LIQUIDITY AS AN INVESTMENT STYLE:
EVIDENCE FROM THE JOHANNESBURG STOCK EXCHANGE

by

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Declaration

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L. Theart   8 January 2014

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Abstract

Individual and institutional investors alike are continuously searching for investment styles and strategies that can yield enhanced risk-adjusted portfolio returns. In this regard, a number of investment styles have emerged in empirical analysis as explanatory factors of portfolio return. These include *size* (the rationale that small stocks outperform large stocks), *value* (high book-to-market ratio stocks outperform low book-to-market ratio stocks) and *momentum* (stocks currently outperforming will continue to do so).

During the mid-eighties it has been proposed that *liquidity* (investing in low liquidity stocks relative to high liquidity stocks) is a missing investment style that can further enhance the risk-adjusted performance in the United States equity market. In the South African equity market this so-called liquidity effect, however, has remained largely unexplored. The focus of this study was therefore to determine whether the liquidity effect is prevalent in the South African equity market and whether by employing a liquidity strategy an investor could enhance risk-adjusted returns.

This study was conducted over a period of 17 years, from 1996 to 2012. As a primary objective, this study analysed liquidity as a risk factor affecting portfolio returns, first as a residual purged from the influence of the market premium, size and book-to-market (value/growth) factors, and then in the presence of these explanatory factors affecting stock returns. Next, as a secondary objective, this study explored whether incorporating a liquidity style into passive portfolio strategies yielded enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral passive 'style index' strategies.

The results from this study indicated that liquidity is not a statistically significant risk factor affecting broad market returns in the South African equity market. Instead the effect of liquidity is significant in small and low liquidity portfolios only. However, the study indicated that including liquidity as a risk factor improved the Fama-French three-factor model in capturing shared variation in stock returns. Lastly, incorporating a liquidity style into passive portfolio strategies yielded weak evidence of enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral passive 'style index' strategies.

This research ultimately provided a better understanding of the return generating process of the South African equity market. It analysed previously omitted variables and gave an

indication of how these factors influence returns. Furthermore, in analysing the risk-adjusted performance of liquidity-biased portfolio strategies, light was shed upon how a liquidity bias could influence portfolio returns.

Opsomming

Individuele en institusionele beleggers is voortdurend op soek na beleggingstyle en strategieë wat verhoogde risiko-aangepaste portefeulje-opbrengste kan lewer. In hierdie verband is 'n aantal beleggingstyle deur empiriese analise geïdentifiseer as verklarende faktore van portefeulje-opbrengs. Hierdie style sluit in: *grootte* (die rasionaal dat klein aandele beter presteer as groot aandele), *waarde* (hoë boek-tot-mark verhouding aandele presteer beter as lae boek-tot-mark verhouding aandele) en *momentum* (aandele wat tans oorpresteer sal daarmee voortduur).

Gedurende die midtagtigs is dit aangevoer dat *likiditeit* (die belegging in lae likiditeit aandele relatief tot hoë likiditeit aandele) 'n ontbrekende beleggingstyl is wat die risiko-aangepaste prestasie in die Verenigde State van Amerika (VSA) aandelemark verder kan verhoog. In die Suid-Afrikaanse aandelemark bly hierdie sogenaamde likiditeit-effek egter grootliks onverken. Die fokus van hierdie studie was dus om te bepaal of die likiditeit-effek teenwoordig is in die Suid-Afrikaanse aandelemark en of dit vir 'n belegger moontlik is om risiko-aangepaste opbrengste te verbeter deur 'n likiditeit-strategie te volg.

Die studie is uitgevoer oor 'n tydperk van 17 jaar, vanaf 1996 tot 2012. As 'n primêre doelwit het hierdie studie likiditeit ontleed as 'n risiko faktor van portefeulje-opbrengste, eers as 'n residu-effek vry van die invloed van die markpremie, grootte en boek-tot-mark (waarde/groei) faktore, en daarna in die teenwoordigheid van hierdie verklarende faktore van aandeel opbrengste. As 'n sekondêre doelwit, het hierdie studie ondersoek of die insluiting van 'n likiditeit-styl in passiewe portefeulje-strategieë verbeterde risiko-aangepaste prestasie kan lewer relatief tot ander suiwer-likiditeit en likiditeit-neutrale passiewe 'styl indeks' strategieë.

