluded from this research. Returns for firms that are delisted from the JSE during the sample period are adjusted for this event. The monthly return for the month prior to the first month in which the stock is delisted is adjusted to yield a return of -100%. This method was chosen as the study would otherwise fall prey to survivorship bias and other methods would detract from the objectivity of this study and could adversely influence the power of the results. This method of accounting for delisted stocks should, if anything, understate returns to an illiquid portfolio as those stocks that are more at risk to delist completely during times of crisis tend to be more illiquid on average.

Although previous South African studies such as van Rensburg and Robertson (2003) and Auret and Sinclaire (2006) have historically implemented a liquidity filter, this study makes use of a weak liquidity filter to eliminate only those firms with extreme illiquidity, in which case the feasibility of actually trading such stocks is minimal. These past studies in particular did not analyse the liquidity effect as an explanatory variable in particular. The filter used in this study calculates the annual average zero trading days each month for the prior year and eliminates those companies with an overall average of more than 200 zero trading days. This is because the purpose of this study is to analyse the viability of the liquidity effect as an explanatory factor to stock returns, and thus a stringent filter based on the very same liquidity effect would detract from the power of the sample and could create a bias in the results. The analysis will examine the returns across the different liquidity quartiles and as such will benefit from a larger liquidity range and sample. It should also be noted that the liquidity variables will be tested through the ranked quartiles methodology, effectively eliminating the need for a severely limiting filter. This study also employs the use of a R3.00 price filter for the purposes

of the portfolio sorting procedure as discussed in section 4.1.2. This is done in order to isolate the liquidity effect as the influence of large movements in the prices of 'micro-stocks' can create spurious representations when compounded through time. The use of such a filter is commonplace and in line with previous South African research such as that of Basiewicz and Auret (2009).

The financial ratios used in the analysis (book-to-market, cash flow-to-price) are sourced from the published annual financial statements of each company, with the interim results being ignored. The earnings-to-price ratio is provided monthly for all stocks in the sample period from the iNet BFA database. Companies that have a negative book-to-market ratio are ignored for the purposes of the study. Due to the regulations of the JSE, this study assumes a four-month gap between company year end and report release date. This is a conservative estimate that will ensure the data used in this study was observable by investors to act and trade on during the sample period.

Once all exclusions and adjustments have been made, the full sample comprises 592 JSE main board listed firms in total.

3.2 DESCRIPTION AND METHODOLOGY

The methodology of this research report is categorised into two major sections, the first of which analyses the different liquidity factors in the manner of Liu (2006) and observes the efficacy of the different factors in capturing the multidimensional nature of liquidity in an emerging market, as opposed to the aforementioned study on the developed market.

The second section of testing will analyse the explanatory power of the applicable liquidity variables within a regression analysis following the methodology of Auret and Sinclaire (2006) that will then extend to include other variables such as Size and book-to-market ratios in order to determine whether liquidity is a recurrent and systematic factor or whether one or more fundamental factors subsumes the other. This second section will then extend to analyse, through the construction of mimicking portfolios in accordance with the methodology of Liu (2006) and Fama and French (1993), the performance of existing asset return models in conjunction with the liquidity effect.

The market premium for purposes of the CAPM formula used in the regression analysis is calculated in accordance with the seminal literature on the topic such as Sharpe (1964) and Lintner (1965), and is defined through the following formula for each month under study:

$$R_m = R_{J203} - R_f$$

Where:

R_m = Market excess return (premium)

R_{J203} = Return to the J203 (JSE All Share Index)

R_f = 91-day treasury bill rate

The liquidity measures used in the second section will be chosen in accordance with the methodology of Liu (2006) as well as the results of the first section dealing with the comparison of liquidity measures.

3.2.1 Hypotheses

In line with the existing literature in South Africa such as Auret & Sinclaire (2006) and van Rensburg & Robertson (2003), and the results thereof, the following null hypotheses are posited in this study:

1. A liquidity premium does exist for assets on the JSE and this effect is captured accurately through the multidimensional liquidity variable (denoted LMx) posited by Liu (2006).
2. The liquidity effect is not significant in explaining stock returns when included with size, Beta, earnings-to-price, cash flow-to-price or book-to-market variables.

3.2.2 Liquidity Factors

The data collected is refined into three measures of liquidity for testing in order to encompass multiple dimensions of the liquidity effect. The measures that are constructed for testing are:

- **Turnover:** Average monthly turnover over the past 12 months; this measure captures trading quantity.
- **Return-to-Volume:** In accordance with Amihud (2002), calculated as the average monthly absolute return/rand value traded over the prior year excluding zero monthly trading volumes; this measure captures price impact. It should be noted that the original methodology makes use of daily data for determining price impact, thus the use of

monthly determinants for this variable in this study may affect the power of the variable. The variable does, however, still capture the price impact of the data in that it captures the monthly return per rand value traded of a company, and as such it is considered a viable liquidity variable for this study.

- **LM:** Liquidity measure posited by Liu (2006) that captures multiple dimensions of liquidity, this is calculated as follows:

$$LMx = \left(Number\ of\ zero\ daily\ trading\ volumes\ in\ prior\ x\ months + \frac{1}{\frac{x-month\ turnover}{Deflator}} \right) \times \frac{21x}{NoTD} \quad (1)$$

Where:

- $x - month\ turnover$ refers to the turnover over the prior x months
- $NoTD$ refers to the total number of trading days over the prior x months
- $Deflator$ is a constant determined such that $\frac{1}{\frac{x-month\ turnover}{Deflator}}$ lies between 0 and 1 for all sample stocks

This measure is calculated in accordance with the original methodology of Liu (2006) and exhibits a specific focus on trading speed as a dimension of liquidity.

These measures are tested in order to ascertain the multidimensional nature of liquidity and the extent to which each dimension explains stock returns.

3.2.3 Regression Factors

In order to test the efficacy of the variables for predicting asset returns the variable for each stock is given as the most effective variable in the first section measured over a period of 12 months prior. For the purposes of analysing the liquidity variables in conjunction with other variables, the regression test variables are defined as follows:

- **MRP:** defined as the difference between the return to a market portfolio and the risk-free rate in accordance with the seminal research of Sharpe (1964) and Lintner (1965). This variable forms the basis of the Capital Asset Pricing Model.

- **SIZE:** natural log of company market value as calculated in Auret and Sinclaire (2006) for the previous month prior to return date.
- **BTM:** book-to-market ratio of the firm (book equity value/market equity value). This ratio is defined as the prior year average book-to-market ratio for each stock for the purposes of regression.
- **EP:** calculated as earnings per share divided by price per share for one month prior to the return date.
- **CF/P:** calculated as the prior year average cash flow per share divided by the share price.

All data is collected on a monthly basis. The interaction between size and liquidity is of particular interest in this research as the existing Fama-French factors may capture distress risk and subsume liquidity effects, or alternatively, the hypothesis may be rejected and the liquidity effect may be independent of these effects.

The regression also incorporates an analysis based upon the construction of mimicking portfolios similar to that of Fama and French (1993) and Liu (2006). The variables for this model regression are defined as follows:

- **MRP:** the same variable defined as earlier, this variable is tested with the mimicking portfolios in order to ascertain the coefficient $Beta$ from the CAPM (Sharpe, 1964) (Lintner, 1965) and the significance of this coefficient.
- **SMB:** calculated as the return to the portfolio of the smallest stocks (S) less the return to the portfolio of the largest stocks (B). The data is sorted into quartiles based on size, similarly to the liquidity sorts performed in this study. The return of the Small quartile portfolio less the Big quartile portfolio at each month yields the value for the SMB variable. This mimicking portfolio methodology is performed in line with the seminal work of Fama and French (1993).
- **HML:** This variable is determined similarly to the SMB value. The total sample is sorted into quartiles based on the book-to-market ratio of each firm at each point in time. The return of the High BM portfolio less the return to the Low BM portfolio at each month is then the HML value for that month. This is again calculated in accordance with Fama and French (1993)

- **LIQ:** calculated as the return to a mimicking portfolio, similarly to that of the SMB and HML portfolios above, based on the LM factor of Liu (2006). The reason that the LM variable is chosen as a sorting variable for the liquidity effect is that LM is the only variable that captures multiple dimensions of liquidity and thus provides the best representation of overall liquidity costs. The return to the Small LM (liquid) portfolio is subtracted from the return to the High LM (illiquid) portfolio at each month in order to yield the LIQ value.

It should be noted that Liu (2006) in his methodology makes use of the HML and SMB values supplied by Kenneth French on his website for the period under evaluation. However, as these values are not applicable to a South African market, the relevant factors in this study are constructed through mimicking portfolios.

3.3 DESCRIPTION OF OVERALL RESEARCH DESIGN

Following the historical methodology of Liu (2006), the first section of analysis testing hypothesis 1 is performed by first examining the Spearman rank correlations between the different liquidity variables for the sample. For the sake of simplicity, the study uses 12-month measures ($x = 12$) for all liquidity variables as these are found to be the most robust in past literature (Liu, 2006). The efficacy of the chosen liquidity variable is then tested by undertaking a portfolio sort dividing the data into quartiles based on the liquidity measure in question, with the most liquid portfolio constituting the "short" portfolio and the least liquid constituting the "buy" portfolio. Quartiles are used as opposed to quintiles or deciles in this study due to the small amount of stocks traded on the JSE relative to developed markets such as the NYSE.

Portfolios are rebalanced on a monthly basis in order to provide the most accurate measure of the current market condition at the most regular interval. The use of monthly rebalancing can have the effect of buying past losers and selling past winners, and the sometimes extremely large returns of 'penny' stocks can thus be compounded. However, Sadka (2010) shows that the return to liquidity risk-loading portfolios does not significantly vary with holding periods. Ibbotson et al. (2013) also show that the turnover rate of stocks in their liquidity portfolios is rather low, with 62.93% of stocks remaining in the same liquidity tranche year on year (p. 39). Lastly, the analysis of Liu (2006) makes use of different holding periods and finds that the liquidity effect is persistent throughout, thus for the purposes of this study a monthly holding

period is analysed in order to capture changes in company liquidity. One final caveat is that although the monthly rebalancing of portfolios makes for a strong theoretical view on the asset-pricing effects, the viability of such a strategy in practice is questionable for the more illiquid companies. The purpose of this study is not however to analyse the viability of a liquidity trading strategy, which would involve taking into account variables such as trading costs, but rather to discern whether liquidity is a priced risk and whether this risk is independent of the size effect.

A t-test will then be conducted to determine the significance of the difference between the extreme portfolios. The results of this sort and test will then indicate the effect of a liquidity measure on returns and whether there is an identifiable liquidity premium. The test may additionally identify which liquidity premium may be the most applicable in the context of the South African market and other developing markets.

The second section tests the efficacy of the liquidity factor by following the methodology of Auret and Sinclaire (2006) with the inclusion of the applicable liquidity variables into a regression model that comprises various fundamental factors. A univariate regression is run on each of the variables with a particular focus on the liquidity variable regressions. The analysis is then extended to multivariate regressions including both size and liquidity, before extending further to incorporate all of the defined variables.

Market Beta (β) is included in the regression analysis, however, previous South African literature such as the work of van Rensburg and Robertson (2003) and Auret and Sinclaire (2006) found Beta to have little to no explanatory power within the South African market.

The initial regressions thus follow the forms set out below:

Univariate Regressions:

$$R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1}A_t + \varepsilon_t \quad (2)$$

Multivariate Regressions:

$$R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1}A_t + \lambda_{2,t+1}B_t + \lambda_{3,t+1}C_t + \cdots + \varepsilon_t \quad (3)$$

Where A, B, C and so on refer to the regression test variables as defined in the previous section. The variables chosen for the multivariate regressions will be dependent on the preliminary findings of the univariate regressions and the relevance to the objective of this study. Particular attention is paid to the Fama-French variables and their interaction with the liquidity variables. The methodology for the second section follows similarly to past South African literature (Auret & Sinclaire, 2006). Each univariate regression is run and tested separately, with the regressions being run and the coefficients tested through the use of Microsoft Excel's Data Analysis toolkit.

The main difference to the methodology of Auret and Sinclaire (2006) is that the portfolio (equally-weighted) average returns and explanatory variables for each portfolio are obtained at each point in time and the regression is then performed on these averages, thus treating each portfolio as a single asset. Although this may result in the loss of some explanatory power, this loss is not deemed to be significant, as the independent observations for each univariate regression run exceed 190. This methodology also allows the simple, intuitive analysis of the effect of changes in portfolio characteristics (size, liquidity, etc.) on that portfolio's returns through time. This is then supported by another portfolio returns regression with mimicking portfolio returns as independent variables, and finally a stacked-sample cross-sectional regression on all stocks in the total portfolio with these mimicking portfolio independent variables.