Die resultate van hierdie studie het aangedui dat likiditeit nie 'n statisties beduidende risiko faktor is wat die breë markopbrengs in die Suid-Afrikaanse aandelemark beïnvloed nie. In plaas daarvan is die effek van likiditeit beperk tot slegs klein en lae likiditeit portefeuljes. Die studie het wel aangedui dat die insluiting van likiditeit as 'n risiko faktor die Fama-French drie-faktor model verbeter in sy vermoë om die gedeelde variasie in aandeel opbrengste te verduidelik. Laastens lewer passiewe portefeulje strategieë, geïnkorporeer

met 'n likiditeit-styl, swak bewyse van verbeterde risiko-aangepaste opbrengs relatief tot ander suiwer-likiditeit en likiditeit-neutrale passiewe 'styl indeks' strategieë.

Hierdie navorsing verskaf 'n beter begrip van die opbrengs-genererende proses van die Suid-Afrikaanse aandelemark. Dit ontleed voorheen weggelate veranderlikes en gee 'n aanduiding van hoe hierdie faktore opbrengste beïnvloed. Daarbenewens word lig gewerp op die invloed van 'n likiditeit vooroordeel op portefeulje-opbrengste deur die risiko-aangepaste opbrengs van likiditeit-bevooroordeelde strategieë te analiseer.

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It always seems impossible until it is done.

N.R. Mandela

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List of acronyms and abbreviations

ADF	Augmented Dickey-Fuller (test)
ALSI	All-Share Index
APT	Arbitrage Pricing Theory
AR	autoregressive
ARCH	autoregressive conditional heteroskedasticity (model)
BER	Bureau for Economic Research
BM	book-to-market (return of a portfolio of high book-to-market ratio stocks minus the return of a portfolio of low book-to-market ratio stocks)
CAPM	Capital Asset Pricing Model
DD	downside deviation
EOB	Electronic Order Book
EPS	earnings per share
GARCH	generalised autoregressive conditional heteroskedasticity (model)
GDP	gross domestic product
HPR	holding period returns
ICB	Industry Classification Benchmark
ILLIQ	illiquidity ratio
IR	Information ratio
JSE	Johannesburg Stock Exchange
LIBOR	London Interbank Offered Rate
LIQ	Liquidity
LTCM	Long Term Capital Management
MAR	minimum acceptable return
MEC	market efficiency coefficient

MKT	market premium (return on the market portfolio minus the risk-free rate)
NCD	negotiable certificate of deposit
OLS	ordinary least squares
P/E	price-earnings (ratio)
SARB	South African Reserve Bank
SIZE	size (return of a portfolio of small stocks minus the return of a portfolio of large stocks)
TED	Treasury bills
US(A)	United States (of America)
V/E	volume-to-earnings (ratio)
Var	variance
VIX	volatility index

CHAPTER 1

INTRODUCTION TO THE STUDY

The brass assembled at headquarters at 7 a.m. that Sunday. One after another, LTCM's partners, calling in from Tokyo and London, reported that their markets had dried up. There were no buyers, no sellers. It was all but impossible to manoeuvre out of large trading bets. They had seen nothing like it.

Siconolfi, Raghavan & Pacelle (1998: A1)

1.1   INTRODUCTION

An illiquid asset is an asset that lacks ready and willing buyers. Such illiquidity becomes a problem once investors need to sell large quantities of assets over a short-term period. The 1998 Long Term Capital Management (LTCM) debacle is a good example of the perils that are often associated with illiquidity. By design, LTCM's highly-levered hedge fund was sensitive to market-wide liquidity by means of long positions in less liquid instruments and short positions in more liquid instruments. When the 1998 Russian debt crisis precipitated a widespread decline in overall market liquidity, LTCM's liquidity sensitive portfolio dropped significantly in value, triggering numerous margin calls and forcing the fund to liquidate positions at significantly decreased values. The complete $3.625 billion bailout was eventually funded by a consortium of 14 Wall Street banks organised by the United States Federal Reserve Bank (Pástor & Stambaugh, 2003: 644).

The growing body of research on the effect of liquidity on asset prices and asset returns is primarily focused on the United States (US), arguably the most liquid market in the world (Bekaert, Harvey & Lundblad, 2003: 1). Studies on the effect of liquidity in an emerging market space and more specifically in the South African context, however, are only starting to become popular. These studies are still few in number and limited with regards to the methodologies employed. Chuhan (1994: 2) identified liquidity as one of the main impediments preventing foreign investors from investing in emerging markets, with the result of even higher liquidity premiums in these markets. Even though liquidity in the South African equity market have increased since 1994 (presented in Section 2.5), the focus on an emerging market like South Africa should still yield particularly useful and independent evidence.

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Evidence of priced liquidity premiums was introduced by Amihud and Mendelson (1986) in their seminal work: *Asset pricing and the bid-ask spread*. In this study, they attested to the outperformance of less liquid stocks relative to more liquid stocks in the US equity market and suggested that liquidity is a priced variable. Numerous other studies, such as Amihud (2002), Pástor and Stambaugh (2003) and Liu (2006) confirmed these results. In the emerging market space most studies focus on liquidity on an aggregate market level. Studies such as the one by Jun, Marathe and Shawky (2003: 1) found average stock returns over 27 emerging countries (including South Africa) to be positively correlated with aggregate market liquidity. These results hold in both cross-sectional and time-series analyses, and are robust even after controlling for world market beta, market capitalisation and the price-to-book ratio. Reisinger (2012), focused only on the South African equity market and found, however, no significant effect of liquidity on stock returns. In this regard Muller and Ward (2013) suggested that the liquidity premium has diminished over the last nine years.

This study focuses on the effect of liquidity in the South African equity market by employing a similar methodology to that of Keene and Peterson (2007), Hearn, Piesse and Strange (2010) and Chen, Ibbotson and Hu (2010; 2013). The results aim to contribute to the limited body of knowledge with regard to the liquidity effect in the South African equity market. Specifically, in an endeavour to understand the return generating process of stocks more thoroughly, it addresses liquidity as a risk factor affecting stock returns. This endeavour should be of value to students, academics and researchers in the field of finance and investments. To take advantage of possible priced liquidity premiums, as suggested in previous literature, the study also sheds light on whether portfolio strategies incorporating a liquidity bias could yield superior risk-adjusted performance. These results should be of value to individual and more specifically to institutional investors.

This chapter continues with a background sketch, research problem and introduction to the research design. This is followed by the research methodology and data analysis techniques employed. Lastly, reference is made to the contribution of the research results and an orientation towards the rest of the study concludes this chapter.

1.2   BACKGROUND

Liquidity is the ability to trade large quantities of assets at low costs generating a small price impact (Liu, 2006: 631). In theory, less liquid assets will sell at a discounted price,

whereas more liquid assets will sell at a higher price given the same set of expected cash flows. This theory is based on the rationale that all else equal, investors would prefer higher liquidity within the assets they hold and to induce investors to hold less liquid assets they will need to be compensated by the expectation of a liquidity-induced return premium (Idzorek, Xiong & Ibbotson, 2010: 3). Stated differently, an investor will be willing to buy more liquid assets at an inflated price reflecting a liquidity premium, whereas the investor will only buy less liquid assets if it trades at a reduced price reflecting a liquidity discount.