The regression section utilises excess returns (given as stock return for the month less the monthly risk-free rate) due to the inclusion of the market risk premium as an explanatory variable. Given that the CAPM is defined as follows for stock i:

$$R_i = r_f + \beta(r_m - r_f) \tag{4}$$

It is clear to see that a linear relationship with the market risk premium $(r_m - r_f)$ can be examined by adjusting the equation as follows:

$$R_i - r_f = \beta(r_m - r_f) \tag{5}$$

Where $R_i - r_f$ refers to the excess return dependent variable used in the regression analysis.

Once the initial univariate regressions are run, multivariate regressions are conducted in a first attempt to answer the second hypothesis of the paper relating to the interaction between liquidity and size effects. The regressions conducted are based on the results of the univariate regressions and pairwise correlations. The regressions are extended to include variables based on the purported relationship between liquidity and size as well as the findings of the initial univariate regression analysis and the preliminary analysis of liquidity factors in section 4.1. The third set of regressions then analyses the explanatory power of a model containing all additional variables mentioned with applicable liquidity variables.
Lastly, mimicking portfolios are created in a similar fashion to the methodology of Fama and French (1992) and in accordance with Liu (2006) in order to analyse three notable models in the seminal literature, namely:

- CAPM, developed by Sharpe (1964) and Lintner (1965), which measures the coefficient of MRP (the Market Risk Premium defined earlier).
- Fama-French 3 Factor model (Fama & French, 1992), which measures the coefficients of HML and SMB, both mimicking portfolios constructed by calculating the difference in returns between the extreme high and low BTM-sorted and Size-sorted portfolios at each point in time. This is elaborated on in the methodology section.
- Liquidity-Augmented CAPM (Liu, 2006), which measures the coefficients of MRP (defined earlier) and LIQ, a mimicking portfolio constructed similarly to the methodology of Liu (2006) by calculating the difference between the extreme liquidity-sorted portfolios at each point in time.

The mimicking portfolios provide the independent variables required for the secondary set of regression analyses. This analysis is performed on all sorted liquidity portfolios (sorted according to Liu (2006)'s LM variable) with the differential returns to the mimicking portfolio constituting the same fundamental and liquidity effects present in the seminal literature. Once determined, the variables are then tested for pairwise correlations in order to ascertain whether the variables capture separate effects or subsume one another.

All regressions are performed on liquidity-sorted portfolios as well as the total portfolio itself in order to ascertain whether the analysed relationships are systematic to the return-generating

process or whether the liquidity of the underlying portfolio will affect the most applicable explanatory factors to be used.

Once the regressions on portfolio-level variables are run, a cross-sectional test is performed on the entire portfolio of stocks. This is performed by ‘flattening’ and stacking the data in order to provide a two-dimensional cross-section for analysis. The process yields 68 696 testable observations per variable (excluding observations where firms have not listed yet etc.) and provides a thorough robustness test. The models tested earlier (CAPM, Fama-French and Liquidity-Augmented CAPM) through the use of mimicking portfolios and market risk premium are then tested on the total portfolio cross-section in order to determine the robustness of the findings relating to individual stocks. In this manner, and through the use of different methods of testing, conclusive deductions can be made regarding the power of these models and the validity of the results.

The purpose of this methodology is firstly to determine which variables best capture the liquidity effect, and secondly to conduct an analysis including the liquidity variables in order to determine whether liquidity has a significant effect on stock returns or if it is instead an imperfect proxy for other effects such as size.

4 RESULTS AND ANALYSIS

The following sections cover the two main hypotheses of this study separately. The first section analyses the liquidity variables posited in the previous section by conducting a sorting procedure in accordance with the methodology of Liu (2006). The results of this primary analysis will provide an indication as to the effectiveness of the different liquidity variables in predicting stock returns on the JSE.

The second section will cover the regression analysis and test the second hypothesis of this research report. The results of the first section will provide context to the nature of these regressions, and the regressions will specifically focus on the interaction between Fama-French variables (Fama & French, 1992) and the liquidity variables defined in the first section.

The second section will also include an analysis of the efficacy of the traditional asset pricing models and the model posited by Liu (2006) through the construction of mimicking portfolios and a regression analysis on the aforementioned models.

All analyses are conducted on the full sample of JSE stocks described in section 3, sorted in accordance with the analysis being conducted and covering the full sample period from January 2000 to December 2015.

4.1 LIQUIDITY FACTORS

4.1.1 Total Portfolio Descriptive Statistics

Table 1 shows the descriptive statistics for the total portfolio liquidity variable averages as well as the size variable averages. The LM, RtV, Turnover and Size variables portrayed are averages of the total portfolio at each month of the sample period for the full period of 192 months. The variable means portrayed are thus means of the monthly variable averages over the entire sample.

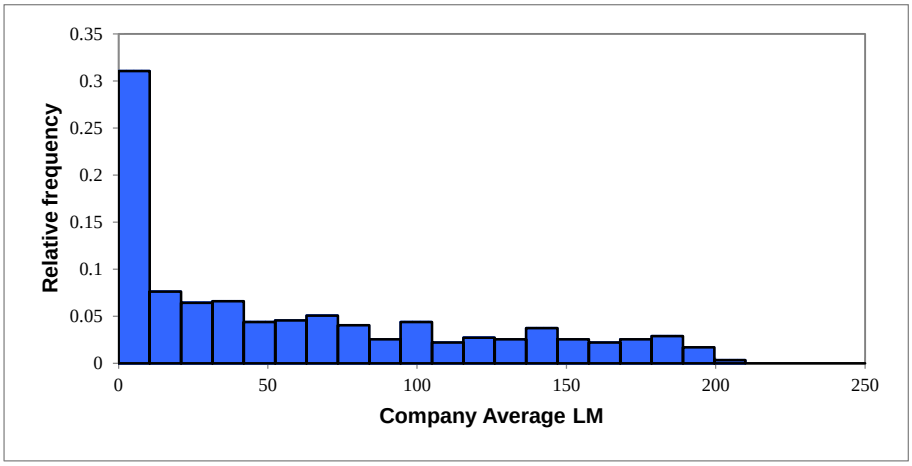
Table 1: Total Portfolio Descriptive Statistics (Liquidity and Size variables)

LM		*RtV*		*Turnover*		*Size*	
Mean	55.82604139	Mean	0.006052%	Mean	2.39266%	Mean	20.40366583
Standard Error	0.902123797	Standard Error	0.001000%	Standard Error	0.02198%	Standard Error	0.047527995
Median	53.95304285	Median	0.001819%	Median	2.29979%	Median	20.57343985
Standard Deviation	12.50019401	Standard Deviation	0.013855%	Standard Deviation	0.30461%	Standard Deviation	0.658567214
Sample Variance	156.2548504	Sample Variance	0.000002%	Sample Variance	0.00093%	Sample Variance	0.433710775
Kurtosis	-0.81	Kurtosis	10.96	Kurtosis	-0.05	Kurtosis	-1.32
Skewness	0.34	Skewness	3.48	Skewness	0.93	Skewness	-0.13
Count	192	Count	192	Count	192	Count	192

As shown in Table 1, the data is vastly different for the South African market than it is for the NYSE. Comparing the summary statistics to that of Liu (2006), it is relatively simple to deduce that the South African market is far less liquid. The relatively high mean for the LM variable (55.83) is indicative of an illiquid market when compared to the LM value of Liu (2006), which is 10.39 for the NYSE/AMEX sample and 35.63 for the NASDAQ sample (pp. 640-641). The sample standard deviation for the LM variable (12.5) indicates that the liquidity variable is well dispersed, and the lack of skewness contributes to the possible power of tests involving the LM variable. The high average value for the LM variable may be attributable to the lack of a stringent trading filter (the methodology used only filters out stocks with more than an annual average of 200 zero trading days), however the inclusion of a stronger filter, as discussed previously, could obscure results and detract from the liquidity effect. The sample statistics of Liu (2006) do not include a filter and still obtain reasonably liquid observations, thus suggesting a liquidity difference between the South African and United States markets. This notion that emerging markets are less liquid than developed markets such as the US market is well supported in the literature (Kang & Zhang, 2014). The effect of relative liquidity between securities on asset pricing in emerging markets may therefore be more pronounced than in developed markets. Although the LM value is high, dividing the data into quartiles should allow for reasonable inferences to be made regarding the effect of the liquidity factors. The turnover variable is likewise statistically sound and an appropriate candidate for analysis.

Figure 1 shows the distribution of the LM variable around the average LM of 59 for JSE companies. As this variable is analogous to the number of zero daily trades, an inference on the overall liquidity of the market can be made. It is clear that the majority of listed companies are not continuously traded and that a small tranche of JSE listed companies are traded regularly. As such, considering that liquidity can be priced as a risk by rational investors, the effect may be more pronounced on the South African market and perhaps in developing markets in general.

Figure 1: Histogram (Company Average LM)



Size is not intuitively comparable as this study defines size as the natural logarithm of the market capitalisation, and not simply the value itself. As these monthly portfolios are equally weighted they encompass all firms within the JSE with no bias to those of a larger size. This is an important note, as the JSE displays a large disparity between large, liquid firms and small, illiquid firms (this is confirmed in table 3 below wherein the high negative correlation between size and the LM variable, which denotes illiquidity, portrays this intuitive relationship between the two variables). Thus, the findings of this study are expected to differ from those of Liu (2006), given the polarised liquidity factors of firms on the JSE.

Table 2: Total Portfolio Descriptive Statistics (BM, EP and CFP variables)

BM		*EP*		*CFP*	
Mean	1.24305	Mean	-0.106014028	Mean	2.97509
Standard Error	0.01688	Standard Error	0.008851797	Standard Error	0.55101
Median	1.27500	Median	-0.096530136	Median	0.10454
Standard Deviation	0.23394	Standard Deviation	0.122654094	Standard Deviation	7.63504
Sample Variance	0.05473	Sample Variance	0.015044027	Sample Variance	58.29384
Kurtosis	-0.21	Kurtosis	2.172720406	Kurtosis	4.80
Skewness	-0.90	Skewness	-0.102123164	Skewness	2.54
Count	192	Count	192	Count	192

Table 2 reports descriptive statistics for the financial ratios used in the study, namely Book/Market ("BM"), Earnings/Price ("EP") and Cash Flow/Price ("CFP"). As stated previously, the BM and CFP ratios are drawn from the published annual financial results of the companies in question and adjusted to account for investor access to the information. The EP ratios are provided from the iNet BFA database and are updated monthly. The BM and CFP ratios are given as the relevant ratios averages over the prior years. The ratios themselves seem to be somewhat affected by the presence of outliers, although this was somewhat mitigated through using the prior year average for the BM and CFP variables. The EP variable seems to be slightly negatively skewed.

Table 3: Total Portfolio Correlation Matrix

	LM	*RtV*	*Turnover*	*Size*	*BM*	*EP*	*CFP*
LM	1						
RtV	0.117393	1					
Turnover	-0.62688	-0.04517	1				
Size	-0.78215	-0.18939	0.284849	1			
BM	0.455237	0.067355	-0.74451	-0.35894	1		
EP	-0.01418	0.039066	0.518757	-0.36636	-0.26396	1	
CFP	-0.48833	-0.09143	0.744622	0.241486	-0.74036	0.449705	1

Table 3 portrays the correlation coefficients of the different independent variables used in the study. As expected, there is a high negative correlation between the liquidity variable of Liu (2006) and the size variable. This preliminary examination supports the notion that perhaps the existing size factor proxies for liquidity risk, or that there is at least a relationship between the two factors. Another interesting relationship to note is the relationship between the turnover, CFP and BM variables. Although the relationship between BM and CFP is intuitive in that the cash flow of a company will affect its book value and the denominator for both variables is the same, the interesting connection is that of these financial ratios with turnover. Although turnover is somewhat negatively correlated with LM and thus lending credence to its use as a liquidity factor, the strong positive relationship with the financial ratio variables provides an interesting avenue for further investigation. The EP variable seems to exhibit no strong pervasive relationships.

The three liquidity variables being tested are used to sort the data into quartiles in order to isolate the liquidity effect and determine if there is a significant difference between illiquid and liquid stock returns. Throughout the study portfolios are ranked for liquidity and size as follows:

Liquidity	Size
VL: Very Liquid (Most liquid quartile)	B: Big (Largest company quartile)
3	3
2	2
IL: Illiquid (Least liquid quartile)	S: Small (Smallest company quartile)

4.1.2 Extreme IL Returns and Use of a Price Filter

Throughout this section a rudimentary graphical analysis on the compounding returns to the liquidity-sorted portfolios are used. However, due to the fairly weak liquidity filter (through excluding stocks with LM > 200) combined with the use of monthly portfolio rebalancing, the compounded indexed returns to this extreme illiquid portfolio are often disproportionately large and an intuitive graphical comparison becomes impossible. In order to compare these portfolios, a price filter of R3.00 was put in place for the purposes of an accurate graphical analysis. This price filter was applied such that if a company's median price over the sample period is less than 300 cents (R3.00) then it is excluded from the representation. This was done to avoid the effect of excessive returns associated with large percentage movements in low-

priced stocks as well as to provide a rudimentary robustness test on whether the portfolio-sorted effect is merely an anomaly of low-price illiquid stocks or robust to the greater market portfolio. This allows ease of interpretation without the initial observational analysis being distorted by micro-stock returns.

Although the sometimes profoundly large returns to the extreme portfolio sorts may seem to indicate the presence of outliers in the data, the removal of any of the large monthly stock returns from the data would harm the overall power of the test itself. The returns data was examined in depth and determined to provide an accurate representation of the returns to the stock in question.

It should be noted that although these returns may seem to provide an ideal trading strategy the effect of these abnormally large returns is likely exacerbated due to the monthly rebalancing of the portfolio as discussed earlier. The effect of a high bid-ask spread could also likely be a culprit of any large movements in the returns to illiquid shares.

4.1.3 LM-sorted portfolios

The first variable that is used to sort portfolios is LM, the liquidity measure of Liu (2006) that captures multiple dimensions of liquidity with a particular focus on trading speed. The sorted portfolio analysis diverges from that of Liu (2006) in that there is no characteristics adjustment to the returns of the portfolios. This was omitted as the analysis by Liu (2006) determined that the liquidity effect is robust to these adjustments, and additionally this study explores the relationship and accounts for the potential interaction between the characteristic variables and liquidity in the regression section. Table 4 shows the mean monthly returns to the quartile portfolios as well as the difference portfolio (IL-VL).

Table 4: LM Quartiles Mean Monthly Returns

LM quartiles	IL	2	3	VL	IL-VL
Mean monthly Return	3.322%	0.681%	0.700%	0.705%	2.617%

From Table 4 a large difference can be observed between the extreme portfolios. The mean monthly returns to the 2, 3 and VL portfolios are very similar, creating the impression of a significant illiquidity premium on the extreme illiquid portfolio. This is reinforced by the

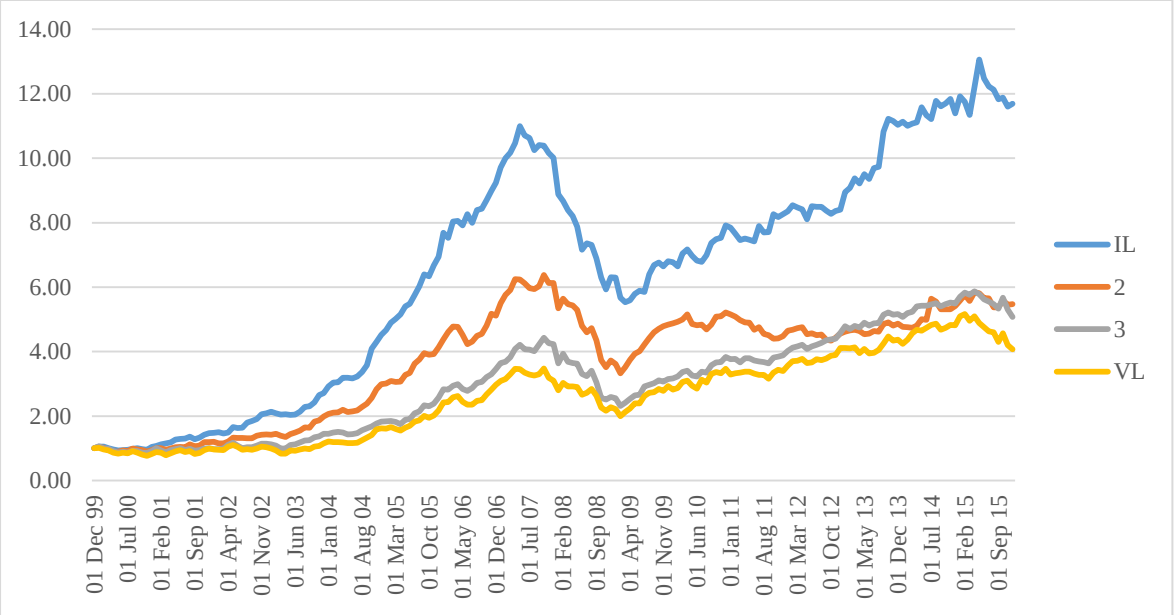
findings in Table 5, which portrays the results of a Student's t-test for differences in means between the illiquid (IL) and very liquid (VL) portfolios.

Table 5: LM Quartiles t-Test

	IL	*VL*
Mean	0.033221	0.0070497
Variance	0.005022	0.0022656
Observations	192	192
Pooled Variance	0.003644	
Hypothesized Mean Difference	0	
df	382	
t Stat	4.247897	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.648852	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.966194	

The results of this test are seemingly conclusive. The difference between the two extreme portfolios based on the liquidity measure of Liu (2006) is indeed significant at the 1% level. The most striking observation, however, is the magnitude of the difference. Figure 2 provides a graphical representation of the growth of a R1 investment into each of the LM-sorted portfolios at the beginning of 2000 until the end of 2015 using the R3.00 price filter discussed in Section 4.1.2. From a purely graphical analysis, a liquidity premium pattern is visible, with the most illiquid portfolio (IL) outperforming the rest. The liquidity premium also seems to be a priced risk as the effect of the global financial crisis was most pronounced on the illiquid portfolios. It should be noted at this point that although the IL portfolio performed exceptionally over the period, it is doubtful that this portfolio could ever be replicated in practice. This is because the methodology of this paper assumes that all shares can be bought every month in any quantity, however with a portfolio as illiquid as the IL portfolio it may be difficult, if not impossible, to trade the constituents on a monthly basis and continually rebalance the portfolio. The graphical analysis shows a relationship that is highly consistent with a liquidity premium as the returns to the portfolios decrease as liquidity increases.

Figure 2: LM-sorted portfolios (R3 Price Filter)



4.1.4 RtV-sorted portfolios

The second sorting variable is the return-to-volume (RtV) variable defined earlier in section 3, and this analysis is performed in a similar vein to that of the previous analysis of the LM variable. This variable posited by Amihud (2002) captures the price impact effect of liquidity and is expected to have a positive correlation with returns.

Table 6: RtV Quartiles Mean Monthly Returns

RtV	IL	2	3	VL	ILL - VL
Average	3.73%	0.70%	0.48%	0.63%	3.10%

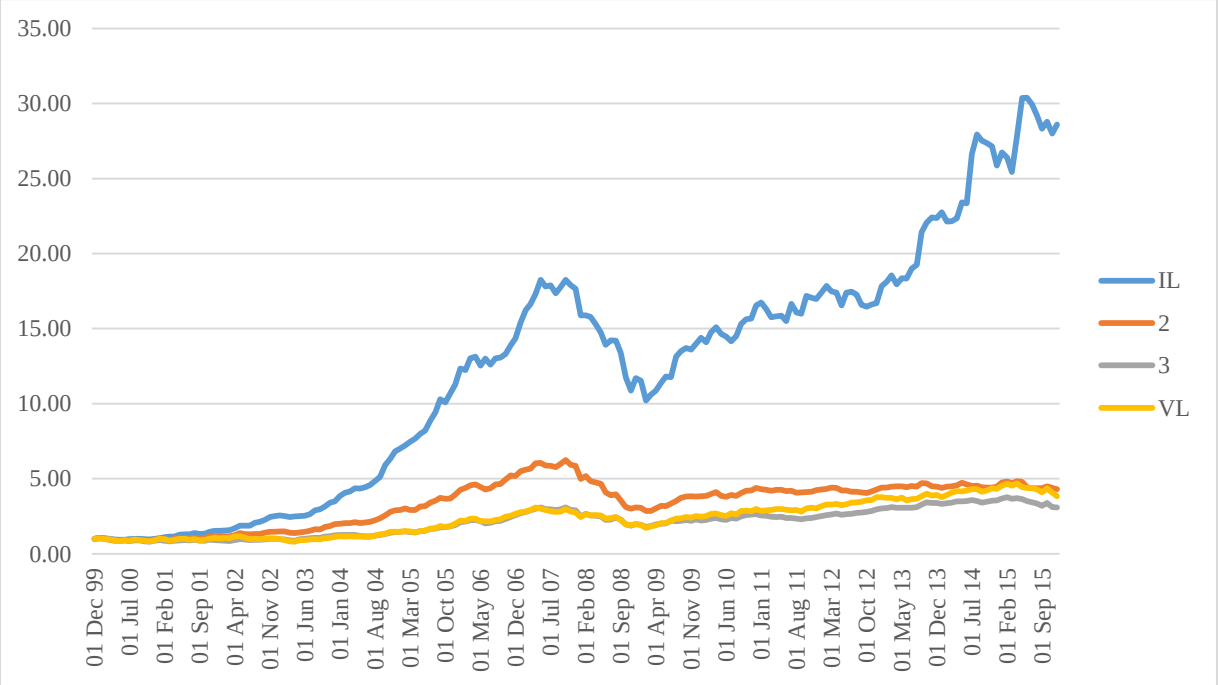
Table 6 shares a familiar pattern with the previous analysis on the LM variable. The large difference between the extreme portfolios is once again present, however portfolios 2 and 3 show a larger difference than previously found in the corresponding LM sorted portfolios. The similarities persist in the t-test (Table 7), with a nearly identical pattern to the LM variable. The difference between the average returns to the extreme liquid and illiquid portfolios is once again significant, this suggests a particularly pervasive liquidity premium is present in the data. The question on whether these liquidity variables are proxies for different dimensions of liquidity will be addressed in the regression section.

Table 7: RtV Quartiles t-Test

	IL	*VL*
Mean	0.037311	0.006317893
Variance	0.005427	0.001991033
Observations	192	192
Pooled Variance	0.003709	
Hypothesized Mean Difference	0	
df	382	
t Stat	4.986174	
P(T<=t) one-tail	0.00	
t Critical one-tail	1.648852	
P(T<=t) two-tail	0.00	
t Critical two-tail	1.966194	

Once again, the same indexed graph is portrayed with the price-filter adjusted sample in Figure 3. This figure shows that the most illiquid portfolio exhibits performance consistent with that expected by Liu (2006) due to the effect of a liquidity premium. Although these indexed values remain very large, the IL portfolio is probably not tradeable as discussed earlier. It is also possible that the RtV variable is a proxy for return-based effects such as momentum or mean-reversion effects. As such this may not capture the liquidity effect only.

Figure 3: RtV-sorted portfolios (R3 Price Filter)



4.1.5 Turnover-sorted portfolios

The last liquidity variable to be analysed through this sorting procedure is the turnover variable. This variable captures the trading quantity dimension of liquidity and provides an intuitively simple view of liquidity as the percentage of a company's shares that are traded on a monthly basis. Under the assumption that a liquidity premium exists, turnover is expected to have a negative relationship with monthly returns.

Table 8: Turnover Quartiles Mean Monthly Returns

Turnover	IL	2	3	VL	IL - VL
Average	2.39%	1.29%	0.88%	0.73%	1.67%

Table 8 portrays the monthly averages for each of the monthly turnover-sorted portfolios. Once again, a liquidity premium seems to be present, with the illiquid portfolio outperforming the others. However, the performance increases monotonically as the illiquidity of the portfolio increases. This is in contrast to the previous liquidity variables' preliminary analysis which portrayed a more sporadic relationship amongst the more liquid portfolios.