In the mid-eighties Amihud and Mendelson (1986) were the first to suggest that liquidity might be a missing factor influencing stock returns. This suggestion was later confirmed by researchers such as Chen *et al.* (2013), who proposed that liquidity, which favours less liquid stocks at the expense of more liquid stocks, might be a missing investment style. An investment style refers to the method that investors use to select assets. Numerous empirical studies indicated that investment styles, such as size (Banz, 1981; Reinganum, 1981; Fama & French, 1992), value (Basu, 1977; Reinganum, 1981) and momentum (Jegadeesh & Titman, 1993; Brennan, Chordia & Subrahmanyam, 1998) can yield consistent superior returns on a risk-adjusted basis. This is contrary to the efficient market hypothesis which states that financial markets are 'fully reflective' of available information. A 'fully reflective' market indicates that, given publicly available information, stocks are efficiently priced, leading to investors not being able to consistently outperform average market returns on a risk-adjusted basis (Fama, 1970: 413).

Some studies contested the legitimacy of liquidity as a distinct investment style, suggesting that the liquidity effect may already be captured in other factors affecting stock returns such as size and book-to-market (value/growth) factors (Stoll & Whaley, 1983; Fama & French, 1992). This would suggest that liquidity is not a risk factor significantly influencing stock returns after controlling for these factors. Brennan *et al.* (1998) tested the validity of this statement in the US market by extending the Fama and French (1992) three-factor model with a liquidity factor (the Fama and French three-factor model is discussed in more detail in Section 3.11.6). Their study found that liquidity remains an important factor in explaining returns even after controlling for the market premium, size, and book-to-market factors. Similarly, employing a different methodology, Chen *et al.* (2010) confirmed that liquidity is an economically significant investment style in the US stock market, distinct from traditional investment styles such as size, value and momentum.

Variation in the demand for liquidity among investors implies that investors (usually investors with a long investment time horizon), who value liquidity less than the rest of the market, may be able to exploit that difference by buying illiquid investments at a discount. Less liquid investments can thus be a good buy to long-term investors who buy these assets at liquidity discounted prices, which over time, leads to superior returns (Damodaran, 2010: 73). It is expected then, that those investors who do not require the characteristics associated with liquid assets can benefit from employing a liquidity-biased portfolio strategy which favours less liquid stocks at the expense of more liquid stocks.

In their US-based study, Chen *et al.* (2010) found superior performance of liquidity-biased portfolio strategies and attributed this phenomenon to three trends. Firstly, in equilibrium less liquid stocks will trade at a liquidity discount and more liquid stocks at a liquidity premium. Secondly, due to growing globalisation, illiquid stocks are found to become more liquid over time. Bekaert *et al.* (2003: 11) supported this finding in emerging markets which have undergone an equity market liberalisation process. Thirdly, both heavily traded and out-of-favour less liquid stocks tend to revert to more normal trading over time.

To the researcher's knowledge, no attempt has been made to directly incorporate a liquidity style into portfolio weights in order to take advantage of possible priced liquidity premiums in the South African equity market.

1.3   RESEARCH PROBLEM

Individual and institutional investors alike are continuously searching for investment strategies and styles that can yield consistent and superior returns. The question that becomes evident is whether liquidity is a risk factor affecting stock returns in the South African equity market and whether by incorporating liquidity into portfolio strategies investors will be able to achieve superior risk-adjusted returns.

1.3.1   Objectives and hypotheses

Once a researcher has defined the research problem, the formal objectives of a study can be stated. Hypotheses can then be used to test statistical significance of the stated objectives. A hypothesis is an unproven proposition that tentatively explains a certain assumption regarding the phenomenon in question. The null hypothesis (H_0) is a statement of the status quo, communicating the notion that any change from what has been thought to be true or observed in the past will be due entirely to random error

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(Zikmund, 2003: 499). By means of statistical techniques, the researcher will be able to determine whether the empirical evidence confirms the theoretical hypothesis.

As a primary objective this study aimed to determine whether liquidity is a risk factor affecting stock returns in the South African equity market. When used as an independent variable, liquidity is likely to be highly correlated with the other variables in the model (Keene & Peterson, 2007: 94; Achour, Harvey, Hopkins & Lang, 1999: 10). Therefore, this study examined liquidity as a residual effect measured independently of the market premium, size and book-to-market factors. The null hypothesis in this regard was that liquidity has no significant effect on stock return after controlling for the market premium, size and book-to-market factors. To determine statistical significance of liquidity as an important risk factor to be considered in investment decisions in South Africa, nine sets of hypotheses were employed:

$H_{0,1\text{-}9:}\ \beta_{LIQ} = 0$;

$H_{A,1\text{-}9:}\ \beta_{LIQ} \neq 0$.