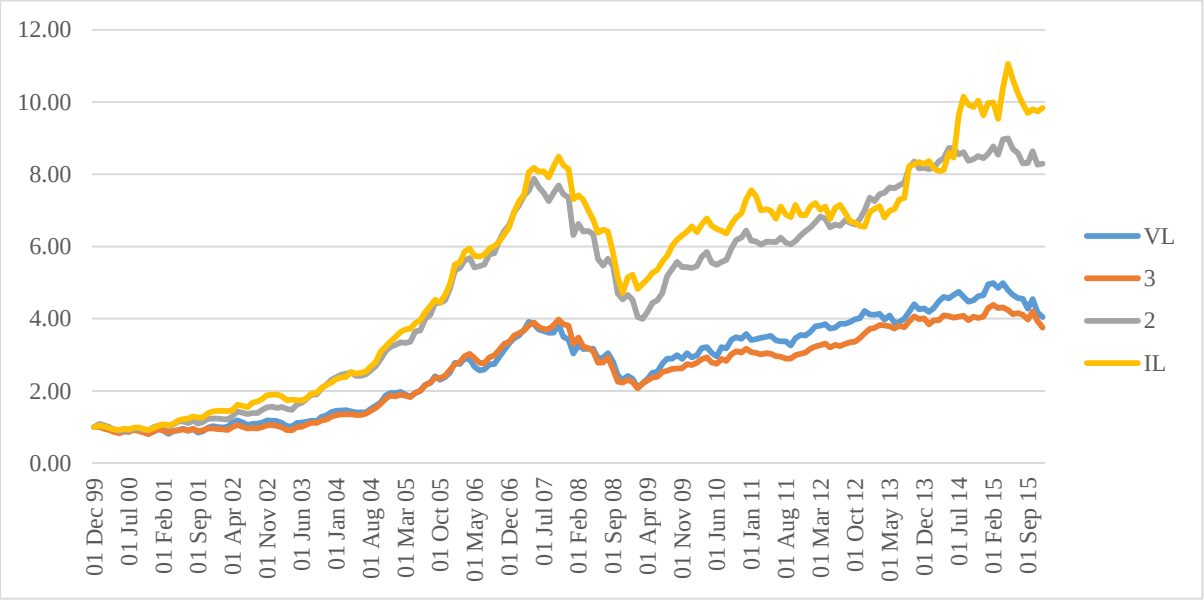
Table 9 below shows the results of the t-test for significant differences of mean monthly returns between the extreme turnover-sorted portfolios. The p-values indicate that there is a significant difference between the mean of the two portfolios with over 99% confidence. This is in line with the previous findings of this paper in providing evidence of a liquidity premium. The specific differences in liquidity dimensions between the three variables and between the extreme portfolios for each suggest either a multi-dimensionality to liquidity in concordance with Liu (2006), or a degree of correlation between the three variables proxying for the same effect.

Table 9: Turnover Quartiles t-Test

	VL	*IL*
Mean	0.007261	0.02393
Variance	0.002127	0.004523
Observations	192	192
Pooled Variance	0.003325	
Hypothesized Mean Difference	0	
Df	382	
t Stat	-2.83237	
P(T<=t) one-tail	0.002433	
t Critical one-tail	1.648852	
P(T<=t) two-tail	0.004865	
t Critical two-tail	1.966194	

Figure 4 shows the indexed growth of R1 invested in the relevant turnover-sorted portfolios of the price-filtered sample over time. This representation shows that the turnover effect remains significant for the adjusted sample and as such provides supporting evidence for the existence of a liquidity premium. This provides evidence towards the position that the liquidity effect is a priced risk and not merely capturing the excessive returns to low price 'micro-stocks'.

Figure 4: Turnover-sorted portfolios (R3 Price Filter)



4.1.6 Liquidity Quartile Characteristics

The liquidity variables analysed in this paper have exhibited similar behaviours with regard to sorted portfolios' monthly returns. All IL–VL liquidity sorted portfolio differences are significant at the 1% level. In order to further investigate the pervasive effects common to these sorted portfolios and liquidity variables, the characteristics of all sorted quartiles are analysed in Table 10.

Table 10: Liquidity Quartiles Characteristics (LM, RtV and Turnover-sorted Portfolios)

	LM				RtV			
	IL	2	3	VL	IL	2	3	VL
Returns	3.322%	0.681%	0.700%	0.705%	3.73%	0.70%	0.48%	0.63%
ln(MCap)	18.17	19.59	21.12	23.15	17.87	19.56	21.15	23.44
B/M	2.12	1.13	0.88	0.56	2.15	1.19	0.74	0.62
LM	160.6713	54.23819	8.193442	0.174725	141.6059	59.70642	20.0857	1.529401
RtV	0.00024	2.27E-06	2.09E-07	1.42E-09	0.000242	9.01E-08	6.02E-09	2.98E-10
Turnover	0.77%	1.63%	2.38%	5.08%	0.82%	1.66%	2.59%	4.91%
E/P	-0.27	-0.03	0.02	0.06	-0.34	-0.01	0.06	0.07
CF/P	0.35	8.05	4.98	0.14	0.29	11.69	0.91	0.16
	Turnover							
	IL	**2**	**3**	**VL**				
Returns	2.39%	1.29%	0.88%	0.73%				
ln(MCap)	18.87	19.76	20.93	22.24				
B/M	2.08	1.11	0.95	0.73				
LM	135.7499	63.7898	27.06922	9.705609				
RtV	0.000275	3.88E-06	1.07E-05	5.48E-06				
Turnover	0.28%	1.09%	2.42%	5.83%				
E/P	-0.21	-0.06	0.02	0.01				
CF/P	2.77	9.87	0.41	0.13				

The similarity in portfolio composition is clearly portrayed in the table shown above. The similarities between the RtV and LM sorted portfolios are most striking. All three variables are clearly correlated with one another (as the LM and RtV variable values decrease and turnover value increases monotonically as the portfolio is more liquid in all three sorts) and a relationship is present, this likely means that they are all suitable proxies for the liquidity effect. The market cap for all portfolios adheres to the expectation gleaned from the correlation matrix in the descriptive statistics section that as liquidity decreases, the size of the average company in the portfolio decreases steadily. This relationship remains constant in all the portfolio sorting variables. An interesting relationship to note is the strong negative relationship between the BM variable and liquidity in the case of all three liquidity variables, this is observed through the decreasing BM variable value as the portfolio becomes more liquid. This suggests that the illiquid shares are generally value shares with a high book-to-market ratio and that the liquid shares are generally 'glamour' shares with a low book-to-market ratio.

There seems to be a clear relationship between liquidity and the Fama-French core effects of size and value, which are represented in this study as the variables ln(MCap) and BM respectively. This, along with the aforementioned size relationship, suggests that either there

is a strong relationship between these value and size effects and liquidity risk, or that the BM and size variables are proxies for distress and liquidity risk which is more accurately captured through the use of a liquidity variable. This would lead to the most accurate pricing model being that posited by Liu (2006), effectively utilising a liquidity-adjusted CAPM.

It is likewise notable that the CF/P variable seems to have no defined relationship with liquidity and as such the power of cash flow in capturing distress risk seems to be rather limited. The E/P variable seems to increase with liquidity, however the correlation matrix examined earlier shows that the E/P variable is not strongly correlated with any of the liquidity variables and thus this relationship will require further examination in the regression analysis.

4.1.7 Beta-sorted Portfolios

Previous findings by South African studies such as van Rensburg and Robertson (2003) and Auret and Sinclaire (2006) have found that Beta as defined by the traditional CAPM has an insignificant effect on predicting stock returns, however for the sake of completeness a sorting procedure is performed on the pre-ranking Betas of the sample and the results of this procedure are analysed. Beta is estimated using rolling 36-month period prior to the month in question in order to try predict the returns of the month in question. The research of Sharpe (1964) and Lintner (1965) provides that the returns to a stock can be explained by its degree of exposure to the systematic risk of the market. This theory holds the intuitive assumption that idiosyncratic factors of a stock do not factor into its pricing, this is because rational investors will diversify the idiosyncratic stock factors and thus will price the relevant security in accordance with its exposure to undiversifiable systematic risk. As such, it would be expected that those stocks with a higher Beta should provide a higher return due to their increased exposure to systematic risk. However, as shown in Table 11, this is not the case.

Table 11: Beta Quartiles Mean Monthly Returns

Beta	High	3	2	Low
Ave Returns	1.40%	0.76%	1.38%	1.71%

Table 11 shows that the portfolio with the highest average monthly return is the Low Beta portfolio. This is in stark contrast with the seminal literature on the Capital Asset Pricing Model of Sharpe (1964) and Lintner (1965), in fact the overall power of Beta is called in to question

as the portfolios with the highest average returns are the extreme portfolios, and thus no clear relationship is immediately present. Table 12 shows a t-test for difference of means between the extreme monthly portfolios sorted by Beta.

Table 12: Beta Quartiles t-Test

	High Beta	*Low Beta*
Mean	0.01396455	0.017090454
Variance	0.004630794	0.002634739
Observations	192	192
Pooled Variance	0.003632767	
Hypothesized Mean Difference	0	
df	382	
t Stat	-0.508150699	
P(T<=t) one-tail	0.305820482	
t Critical one-tail	1.648852302	
P(T<=t) two-tail	0.611640965	
t Critical two-tail	1.966193507	

The findings of Table 12 concur with the original rudimentary analysis of the average returns to the monthly Beta-sorted portfolios. The p-value for the difference in means between the two extreme portfolios is not significant, thus the analysis confirms the initial observation that sorting portfolios on Beta provides no significant difference in returns. Although this does not bode well for the efficacy of the original CAPM methodology, the market risk premium factor will still be tested within a regression analysis in the next section. Additionally, although the average monthly return to a high beta portfolio may be lower than a low beta portfolio, the Beta variable may have more of an effect on the variance of the portfolio than the average returns, on this note, it should be observed that the High Beta portfolio variance is nearly double that of the Low Beta portfolio.

Figure 5: Beta Quartiles Indexed Returns

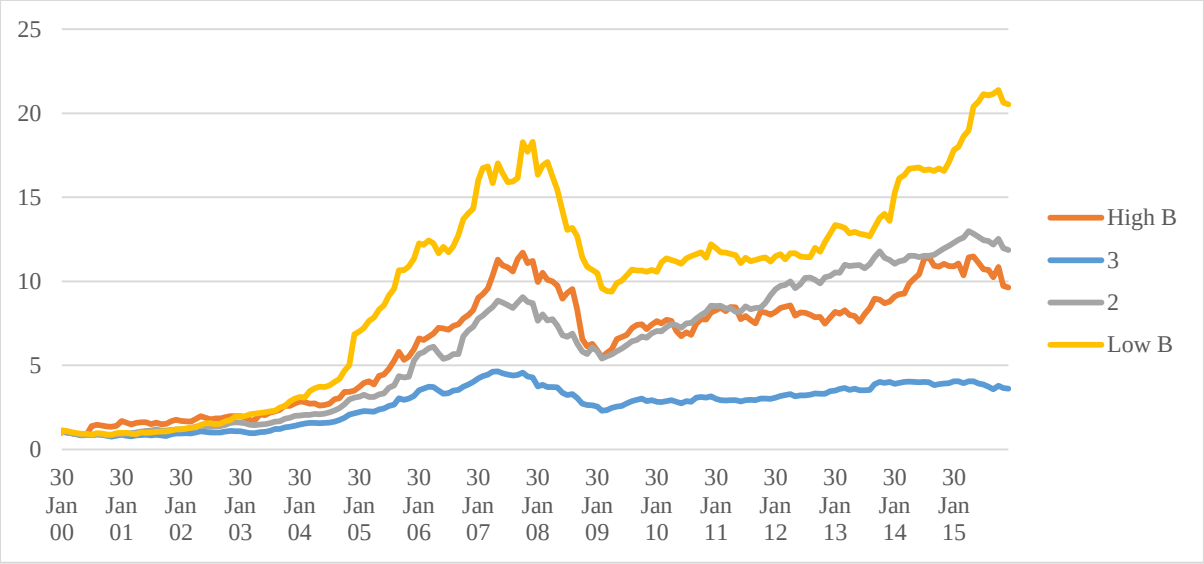


Figure 5 provides a graphical representation of the indexed growth from investing one rand into each of the beta-sorted portfolios, similar to the graphical observations made on the liquidity variables earlier. The portfolios seem to perform similarly and the relevance of Beta is once again called into question, as the low Beta portfolio outperforms the other sorted portfolios over the period. Although this simple graphical presentation of portfolio growth does not provide any ultimate conclusion, the analysis thus far has not supported the role of Beta in determining asset returns in the South African context.