The nine hypotheses were derived from nine intersection group portfolios based on size and liquidity. The construction and rationale behind these intersection group portfolios are discussed in Section 1.6 with more detail on the nine hypotheses presented in Section 3.3.6. The regression coefficient or liquidity influence (β_{LIQ}) was found by regressing the portfolio return in excess of the risk-free rate ($RP_t - Rf_t$) on the monthly residual liquidity factor ($e_{LIQ,t}$), which is free from the influence of the market premium, size and book-to-market factors.

Next liquidity was examined as a risk factor in the presence of the market premium, size and book-to-market factors (Fama-French three-factor model) known to affect returns. In this instance liquidity was used in its original form and not as a residual specifically to address whether the inclusion of a liquidity factor improves the ability of the asset pricing model to capture shared variation in stock returns. To determine statistical significance, the following hypotheses were employed:

$H_{0,10:}\ R^2_{(LIQ\ included)} \leq R^2_{(LIQ\ excluded)}$;

$H_{A,10:}\ R^2_{(LIQ\ included)} > R^2_{(LIQ\ excluded)}$.

In regression analysis, the coefficient of determination (denoted R^2) provides evidence on the combined ability of the independent variables to capture shared variation in stock returns. The R^2 thus measures the ability of independent variables to represent well-specified asset pricing models. In this regard the $R^2_{(LIQ\ included)}$ was the coefficient of determination of regressing excess portfolio return on risk factors including liquidity, whereas $R^2_{(LIQ\ excluded)}$ was the coefficient of determination of a regression model excluding liquidity as a risk factor.

To give effect to the primary objective and to focus on the purpose of the research, as a secondary objective, this study aimed to explore whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral passive 'style index' strategies. In this regard two liquidity-biased, one pure-liquidity and two liquidity-neutral portfolio strategies were constructed, tracked and the risk-adjusted performance analysed using a range of well-known financial ratios and formulas.

1.4   RESEARCH DESIGN

The development of a research design follows logically from the research problem and is a direct function of the research objectives. In the research design it is important for the researcher to anticipate the appropriate research decisions in an endeavour to maximise the validity of the eventual results (Mouton, 1996: 107). In this particular study the research design entailed primary and secondary research methods.

1.4.1   Secondary research

Secondary research refers to information that already exists, is readily available and has been collected for some other purpose than the research at hand (Polonsky & Waller, 2005: 108). According to Boyce (2002: 94), one of the main advantages of secondary research is that it can provide the necessary background information to increase the researcher's understanding of the situation surrounding the impending issues. Secondary research can be obtained from internal records or external sources. External secondary research sources include, for example, libraries, journals, newspapers, the internet or external databases (Boyce, 2002: 96). In this study external data sources were consulted.

Firstly, a vast number of academic publications were consulted in a thorough analysis of the relevant literature. These publications provided the theoretical background to the study.

External databases were used to obtain the data needed for statistical analysis. The data required for the individual stocks as well as stock indices were obtained from the McGregor BFA (Pty) Ltd (2012) database and the accuracy verified by means of the TimbukOne (Pty) Ltd (2012) database when prompted. The reason for using McGregor BFA (Pty) Ltd (2012) as the primary data source is due to its more complete set of data regarding delisted shares and its longer time frame of available data. The data regarding the constituent companies of the sample was obtained from the JSE either directly or from the JSE website indirectly. Data on an appropriate risk-free rate was sourced from the Bureau for Economic Research (BER) (2010) of Stellenbosch University and lastly, data regarding stock trade volumes and stock velocity was obtained from the World Federation of Exchanges (2012).

1.4.2   Primary research

The secondary data obtained for this study, in its original form, was not sufficient to solve the research problem. It was therefore necessary to also perform primary research. Primary research results directly from the particular problem under investigation (McDaniel & Gates, 2001: 25). In the primary research, the researcher is responsible for the research design, collection of data, and the analysis of the obtained information (Stewart & Kamins, 1993: 3). In the primary research of this study the data collected from secondary research was processed to a useable format for the problem at hand. It was only then possible to achieve the objectives by means of analysing the processed data.

A discussion regarding the population and sample frame, research methodology and data analysis techniques performed in this study, will now follow.

1.5   DEFINING THE POPULATION AND SAMPLE FRAME

The target population is the complete group of objects relevant to a specific research project. In this regard the target population consisted of all stocks listed on the JSE over the period under review (from 1995 to 2011). The sample frame refers to the comprehensive list of elements from which the sample can be drawn (Hair, Babin, Money & Samouel, 2003: 166). The year-end FTSE/JSE All-Share index (ALSI) constituents for each year were used as the basis for developing the sample frame for the following year. In other words the FTSE/JSE ALSI constituents of December 1995 were the basis for developing the sample frame for 1996 and the constituents of December 2011 the basis

for developing the sample frame for 2012. To be included in the study, a company had to have available data regarding its Rand trading volume, monthly total returns (including dividends), earnings per share, number of shares outstanding, and stock price, for the preceding 12 months.

1.6   RESEARCH METHODOLOGY

This section sets out the methodological framework of the study. In an endeavour to determine whether liquidity is a risk factor affecting stock returns in South Africa, this study tested the effect of liquidity on the portfolio returns of nine intersection group portfolios based on size and liquidity. Given the intuitive relationship between liquidity and size (it is often suggested in academic and practitioner discussions that less liquidity equals small-capitalisation and that betting on illiquidity must mean that one is betting on small-capitalisation stocks), these factors were used as the distinguishing characteristics of the nine intersection group portfolios.

For the portfolio construction phase, independently sorted liquidity and size terciles were formed at the end of each December. The intersections of the two independent sets of terciles were then taken, to produce nine intersection group portfolios. From each of these groups an equally weighted portfolio was constructed and held for the next 12 months. Next, liquidity was analysed as a risk factor for small-capitalisation (small-cap) stock portfolios with varying degrees of liquidity, medium-capitalisation (mid-cap) stock portfolios with varying degrees of liquidity and then large-capitalisation (large-cap) stock portfolios with varying degrees of liquidity. In this regard, a similar approach to that of Keene and Peterson (2007) and Hearn *et al.* (2010) was employed.

As a secondary objective, this study set out to examine whether liquidity biased portfolio strategies could lead to superior risk-adjusted performance relative to other pure-liquidity and liquidity-neutral passive 'style index' strategies. To incorporate liquidity in a portfolio strategy one can include a turnover or volume factor into a multi-factor return forecasting model and form portfolios based on the return forecasts. This approach, however, may require the researcher to model estimation risk. Instead, the researcher can simply buy a portfolio of low-liquidity stocks. Such an approach, however, favours small-cap stocks that place a limit on the maximum capacity that can be accommodated (Chen *et al.*, 2010: 5). This study followed the approach of Chen *et al.* (2010) and over-invested in less liquid stocks while under-investing in more liquid stocks, relative to some liquidity-neutral

benchmark. These liquidity-biased portfolio strategies are passive in nature and were studied in comparison with other known passive indexation strategies such as the pure-liquidity volume weighted strategy and liquidity-neutral market capitalisation weighted and earnings weighted strategies.

1.6.1   Measure of liquidity

To construct the nine intersection group portfolios based on size and liquidity, in line with Chen *et al.* (2010), market capitalisation was used as a proxy for size and turnover as a proxy for liquidity. Turnover for each stock was calculated by dividing the annual Rand volume traded of each stock by the number of issued ordinary shares (adjusted for free-float) multiplied by the average monthly closing prices during the year.