Table 13: Beta Quartiles Characteristics

	Beta			
	High	3	2	Low
Returns	1.40%	0.76%	1.38%	1.71%
ln(Mcap)	20.68014	21.22732114	20.66453	18.92119
B/M	1.406124	0.969145543	1.052362	1.62119
LM	45.86806	35.05729906	50.90028	98.27851
RtV	0.014%	0.002%	0.003%	0.006%
Turnover	2.92%	2.86%	2.18%	1.50%
E/P	-0.15622	-0.04967438	-0.06805	-0.14791
CF/P	0.807009	1.432036327	4.77369	4.838836

Table 13 above outlines the characteristics of each of the Beta-sorted portfolios and once again displays a lack of a significant pattern. The Low Beta portfolio consists of the smallest companies, as well as those with highest CF/P and B/M variables.

The Fama-French variables do not provide a consistent pattern across the beta portfolios however and no real inferences can be made using the Fama French factor variables. The liquidity variables likewise do not present a strong relationship across the portfolios as the ranked liquidity order of beta-sorted portfolios differs for each liquidity variable. One relationship that does seem to stand out however is the inverse relationship between CF/P and Beta, showing that as Beta increases, the CF/P of the company decreases. This could provide some insight into the characteristics of low Beta firms and supports the returns findings in the table above in showing that the low Beta portfolio is the best performing quartile overall, thus portraying an intuitive relationship between cash flow and returns.

Although this analysis is by no means final, the theoretical relationship of Beta seems to not hold well in the South African Market.

The findings of the above analysis agree with those of van Rensburg and Robertson (2003). The Beta variable seems to hold no explanatory power on JSE returns, whether this is due to the illiquidity of the market, the relatively high risk-free rate, the disparity in liquidity on the JSE or some unknown factor is unclear. Whether this irrelevance of the Beta variable is confined to the JSE or is systematically found amongst developing markets merits further research.

4.2 REGRESSION ANALYSIS

4.2.1 Regression Variables

For the purposes of the initial regression testing, the analysis follows a similar methodology to that employed by Auret and Sinclaire (2006). Initial univariate regressions are run on each of the regression variables defined previously, and then the regression is extended to include multiple variables in order to assess whether effects are subsumed. The regressions are run on the LM-sorted portfolios described in the previous section as well as on the entire portfolio of stocks. The choice of the LM variable for sorting was made in order to ascertain whether meaningful differences could be inferred on the behaviour of portfolio returns and how this is affected by their liquidity as defined by Liu (2006).

It is important to note that the initial regressions are performed given the assumption that each portfolio is treated as an individual asset for the purposes of the explanatory variable analysis. This means that the variables for the initial regression are as follows:

Univariate Regressions:

$$R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} A_t \quad (2)$$

Multivariate Regressions:

$$R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} A_t + \lambda_{2,t+1} B_t + \lambda_{3,t+1} C_t + \cdots + \varepsilon_t \quad (3)$$

Dependent variables ($R_{i,t+1}$) refer to the excess returns to the equally-weighted portfolio in question at month $t + 1$. Independent variables (A_t, B_t, C_t) refer to the portfolio variable value (BM, RtV, LM, etc.) for the portfolio in question at month t.

This methodology would therefore test, for example, the effect of the portfolio average BM ratio movements on the portfolio returns over time, thus treating each portfolio as an individual asset with dependent and independent variables equal to the average variables for the portfolio at each month. Although this approach to regression may not be powerful on its own, the second set of regressions will analyse the portfolio returns in a similar fashion to that of Liu (2006) and Fama and French (1992), through the construction of mimicking portfolios in order to determine the explanatory power of existing models. The efficacy of each of the models tested through this set of regressions will be analysed by observing the significance of the intercept term in accordance with the methodology of Jensen (1968). Thus, the two approaches to the regression independent variables will together provide an in-depth and accurate analysis on the variable effects.

4.2.2 Portfolio Univariate Regressions

The first set of regressions run is an analysis on the separate explanatory of each variable on the returns to the total and liquidity-sorted portfolios. Univariate regressions are run in accordance with the methodology described previously, and the results of these separate univariate regressions are described in Table 14.

Table 14: Univariate Regressions

Regressions are run using the following model: $\boldsymbol{R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1} A_t}$. IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{A_t}$ refers to the independent variables denoted in the leftmost column.

	IL	2	3	VL	Total Portfolio
LM	**0.0009 (0.00)**	**0.00045 (0.00)**	0.000757 (0.08)	-0.0060 (0.44)	**0.000881 (0.00)**
RtV	**30.43 (0.00)**	**1599.77 (0.00)**	2466.07 (0.33)	-2074568.96 (0.36)	**70.92 (0.00)**
Turnover	-2.366 (0.42)	-1.52 (0.09)	-0.3714 (0.59)	-0.489 (0.21)	**-3.51 (0.00)**
Size	**-0.031 (0.00)**	-0.0086 (0.06)	-0.0024 (0.49)	0.0027 (0.67)	**-0.0134 (0.00)**
BM	**0.0186 (0.00)**	**0.0148 (0.02)**	-0.01102 (0.22)	0.012 (0.74)	**0.038 (0.00)**
EP	0.0086 (0.64)	0.00005 (0.99)	0.002615 (0.88)	-0.003 (0.94)	-0.01 (0.67)
CFP	0.0058 (0.35)	**-0.00039 (0.00)**	-0.0001 (0.48)	0.1139 (0.07)	**-0.001372 (0.00)**
MRP	**0.331 (0.00)**	**0.501 (0.00)**	**0.607 (0.00)**	**0.82 (0.00)**	**0.557 (0.00)**

The amounts before the parentheses represent the coefficient of each variable in its univariate regression, and the amounts within the parentheses reflect the p-values of the coefficients of each variable in each univariate regression. Those values that are significant at the 5% level are bold to signify such.

The LM liquidity variable of Liu (2006) shows significant explanatory power in the two more illiquid quartiles of the portfolio sort as well as in the total portfolio. The coefficient for the most liquid portfolio however, is not significant even at the 10% level. This suggests that the liquidity effect is more pronounced among less liquid stocks and perhaps that in the South African market, once a certain threshold of liquidity is reached, the premium on relative liquidity becomes insignificant. The findings for this variable agree with the research of Liu (2006), who finds that the less liquid portfolios have higher, more significant coefficients with the LM variable, suggesting that they are more affected by liquidity risk than the liquid

portfolios. The RtV variable exhibits similar traits to the performance of the LM variable, in that the explanatory power of the variable seems to fall away in the more liquid quartiles. It is, however, also significant at the total portfolio level. Both variables also exhibit the expected positive relationship in those portfolios that they hold significant explanatory power. It is interesting to note that in the most liquid portfolio, both variables exhibit the opposite relationship to that which is expected, although not much can be drawn from this observation due to the insignificance of the coefficients. The Turnover variable is anomalous in that it is only significant at the 5% level in terms of the overall portfolio and not in any of the LM-sorted quartiles. The variable is significant at the 10% level for quartile 2 however. The relationship, although insignificant, is negative as expected.

The univariate analysis on the liquidity variables proves promising for evidence of a liquidity premium as all three variables are significant in explaining the total portfolio returns at the 1% level, although this is somewhat muted by the fact that none of the liquidity variables are significant in the more liquid quartiles of the portfolio sorts.

The variables that provide a base for the Fama-French model also exhibit non-static relationships with the sorted liquidity portfolios. Size (calculated as the average natural logarithm of the portfolio constituents' market caps) seems to likewise only significantly explain portfolio returns for the least liquid quartiles and the total portfolio. The size variable is significant at the 1% level for the IL portfolio and at the 10% level for the second quartile. It is significant at 1% for the total portfolio as well. Clearly there is a size factor present, particularly in the less liquid portfolios, and this variable is therefore further analysed in the multivariate regressions and mimicking portfolio regression analysis. Likewise, although significant at a 1% level for the overall portfolio, the book-to-market ratio variable is only significant at the 5% level for the two least liquid quartiles. This transient relationship across the liquidity spectrum merits further investigation and as such a further test of the HML portfolio, for which this variable provides a theoretical base, is performed in the final sets of the regressions. Overall the Fama-French effects seem to provide explanatory power on a univariate basis, however the extent to which these variables explain similar effects remains to be tested.

The earnings-to-price ratio is the only variable that is not significant in explaining returns of the total portfolio. The variable seems to have no significant explanatory power on any of the

portfolio quartiles with p-values of more than 50% for all dependent variable sets. Whether this is due to an anomaly in the data or an unknown latent effect is unknown. The findings of van Rensburg and Robertson (2003) state that Price/Earnings is one of the most powerful variables in explaining asset returns on the South African market, however these findings have failed to concur with that sentiment. The difference in findings may have arisen from the fact that the EP ratios drawn from the iNet database are updated continuously in accordance with the latest market price of the security. Accordingly, the earnings-to-price ratio may be affected by large shifts in the monthly price or earnings which could theoretically distort the explanatory power of the variable. The accuracy of the continuously updated variable is, however, deemed sufficient for the purposes of this study. The cash flow-to-price ratio is significant at the 1% level for the total portfolio and for quartile 2. It is also significant at the 10% level for the most liquid quartile. These findings suggest that the cash flow of a firm may not play as important of a role in explaining asset returns, thereby disagreeing with the findings of Da (2009), who found that cash flow models have significant explanatory power on firm returns.

Lastly, the market risk premium yields, in a univariate analysis, a Beta of 0.557 for the overall portfolio and is significant for each of the portfolio quartiles in question. This bodes well for the traditional CAPM formula however the extent to which this variable explains the variance in portfolio returns over time is unclear from this initial regression. This will be tested in the later regression section. It is also noted that the coefficient of the market premium (Beta) seems to decrease monotonically across the liquidity quartiles as liquidity decreases. This confirms the original analysis of Table 13 in showing that lower Beta firms are in fact less liquid, thus the higher returns generated by lower beta firms as shown in the same table must be explained by some factor other in addition to Beta. It should also be noted that the seemingly stable positive relationship between MRP and liquidity in Table 13 contrasts with the lack of pattern exhibited in the liquidity variables sorted across Beta quartiles in Table 12.

Overall the univariate regression analysis provides support for the liquidity premium, although mainly concentrated on the illiquid portfolios, as well as the traditional CAPM methodology. The size and BM variables provide support for the explanatory power of the Fama-French fundamental effects from the perspective of the total portfolio, but this is hampered somewhat by the fact that these relationships are not significant across all quartiles of the sample.

The EP and CFP variables are found to be sporadic in explaining asset returns and provide no consistent relationship with the dependent variables.

4.2.3 Portfolio Multivariate Regressions

In order to elaborate on the findings of the univariate regressions, various multivariate regressions are run. As before, this section treats each portfolio as a single asset for the purposes of this time-series regression, and as such measures the effect of a change in the portfolio average explanatory variable on the portfolio average return. The findings of the various multivariate regressions run in this manner are shown in Table 15.

Table 15: Multivariate Regressions

Regressions are run using the following model: $\boldsymbol{R_{i,t+1} = \lambda_{0,t+1} + \lambda_{1,t+1}A_t + \lambda_{2,t+1}B_t + \lambda_{3,t+1}C_t + \cdots + \varepsilon_t}$. IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{A_t}$, $\boldsymbol{B_t}$, etc. refer to the independent variables that form part of the multivariate regression which is denoted in the leftmost column.