To analyse the risk-adjusted returns associated with liquidity-biased, pure-liquidity and liquidity-neutral portfolio strategies, annually rebalanced portfolios for each of the identified passive portfolio strategies were constructed. During portfolio formation of liquidity-biased strategies, in line with Chen *et al.* (2010), annual Rand volume traded was used as a direct measure of liquidity for each stock.

1.7   DATA ANALYSIS

The purpose of data analysis is to generate meaning from the raw data collected (Coldwell & Herbst, 2004: 92). The data for this study was analysed in four phases. Firstly, monthly returns were calculated for the constituents of the liquidity-size intersection group portfolios and the pure-liquidity, liquidity-biased and liquidity-neutral portfolio strategies. Secondly, the total return of the intersection group portfolios, portfolio strategies and benchmark portfolio indices were calculated. Thirdly, the research hypotheses for the primary objective were tested. Lastly, for the secondary objective, the risk-adjusted returns of the pure-liquidity, liquidity-biased and liquidity-neutral portfolio strategies were evaluated using market independent and market dependent risk-adjusted performance measures.

1.7.1   Descriptive statistics

Numerical descriptive statistics were used in the study to summarise and present the analysed data. According to Zikmund (2003: 473), descriptive analysis refers to the transformation of raw data into a form that will make it easy to understand and interpret. It is also an important step towards the development of inferential statistics. In line with

DeFusco, McLeavey, Pinto and Runkle (2011: 61), this study explored four properties of return distributions namely central tendency, dispersion, skewness and kurtosis.

1.7.2   Inferential statistics

Inferential statistics is a body of methods used to draw conclusions or inferences about the characteristics of a population (Keller, 2005: 3). According to McDaniel and Gates (2001: 413), the basic principle of statistical inference is that it is possible for numbers to be different in a mathematical sense but not significantly different in a statistical sense. Statistical significance indicates that differences noted are real differences and are not the result of chance. Statistical differences are defined by a selected level of significance. The five per cent level of significance was considered for the testing of hypotheses in this study.

To determine whether liquidity is a risk factor affecting stock returns in the South African equity market, two sets of regressions were employed. Regression analysis explains the relationship that exists between variables (Keller, 2005: 578). Simple regression analysis examines how one variable (the dependent variable) is influenced by another variable (the independent variable), whereas multiple regression analysis examines how multiple independent variables influence the dependent variable (Keller, 2005: 627). Firstly, a measure of liquidity free from any influence from the market premium, size and book-to-market factors was determined. This was done by means of regressing liquidity (LIQ) on the market premium (MKT) and factor-mimicking portfolios based on size (SIZE) and book-to-market (BM) values.

To test for liquidity as a risk factor or determinant of return, the excess monthly portfolio return of the nine intersection group portfolios based on size and liquidity were then regressed on the monthly liquidity residual free from the influence of the other explanatory risk factors.

Next, to examine the effect of liquidity on returns in the presence of the Fama-French market premium, size and book-to-market factors, liquidity was used in its original form and not as a residual specifically to address whether the inclusion of a liquidity factor improves the ability of the asset pricing model to capture shared variation in stock returns. In this regard, the first regression included liquidity as a risk factor whereas the second regression was similar, but with liquidity removed.

For the secondary objective, to determine whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance, risk-adjusted performance measures for each of the portfolio strategies under review were compiled. This was done by means of simple calculation and further regression analysis.

1.8   CONTRIBUTION OF THE RESEARCH

A number of contributions are evident in the purpose and nature of the research objectives. This study is the first to determine the effect of liquidity as a risk factor, as a residual on excess portfolio return in the South African equity market. Next, focusing on liquidity in its original form, it expands on the available research such as that of Hearn *et al.* (2010) and Reisinger (2012) in that it covers a much larger time frame. This research further contributes to the body of knowledge by presenting empirical findings on the risk-adjusted performance of liquidity-biased portfolio strategies in South Africa.

1.9   ORIENTATION OF THE STUDY

The orientation of the study is as follows:

Chapter 1: Introduction to the study: This chapter sketches the background to the study. It formulates the research problem, objectives, and hypotheses and provides the research methods employed in this study.