		IL		2		3		VL		Total Portfolio	
All Liquidity Variables	LM	0.001	*0.00*	0.000	*0.00*	0.001	*0.11*	-0.009	*0.32*	0.000	*0.10*
	RtV	21.24	*0.02*	1 290	*0.03*	1 926	*0.46*	-5 194 017	*0.09*	63.840	*0.00*
	Turnover	4.040	*0.22*	0.054	*0.96*	-0.079	*0.91*	-1.271	*0.01*	-2.190	*0.06*
Fama-French Variables	Size	-0.027	*0.00*	-0.004	*0.38*	-0.004	*0.14*	0.001	*0.84*	-0.010	*0.00*
	BM	0.010	*0.06*	0.012	*0.07*	-0.010	*0.17*	0.009	*0.66*	0.018	*0.06*
	MRP	0.286	*0.00*	0.502	*0.00*	0.602	*0.00*	0.821	*0.00*	0.548	*0.00*
Fama-French & Turnover	Size	-0.026	*0.00*	-0.004	*0.37*	-0.006	*0.04*	0.003	*0.44*	-0.010	*0.00*
	BM	0.011	*0.05*	0.011	*0.16*	-0.017	*0.04*	-0.002	*0.94*	-0.005	*0.73*
	MRP	0.283	*0.00*	0.501	*0.00*	0.599	*0.00*	0.817	*0.00*	0.543	*0.00*
	Turnover	-2.237	*0.41*	-0.194	*0.82*	-1.032	*0.07*	-0.276	*0.32*	-2.366	*0.02*
Fama-French & RtV	RtV	11.890	*0.21*	557	*0.27*	1 419	*0.43*	-289 265	0.90	**39.180**	***0.00***
	Size	-0.025	*0.00*	-0.004	*0.39*	-0.004	*0.14*	0.000	1.00	**-0.007**	***0.03***
	BM	0.008	*0.19*	0.010	*0.12*	-0.010	*0.16*	0.010	0.65	**0.029**	***0.01***
	MRP	0.276	*0.00*	0.494	*0.00*	0.601	*0.00*	0.820	0.00	**0.531**	***0.00***
Fama-French & LM	LM	0.000	*0.95*	0.001	*0.00*	0.002	*0.00*	-0.005	*0.36*	0.001	*0.06*
	Size	-0.026	*0.01*	0.015	*0.03*	0.006	*0.17*	-0.002	*0.70*	-0.003	*0.52*
	BM	0.010	*0.06*	0.004	*0.53*	-0.011	*0.12*	0.013	*0.52*	0.013	*0.20*
	MRP	0.285	*0.00*	0.486	*0.00*	0.603	*0.00*	0.820	*0.00*	0.544	*0.00*
All Variables	LM	-0.0005	0.45	0.001	0.00	0.002	0.02	-0.004	0.41	0.00012	0.75
	RtV	6.993	0.47	782	0.11	803	0.66	817 842	0.73	35.216	0.02
	Turnover	-6.653	0.18	1.582	0.13	0.287	0.72	-0.621	0.04	-2.923	0.06
	Size	-0.037	0.01	0.019	0.01	0.007	0.28	-0.003	0.68	-0.002	0.75
	BM	0.030	0.00	0.002	0.80	-0.010	0.23	-0.043	0.16	-0.015	0.36
	EP	0.08028	0.00	0.01424	0.30	0.00281	0.82	-0.00204	0.93	0.05014	0.05
	CFP	-0.020	0.07	0.000	0.01	0.000	0.49	0.141	0.01	-0.001	0.17
	MRP	0.313	0.00	0.465	0.00	0.601	0.00	0.803	0.00	0.531	0.00

The first multivariate regression analyses the interaction between and the explanatory power of the three liquidity variables used in this study. The LM variable of Liu (2006) interestingly becomes insignificant in explaining changes in average returns on the entire portfolio once included with the RtV and Turnover variables (although marginally so). The Turnover variable is significant at the 10% level for the total portfolio and is significant for only the most liquid quartile of the liquidity sort. The RtV portfolio is significant at the 5% level for both the more illiquid quartiles as well as the total portfolio, and at a 10% level for the most liquid portfolio. Although the explanatory power of RtV is clearly shown, the extent to which it captures liquidity alone is unknown. The concerns relating to this variable with regards to its underlying return-based anomalies have been raised and should be kept in mind whilst analysing these outputs. The main effect of including all these variables together in a regression is that the power of both liquidity and turnover has decreased, thus suggesting that they account for similar effects. This is further reinforced by the relatively high negative correlation between liquidity and turnover shown in Table 3.

A multivariate regression is likewise run on the variables that constitute the effects posited by Fama and French (1992). It is noted that all variables are significant at the 10% level for the total portfolio, with the BM variable being the sole variable not significant at the 5% level. The market premium variable remains significant across all liquidity quartiles, whereas the size and BM variables only seem to significantly explain portfolio returns, in conjunction with the market risk premium, for the more illiquid sets of portfolios. The analysis of the Fama-French model (with variables SMB and HML) is performed in the next section, however these findings based on the core portfolio averages of the fundamental variables (rather than the return to the mimicking portfolios) provide moderate support for the efficacy of the model.

In order to test the separate nature of the liquidity effect and size/value effects, three separate multivariate regressions are run, comprising of the Fama-French variables as before and a different liquidity variable for each regression. The first of these is performed by including the portfolio turnover as an explanatory variable along with the portfolio BM and Size ratios, as well as the market risk premium at each point. It is interesting to note that the portfolio turnover, size and market risk premium variables are all significant at the 5% level for the overall portfolio in explaining portfolio returns over time. The book to market ratio of the stocks is insignificant at almost every quartile as well as at the overall level. Comparing this to the initial

univariate findings which found BM to be significant for the total portfolio, it can be inferred that the underlying factor relating to the BM variable is captured by a combination of size and liquidity.

The only regression to have all variables significant at the 5% level for the total portfolio is the model containing portfolio size, BM ratio, Return-to-volume and the market risk premium as explanatory variables. All variables are significant only for the total portfolio however, and the significance varies dramatically for all variables across the liquidity quartiles, with the exception of the market risk premium variable which remains significant throughout. This provides support for the assertions of Liu (2006) and Amihud (2002) that the liquidity effect does play an important role in explaining stock returns and that this effect is a separate effect to the documented size and value effects. The RtV variable shows the importance of price impact in predicting portfolio returns, particularly amongst the lowest quintile of South African firms. The evidence of such an anomaly is sparse in South African literature but this may be due to the weak filter employed in this study. Nevertheless, it seems that there is a persistent effect relating to the price impact and liquidity and this may merit further research.

The inclusion of the LM variable of Liu (2006) with size, BM and MRP in a regression yields interesting results. The inclusion of LM with size has seemed to dull the explanatory power of both variables and size in particular. The LM variable is significant at the 10% level and the MRP variable at the 1% level for the overall portfolio. It is interesting to note that the univariate regression of portfolio LM on portfolio returns exhibited significant explanatory power at the illiquid quartile. With the introduction of the Fama-French-based variables however, the LM variable is deemed to only have significant explanatory power on the two middle quartiles and neither of the extreme quartiles. Given the previously posited relationship between size and liquidity, and as the correlation between the two discovered earlier has shown, it is apparent that there is some overlap between the two effects and a definitive relationship exists.

Lastly, a multivariate regression is run regressing all the portfolio-level variables on the monthly portfolio returns. A model of this many variables is not expected to provide much explanatory power as there will be many conflicting relationships and correlated variables within the model. The only two variables that are significant at the 5% level for the total portfolio are the MRP and RtV variables.

The inclusion of all these variables has the effect that the liquidity variables struggle to explain portfolio returns at the most illiquid quartile, with the most significant factors at this quartile being portfolio EP, size, market risk premium and book-to-market ratio. Overall the inclusion of all the variables has no further enhancing effect on the explanatory power of said variables and no conclusive remarks can be made relating to this all-factor regression.

Through the analysis conducted herein, it has been observed that portfolio average liquidity does have a significant bearing on the expected returns to that portfolio. This finding supports the findings of Liu (2006) who found his LM measure to be significant in explaining the cross-section of returns. The only variable to be significant at every quartile for every regression that it was included in was the MRP variable. This provides resounding support for the work of Sharpe (1964) and Lintner (1965) in validating the usefulness of CAPM in predicting stock returns. However, although this variable is unarguably significant, the extent to which it explains returns may be somewhat muted. According to the CAPM framework, a stock should be priced in accordance with its exposure to systematic risk only. However, this study, and the works of Fama and French (1993), Liu (2006), Auret and Sinclaire (2006) and many others have found that there are elements of idiosyncratic factors that affect the pricing of assets. This time-series regression analysis agrees with the fact that although systematic risk is a significant factor in pricing assets, it does not even nearly fully explain the pricing of assets. Those assets that are less liquid are particularly affected by other factors such as size it seems. This may, however, be due to the fact that illiquid companies are generally smaller (as shown by the correlation in Table 3) and as such will be predicted less reliably by the market risk premium given that the J203 is used as a market proxy. This is because the J203 is a value-weighted index and thus will barely reflect the performance of small firm constituents in its performance.

4.2.4 Portfolio Model Regressions

The regressions conducted thus far have examined the use of core portfolio variables such as size, BM ratio and LM in order to explain portfolio returns. These variables form the basis of many seminal asset-pricing models. Breeden (1979) shows how a mimicking portfolio can provide a suitable proxy for these core variable effects. As such, mimicking portfolios are constructed in order to capture the premium associated with the value and size effects as well as the liquidity effect at each month in the sample period. This regression analysis will analyse

the portfolio returns at each month (over the sample period of 16 years) and their relationship with the mimicking portfolios constructed at each month. These mimicking portfolios are updated monthly in order to provide the maximum amount of accuracy. Although the power of this type of regression may be limited as the dependent variables only consist of the portfolio returns (particularly in the case of the liquidity variable, as portfolios are sorted on the underlying LM variable), the analysis is determined robust from the total portfolio perspective. An additional set of cross-sectional analyses is conducted following this regression analysis in order to provide robustness to the methodology and findings of this study.

Table 16: Correlation Matrix (LIQ, MRP, HML, SMB)

	LIQ	***MRP***	***HML***	***SMB***
LIQ	1			
MRP	-0.33838	1		
HML	0.324265	-0.11176	1	
SMB	0.60112	-0.32854	0.475139	1

Table 16 shows the correlation matrix of the independent variables used in this set of regressions. Although the signs differ due to the nature of the variables' construction, strong similarities are drawn between this Table 16 and Table 3 of the initial portfolio-based analysis. The notable correlation is once again between liquidity and size. As discussed, although intuitively simple to understand, this relationship may have many dimensions. This table shows similar correlations to those found by Liu (2006), with a negative correlation between LIQ and MRP, and between HML and the market. The negative relationship between LIQ and MRP is expected, as Liu (2006) states in his analysis that the liquidity premium becomes more significant in investor decisions when the market performs badly as the market becomes less liquid and thus they would require a higher return in order to take on the extra liquidity risk in a down state. The size variable shows different relationships to that found by Liu (2006) however, as the correlation between SMB and MRP is quite high at 0.6, suggesting that the larger stocks are in fact the more liquid stocks in South Africa. This highlights a factor that perhaps differs between emerging and developed markets. The first regression analysis performed through the use of the independent mimicking portfolio variables is an analysis on the model that constitutes the foundation of asset-pricing theory, the CAPM. The results of this regression are shown in Table 17.

Table 17: CAPM Regression Results

This regression is run using the following model: $\boldsymbol{R_{i,t} = \lambda_{0,t} + \lambda_{1,t} MRP_t + \varepsilon_t}$ as posited by Sharpe (1964) and Lintner (1965). IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{MRP_t}$ refers to the independent variables at time $\boldsymbol{t}$ as discussed in section 3.

CAPM						
		IL	2	3	VL	Total Portfolio
Intercept	Value	**0.025333**	-0.00178	-0.00202	-0.00289	**0.00429230**
	p-Value	*0.00*	*0.46*	*0.36*	*0.11*	*0.05*
MRP	Coefficient	**0.331336**	**0.500423**	**0.606896**	**0.821227**	**0.55765243**
	p-Value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
Regression Statistics						
R Square		**0.05**	**0.36**	**0.50**	**0.73**	**0.47**
Adjusted R Square		0.05	0.35	0.49	0.73	0.47
Standard Error		0.07	0.03	0.03	0.03	0.03

The results for the CAPM regression effectively replicate the MRP univariate analysis shown in Table 14. Further observations can be made, however, now that the reader is armed with the intercept (α) term and the regression statistics. The portfolio coefficient is significant at the 5% level and as such, although the market risk premium significantly explains portfolio excess returns, the model is not satisfactory in accurately predicting the dependent variable. This view is further reinforced by the adjusted R Squared of the model. The adjusted R Squared for the illiquid portfolio is especially low, and R squared values are expected to be relatively high given that the dependent variable is portfolio excess returns and not individual stock returns, thus a lot of idiosyncratic effects which the explanatory variables may struggle to explain are diversified away in the calculation of the dependent variable. Overall, this confirms the findings thus far on CAPM in that it seems to explain the movements in liquid portfolio returns well, but does not explain all the effects present in the illiquid portfolio return-generating process. Additionally, it seems that as the liquidity of a portfolio decreases, the lower its Beta becomes and the higher its return becomes. This is in stark contrast to the seminal literature and theoretical relationship of the market risk premium. As mentioned previously however, the relative lack of power of the market risk premium in fully explaining illiquid stock returns may be due to the construction of the index that is used as a market proxy for this study.

Table 18: Fama-French Model Regression Results

This regression is run using the following model: $\boldsymbol{R_{i,t} = \lambda_{0,t} + \lambda_{1,t} MRP_t + \lambda_{2,t} HML_t + \lambda_{3,t} SMB_t + \varepsilon_t}$ as posited by Fama and French (1992). IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{MRP_t}$, $\boldsymbol{HML_t}$ and $\boldsymbol{SMB_t}$ refer to the independent variables that are obtained through the mimicking portfolio methodology at time $\boldsymbol{t}$ as discussed in section 3.

Fama-French						
		IL	2	3	VL	Total Portfolio
Intercept	Value	0.007233	**-0.00745**	**-0.00492**	-0.00367	**0.00429230**
	p-Value	*0.11*	*0.00*	*0.04*	*0.07*	*0.05*
MRP	Coefficient	**0.601853**	**0.574785**	**0.649418**	**0.834764**	**0.55765243**
	p-Value	*0.00*	*0.00*	*0.00*	*0.00*	*0.00*
HML	Coefficient	0.074052	0.089556	0.016924	-0.00828	0.04217139
	p-Value	*0.41*	*0.07*	*0.72*	*0.84*	*0.28*
SMB	Coefficient	**0.718033**	**0.175333**	**0.111184**	0.03975	**0.29322911**
	p-Value	*0.00*	*0.00*	*0.02*	*0.31*	*0.00*
Regression Statistics						
R Square		**0.36**	**0.44**	**0.52**	**0.73**	**0.63**
Adjusted R Square		0.35	0.43	0.51	0.72	0.63
Standard Error		0.06	0.03	0.03	0.03	0.02

Table 18 constructs a Fama-French model through regression that attempts to explain portfolio excess returns through time. Similar effects are found with mimicking portfolios as previously found with the core variables themselves, thus providing robustness to the underlying effects. The interpretation remains that size is a significant explanatory factor along with beta in explaining stock returns. It is also noted that the adjusted R Squared of this model is 0.63 for the total portfolio, as compared to 0.47 for the traditional CAPM formula. The R Squared is also a lot more consistent across liquidity sorted quartiles. Additionally, the coefficients for the market risk premium (CAPM Beta) do not decrease nearly as much as you move toward the illiquid portfolio. However, the model does exhibit undesirable patterns, as the HML variable that proxies for the value effect is insignificant at the 5% level across all quartiles and for the total portfolio. The intercept is significant at the 5% level for the total portfolio as well, suggesting that there are unexplained factors affecting the variation in portfolio excess returns over time. Once again, the model regression confirms the initial observations of this study and contests the value factor posited by Fama and French (1992). The apparent absence of a value factor may be due to the differing nature of a developing market, or due to the annual variables

used for the purposes of this study and the uncertainty regarding when investors would receive the book-to-market information.

Table 19: Liquidity-Augmented CAPM Regression Results

This regression is run using the following model: $\boldsymbol{R_{i,t} = \lambda_{0,t} + \lambda_{1,t} MRP_t + \lambda_{2,t} LIQ_t + \varepsilon_t}$ as posited by Liu (2006). IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{MRP_t}$ and $\boldsymbol{LIQ_t}$ refer to the independent variables that are obtained through the mimicking portfolio methodology at time $\boldsymbol{t}$ as discussed in section 3.

Liquidity-Augmented CAPM						
		IL	2	3	VL	Total Portfolio
Intercept	Value	-0.00141	-0.0028	-0.00207	-0.00141	-0.001984
	p-Value	*0.47*	*0.28*	*0.39*	*0.47*	*0.32*
MRP	Coefficient	**0.795654**	**0.518239**	**0.607788**	-0.0522	**0.666621**
	p-Value	*0.00*	*0.00*	*0.00*	*0.05*	*0.00*
LIQ	Coefficient	**0.947799**	0.036367	0.001822	**0.795654**	**0.222433**
	p-Value	*0.00*	*0.31*	*0.96*	*0.00*	*0.00*
Regression Statistics						
R Square		**0.88**	**0.36**	**0.50**	**0.73**	**0.61**
Adjusted R Square		0.88	0.35	0.49	0.73	0.60
Standard Error		0.02	0.03	0.03	0.02	0.03

The regression analysis using the liquidity-augmented CAPM model of Liu (2006) shows promising results in Table 19. It should be noted that inferences made based on the results of the extreme quartiles portrayed in Table 19 may be biased as the sorting procedure and LIQ variable make use of the same core LM variable in their computation. Reasonable deductions can be made, however, on the results to the total portfolio. The first and most notable finding is that the intercept term is not significant at the 10% level across quartiles and the total portfolio. The fact that this is true for the middle quartiles as well as the total portfolio strengthens the case for a pervasive liquidity premium. Following the methodology of Jensen (1968), this means that the model performs relatively well in explaining the variation in portfolio returns. The adjusted R squared of the portfolio is 0.61, which is lower than the Fama-French model but higher than the CAPM model. However, both of those models had significant intercept terms. Although these findings will be further analysed in a cross-sectional stock-level excess returns analysis in order to eliminate any bias resulting from the sorting procedure

used, the results are significantly supportive of the model proposed by Liu (2006) from a portfolio excess returns basis.

Lastly, as size is represented as a significant factor throughout this study, a final model regression is run where the LIQ variable is included to the traditional Fama-French model in order to determine whether this 'Liquidity-Augmented Fama-French model' would capture changes in portfolio excess returns more accurately.

Table 20: Liquidity-Augmented Fama-French Model Results

This regression is run using the following model: $\boldsymbol{R_{i,t} = \lambda_{0,t} + \lambda_{1,t} MRP_t + \lambda_{2,t} HML_t + \lambda_{3,t} SMB_t + \lambda_{4,t} LIQ_t + \varepsilon_t}$. IL denotes the most illiquid monthly-rebalanced portfolio at time $\boldsymbol{t}$ and VL the most liquid. The total portfolio dependent variable is simply the return to the entire equally-weighted portfolio at time $\boldsymbol{t}$. $\boldsymbol{MRP_t}$, $\boldsymbol{HML_t}$, $\boldsymbol{SMB_t}$ and $\boldsymbol{LIQ_t}$ refer to the independent variables that are obtained through the mimicking portfolio methodology at time $\boldsymbol{t}$ as discussed in section 3.

Liquidity-Augmented Fama-French						
		IL	2	3	VL	Total Portfolio
Intercept	Value	-0.00261	**-0.006524032**	-0.00415	-0.00261	**-0.0046963**
	p-Value	*0.19*	*0.01*	*0.09*	0.19	*0.02*
LIQ	Coefficient	**0.903121**	**-0.084892807**	-0.07112	**-0.09688**	**0.1272792**
	p-Value	*0.00*	*0.03*	*0.06*	0.00	*0.00*
MRP	Coefficient	**0.8122**	**0.555012528**	**0.632855**	**0.8122**	**0.6991567**
	p-Value	*0.00*	*0.00*	*0.00*	0.00	*0.00*
HML	Coefficient	-0.00031	0.096546038	0.02278	-0.00031	0.0316917
	p-Value	*0.99*	*0.05*	*0.63*	0.99	*0.40*
SMB	Coefficient	**0.105461**	**0.232913871**	**0.159421**	**0.105461**	**0.2068978**
	p-Value	*0.02*	*0.00*	*0.00*	0.02	*0.00*
Regression Statistics						
R Square		**0.88**	**0.45**	**0.53**	**0.74**	**0.67**
Adjusted R Square		0.88	0.44	0.52	0.74	0.66
Standard Error		0.02	0.03	0.03	0.02	0.02

Table 20 shows the regression output of this Liquidity-Augmented Fama-French Model. It is clear that liquidity effect remains significant when included with size, thus suggesting that these variables are not, at least not entirely, proxies for the same underlying factor. The adjusted R Squared is a slight improvement on the original Fama-French model, however the intercept term remains significant, even more so than in the original Fama-French model. As expected, the value effect proxy (HML) is insignificant in explaining portfolio returns over time. It should

be noted that this analysis may also fall prey to the same biases as the liquidity-augmented CAPM due to the sorting procedure followed, however these results will be further analysed with less risk of bias in the relevant total cross-sectional regressions in the next section.

4.2.5 Stacked Sample Cross-Sectional Regressions

The regressions up to this point have analysed the liquidity, market and Fama-French effects from a portfolio-level approach. The analysis has treated portfolios as individual assets in the models of Fama-French (1992) and Sharpe (1964) and Lintner (1965). Although, through the use of different independent variables and portfolio sorts, the findings have been consistent, in this section an additional method of regression analysis is used in an attempt to corroborate the findings of the previous methodology. In this section the regression does not analyse, whether portfolio size or liquidity has significant predictive power on the next month's portfolio returns like the first regression analyses did (sections 4.2.2 & 4.2.3). Nor does this analysis focus on the explanatory power of contemporaneous mimicking portfolio returns in explaining portfolio returns at the given month. This section further tests the previously mentioned mimicking portfolios on a cross-sectional basis across all sample stocks through stacked data, rather than a stratified portfolio-level variable approach. The process analyses whether there is a relationship between the return to the relevant mimicking portfolios and the return to a given stock. This analysis is run on a cross-sectional basis across the entire sample period, with the data being stacked into a single cross-section for analysis. As the dependent variables now relate to specific stocks as assets and not the portfolio itself, the models may lose explanatory power due to the increase in variance to the overall sample of dependent variables, previously this variation was somewhat subdued through the method of calculating portfolio returns on an equally-weighted portfolio (averaging of returns).

Table 21: Stacked Sample Correlation Matrix (LIQ, MRP, HML, SMB)

Correlation Matrix				
	LIQ	MRP	HML	SMB
LIQ	**1**	-0.342	0.327	0.616
MRP	-0.342	**1**	-0.106	-0.325
HML	0.327	-0.106	**1**	0.470
SMB	0.616	-0.325	0.470	**1**

Table 21 shows the correlations between the variables that are used in the stacked sample cross-sectional regression. The correlations follow the same pattern as those found in the previous regressions in Table 16. The liquidity variable has the expected correlations with the other independent variables as found in Liu (2006), with the exception of the SMB variable. This again suggests that the smaller firms are generally less liquid in the South African market. This could suggest that the size factor and liquidity factor may overlap somewhat in their explanatory power. The similarity found in these correlations supports the efficacy of the portfolio-level methodology used earlier and thus supports the inferences made through that analysis. The first stacked sample regression is run on the CAPM following the form:

$$R_i - r_f = \alpha_i + \beta_{i1}(r_m - r_f) \quad (6)$$

Where i refers to a single stock of the sample as opposed to a portfolio. All of the regressions in this section are run over the full sample of stocks in order to arrive at a robust conclusion regarding an appropriate asset-pricing model to be used across the market. The regression results of this traditional model are shown in Table 22.

Table 22: CAPM Stacked Sample Regression Results

CAPM			**Adjusted R^2**	**0.009**
	Value	Standard error	t	Pr > |t|
Intercept	0.004	0.001	3.142	***0.002***
MRP	0.561	0.023	24.442	***< 0.0001***

From the results shown in Table 22 it is clear that the market risk premium is highly significant, at the 1% level, in explaining portfolio returns. The coefficient for MRP is very similar to that obtained in Table 17 and provides support for the explanatory power of the traditional CAPM on the South African market. However, the intercept is likewise significant at the 1% level, which it was also in the previous portfolio-level regression, thus it can be inferred that there are other factors that are not being accounted for in this model. The adjusted R squared is likewise very low which, while expected due to the nature of a cross-sectional regression on

individual stocks as opposed to portfolios of stocks, suggests that there are more factors that must be accounted for in order to obtain a better model.

Overall, the analysis supports the notion that all stocks are exposed to the same base systematic risk, however this analysis rejects the accompanying tenet that a stock is priced only in accordance with its exposure to market risk.

Table 23: Fama-French Model Stacked Sample Regression Results

Fama-French			**Adjusted R^2**	**0.012**
	Value	Standard error	t	Pr > |t|
Intercept	-0.004	0.001	-2.894	***0.004***
MRP	0.670	0.024	27.632	***< 0.0001***
HML	0.043	0.025	1.723	*0.085*
SMB	0.293	0.025	11.805	***< 0.0001***

Table 23 shows the results of the Fama-French model (Fama & French, 1992) regression on the stacked sample. This regression output again confirms the results of the portfolio-level regressions. It is noted that the size and market risk premium variables are significant in explaining stock returns at the 1% level. However, the apparent absence of a value factor is noted once more, as the HML variable is not significant at the 5% level. Although this model improves slightly on the Adjusted R Squared of the CAPM results, the intercept remains significant at the 1% level for all stocks in the sample. As mentioned previously, due to the large size of the stacked sample and the large variability therein the R-squared values may not provide an accurate estimate of the explanatory power of the model. To further illustrate this point, the R-squared for this same model tested on portfolio returns in Table 18 is 0.63 compared to a value of 0.012 for this cross-sectional regression on the stacked sample. As such, model efficacy will continue to be assessed in accordance with past literature by examining the intercept terms of each model (Jensen, 1968). The model itself shows that size is in fact a priced variable along with the systematic risk component and, although the model does not incorporate all factors affecting returns (as shown by the significant intercept), it provides a more accurate depiction than the CAPM alone.

Table 24: Liquidity-Augmented CAPM Stacked Sample Regression Results

Liquidity-Augmented CAPM			**Adjusted R^2**	**0.011**
	Value	Standard error	t	Pr > |t|
Intercept	-0.002	0.001	-1.980	***0.048***
LIQ	0.227	0.017	13.088	***< 0.0001***
MRP	0.670	0.024	27.475	***< 0.0001***

The Liquidity-Augmented model of Liu (2006) is tested on the stacked sample and the results are portrayed in Table 24. The model makes use of mimicking portfolio returns (LIQ), computed as described earlier, as the relevant liquidity proxy for this analysis. It is clear that the liquidity term is significant in explaining stock returns at the 1% level along with the market risk premium. The t-statistic is relatively high, even more so than the size variable in the Fama-French model shown in Table 23. The results of Table 24 corroborate the findings of Table 19 in that the Liquidity-Augmented CAPM provides significant explanatory variables on asset returns. Table 19 also showed that the Liquidity-Augmented CAPM is the only model that has an insignificant intercept term. While the term is significant for the stacked sample in this regression, it should be noted that the term has the lowest t-statistic and value compared to the traditional CAPM and Fama-French models. The variable is also barely significant at the 5% level and is the only variable not significant at the 1% level for the model, suggesting that this model provides the best explanation for individual stock returns tested thus far.

Table 25: Liquidity-Augmented Fama-French Model Stacked Sample Regression Results

Liquidity-Augmented Fama-French			**Adjusted R^2**	**0.012**
	Value	Standard error	t	Pr > |t|
Intercept	-0.005	0.001	-3.861	***0.000***
LIQ	0.127	0.021	6.002	***< 0.0001***
MRP	0.699	0.025	28.279	***< 0.0001***
HML	0.033	0.025	1.326	*0.185*
SMB	0.207	0.029	7.186	***< 0.0001***

A final model regression is performed on the stacked sample, to provide robustness to the findings thus far. The size and liquidity variables seem to both be significant when included in the same model, as shown in the multivariate regressions as well as the model regression of Table 20. Accordingly, the Liquidity-Augmented Fama-French model outlined in the previous section is tested on the full stacked sample to provide clarity on the previous findings, the results of which are shown above in Table 25. The stacked sample regression further corroborates the findings of the portfolio-level regression, with the same variables found to be significant in the model. The HML variable remains insignificant at the 10% level while the size and liquidity proxies remain significant at the 1% level. Although this suggests that the size and liquidity variables do in fact proxy for different effects, the intercept is significant at the 1% level for the model, and as such the model is not improved from the Liquidity-Augmented CAPM through the addition of size. The intercept has in fact the highest t-statistic of all the variables tested in the section thus far, making it the least powerful model according to this analysis' criteria. An interesting note, although not statistically measured, is the change in the size coefficient upon the introduction of the liquidity variable from the previous Fama-French model. Theoretically, a perfect addition to a model would subsume the explanatory power of the intercept and leave the other variable coefficients unchanged. The addition of liquidity into the Fama-French model, however, causes the SMB coefficient to decrease by about a third of its initial value. This, combined with the fact that the MRP and HML coefficients remain largely unchanged, suggests that the liquidity and size variables overlap somewhat in the explanatory power of their underlying effects and that this overlap creates an adverse effect on the explanatory power of the Liquidity-Augmented Fama-French model. This is further reinforced by the correlation between the two variables as well as the fact that both the extreme liquidity and size portfolios outperform the other quartiles significantly.

The analysis of the stacked sample regression results has strongly supported the results found throughout this study. The model regression findings of the portfolio-level regressions are robust to the inclusion of the full stock sample variables. The overall narrative of this regression section has further supported the notion of Amihud and Mendelson (1986) and Liu (2006) that liquidity is a significant variable in the asset-pricing arena and that the exclusion of such a variable would be detrimental to the explanatory power of a model. Although the Fama-French (Fama & French, 1992) model performs better than the traditional CAPM (Sharpe, 1964) and (Lintner, 1965), the model intercept remains large and the HML variable remains insignificant.

The overall consensus of the regressions thus leads to the conclusion that the Liquidity-Augmented CAPM of Liu (2006) provides the best model for use on the South African market. This is in contrast to the findings of Auret and Sinclaire (2006) and van Rensburg and Robertson (2003) who find that models containing the size factor best explain returns on the JSE. The inclusion of the liquidity effect into the Fama-French model provides no improvement to the power of the model as the intercept becomes more significant. There seems to be a definite relationship between size and liquidity and the two variable proxies are perhaps too correlated for simultaneous use in the same model.

5 SUMMARY OF ROBUSTNESS CHECKS

Although the return to volume measure of Amihud (2002) has been adjusted to incorporate only monthly returns, the liquidity effect is still apparent. However, the adjustment to monthly determinants may in fact incorporate other longer term anomalies found in the variable's components, such as returns. Using past monthly returns (the numerator) for the prior year may in fact incorporate widely studied past return anomalies such as momentum or mean reversion. For this reason, amongst others, this study does not rely upon the measure of Amihud (2002) solely and tests three different liquidity variables in order to ensure that the liquidity effect observed is systematic and not an unrelated anomaly unique to the variable itself.

The portfolios analysed throughout this portfolio are equally-weighted portfolios that are rebalanced on a monthly basis. This provides an accurate representation of the most accurate characteristic-based portfolio at every month, however it could lead to the incorporation of a bias in the results based of these portfolio returns as the monthly rebalancing may create returns through the portfolio construction process itself. This is because a portfolio that is rebalanced on a monthly basis will, by virtue of its construction, sell prior month's winners and buy prior month's losers in order to remain equally-weighted. This could lead to an effect on portfolio returns akin to a technical trading strategy. The rationale for the use of monthly rebalancing is that the accuracy of using monthly portfolio rebalancing is seen as of paramount importance to this study in order to ascertain the effects under analysis.

Amihud and Mendelson (1986) provide a bid-ask variable that is presented as capturing the trading costs associated with liquidity. Liu (2006) includes this variable in his study as it captures a dimension of liquidity that is difficult to capture through other means. The omission of such a variable from this study was made only due to the difficulty in obtaining the data required for its accurate construction. As this variable differs greatly in its construction from the other liquidity variables used in this study it may have provided greater insight into the liquidity effect, especially relating to the relationship between size and liquidity. This provides a further avenue for research on the topic within a South African context, as such a variable may benefit existing models (such as the Fama-French model) through its inclusion.

The liquidity filter applied in this study is rather weak as it only excludes stocks with greater than 200 zero-trading days per year. However, as this study is focussed on liquidity effects it seems counter-productive to implement a stringent liquidity filter as this may adversely bias the results, particularly if liquidity is more significant in explaining returns to less liquid firms (as seems to be the case). Any bias incurred through use of this filter level is somewhat mitigated by the fact that, assuming liquidity captures distress risk as posited by Liu (2006), stocks delisting during the sample period are given a -100% return. The construction of the methodology together with such a filter is deemed an accurate methodology for the purposes of this study.

It is noted that the data retrieved from the iNet BFA database may not always be correctly adjusted for stock splits and corporate actions. The analysis uses multiple methodologies in order to provide a robust analysis and provides an analysis in which the data is divided into liquidity quartiles. As such, any bias which may occur due to corporate actions would be unlikely to be concentrated on one specific quartile and thus would not significantly affect the tests for differences between quartiles. The nature of this study is not to determine whether a benchmark can be outperformed through a trading strategy, in which case systematic bias due to non-stationarity caused by corporate actions would be detrimental.

Lastly, the inclusion of return-based time-series anomalies that have been documented in related literature may provide an enhancement of the models tested within this study. The effects of momentum (Carhart, 1997) or mean-reversion variables (De Bondt & Thaler, 1985) may provide a clearer picture on the interaction of fundamental factors and return-based effects within the asset-pricing environment. This provides a further avenue for research particularly within the South African market, as the research on a model incorporating both liquidity and momentum may prove useful in explaining stock returns.

The limitations to this study are deemed to have no significant adverse bias on the results of this study, given that the goal of this study is to determine if liquidity is a significant explanatory variable in the asset-pricing framework and to determine its relationship with size.

6 CONCLUSION

This section reiterates the research objectives and consolidates the analysis of results to present an overall view of the findings as well as recommendations for further avenues of research. The core hypotheses of this research are twofold, namely to analyse the explanatory power of a liquidity variable on asset returns to determine whether a significant liquidity premium exists and to determine the extent to which this liquidity premium interacts with size, thereby determining whether this liquidity effect is separate from the well-documented size effect.

The analysis was performed through various methodologies in order to ensure robust findings. To this end, the analysis was divided into two main sections, a portfolio sort and differences analysis as well as a regression analysis section.

The portfolio sort analysis involved t-tests for significant difference of means between extreme portfolios sorted on 3 different liquidity variables and size as well as a graphical and means analysis of the sorted portfolio performance. This analysis clearly showed that there is a significant difference in performance between the extreme liquidity portfolios and size portfolios. This analysis agreed with the sentiment of Liu (2006) that liquidity is a priced risk and that a liquidity premium does in fact exist on the JSE.

The portfolios were then subjected to a regression analysis on the core regression variables as defined in section 3. The results were consistent with the existence of a liquidity premium as the liquidity variables were significant in the univariate regressions, and remained significant when included in multivariate regressions with factors such as size and book-to-market ratios. The value effect was found to not be significant in any of the regressions, however the size effect was found to be significant. The regression analysis was then expanded by analysing the specific asset pricing models through the use of mimicking portfolios in order to proxy for explanatory effects, similar to the methodology of Fama and French (1993). The regressions in this section confirmed the previous findings of the existence of a liquidity premium. The regressions show that the most effective model for use on the JSE is the Liquidity-Augmented model of Liu (2006). The analysis does however show that size is a significant effect that is somewhat separate from liquidity. The efficacy of the variables also change across different levels of liquidity, with the more liquid stocks being less affected by liquidity. Lastly, the regression analysis was extended to the entire stacked sample cross-section of stock returns.

This analysis confirmed the findings of the previous two sections in validating the existence of a liquidity premium.

From the results of section 4, this analysis makes key findings regarding the null hypotheses of this study. Firstly, this study fails to reject the hypothesis that a liquidity premium does exist for assets on the JSE and this effect is captured accurately through the multidimensional liquidity variable (denoted LMx) posited by Liu (2006). This is because the liquidity variable succeeded in capturing a significant liquidity effect across all methodologies and the variable captures multiple dimensions of liquidity.

This study rejects the hypothesis that the liquidity effect is not significant in explaining stock returns when included with size, Beta, earnings-to-price, cash flow-to-price or book-to-market variables. This was proven as the liquidity variable remained significant when included with the size and book-to-market variables, and the financial ratio variables were found to be insignificant. The size variable was proven to be significant however, therefore the findings of Fama and French (1992) may still proxy for a different and significant underlying factor to liquidity. Although the BM variable was not significant when included in the Fama-French model, there was a definite relationship present when analysing the liquidity quartiles. Perhaps this presents a route for further research into the interaction between the liquidity and value effects specifically. Another recommendation for further analysis on this topic would be to analyse the explanatory power of a liquidity effect with other factors such as momentum and mean-reversion effects.

The results of van Rensburg and Robertson (2003) as well as Auret and Sinclaire (2006) are only partially upheld within this study, with the only commonality being the significance of the size variable. The difference in results, especially regarding the book-to-market variable, may be due to the addition of a liquidity effect which was not explicitly analysed in the two above studies.

There is a clear liquidity premium on the JSE, particularly amongst smaller cap portfolios, however this effect exhibits a relationship with size that cannot be ignored. A final recommendation is that a liquidity variable be included in asset pricing models and asset return analysis in the context of the JSE. As the liquidity effect is robust to existing factors such as

the inclusion of the market risk premium, the omission of such a key factor in the discussion around the return-generating process would be imprudent.

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