Chapter 2: Literature review: This chapter consists of an in-depth discussion of the sources of illiquidity, dimensions of liquidity and the proxies used to measure liquidity. This is followed by an extensive overview of the evidence of the effect of liquidity levels on asset prices and returns, the changes in aggregate market liquidity and liquidity as a risk factor affecting stock returns. The latter part of this chapter gives an outline of the evolvement of liquidity in the South African equity market referred to as the South African equity market liberalisation.

Chapter 3: Research methodology: This chapter provides an in-depth discussion of the research methodology employed in this study. It commences with a discussion of the research process applied in order to achieve the research objectives. The research process is structured in the form of six steps, which include various aspects such as planning the research design, data gathering, data processing and data analysis. The

latter part of this chapter focuses on reliability and validity to ensure the trustworthiness of the research results.

Chapter 4: Research results: The empirical results obtained from the data analysis, as explained in Chapter 3, are presented in this chapter. For the primary objective, determining whether liquidity is a risk factor affecting stock returns, the results from descriptive and inferential statistics are provided. Next, for the secondary objective, the risk-adjusted performance of the liquidity-biased, liquidity-neutral and pure-liquidity portfolio strategies are presented.

Chapter 5: Conclusions and recommendations: This chapter summarises the overall findings of the study. Based on the research results in Chapter 4, the findings are interpreted followed by a discussion of the contribution of the research. This chapter concludes with the limitations of the study and practical recommendations for further areas of research.

CHAPTER 2
LITERATURE REVIEW

I bought sugar and it went limit up... then I bought copper and it went limit up, so I bought some more. Then it went limit down. I called my broker and told him to sell and he said to whom? That's when I realized I had more to learn.

Angell in FWN Group, 1996: 3.

2.1   INTRODUCTION

A fundamental assumption of standard asset pricing and traditional portfolio choice is that securities trade in frictionless (or, perfectly liquid) markets where securities can be traded continuously and in unlimited amounts (Longstaff, 2009: 1119). This assumption also underlies standard option pricing theory, such as that of Black and Scholes (1973), where a number of securities are needed to replicate an option, implying that infinite amounts of securities can be traded.

In reality, however, investors face liquidity constraints in nearly all financial markets, a lesson painfully learned by many hedge fund and portfolio managers facing the dilemma of raising cash to meet margin calls in markets where liquidity has almost disappeared (Longstaff, 2001: 407-408). This has been evident in many financial crises since the 1970s – such as the 1987 stock market crash, the Asian tsunami in 1997, the Russian debt crisis in 1998 and the global financial crisis of 2008 (Puplava, 2000; Adrian & Shin, 2009).

The inability to trade shares immediately is a subtle form of market incompleteness and exposes investors to additional risks. This has important implications for stock pricing because the valuation of liquid relative to illiquid stocks should reflect the loss incurred by investors due to their inability to trade unlimited amounts (Longstaff, 2001: 408). In other words, investors should be compensated for holding less liquid securities, as the associated transactional costs will be higher.

Damodaran (2010) presented evidence that investors price illiquidity and evaluate how illiquidity has a divergent impact on different types of investors. Profitable opportunities firstly arise for long-term investors who care less about liquidity than the rest of the market and secondly, for investors who can time shifts in market liquidity. According to Damodaran (2010: 7-13), liquidity matters to investors because it influences asset pricing and valuation and also because it has an impact on the portfolio management process. None the less,

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much of financial theory is incorrectly predicated on the assumption that assets are liquid or that costs associated with illiquidity are immutably small.

This chapter starts with an in-depth discussion of the sources of illiquidity, dimensions of liquidity and the proxies used to measure liquidity. This is followed by an extensive overview of the evidence of the effect of liquidity levels on stock prices and returns, the changes in aggregate market liquidity and liquidity as a risk factor affecting stock returns. To conclude, this chapter gives an outline of the evolvement of liquidity in the South African equity market, often referred to as the South African equity market liberalisation.

2.2   SOURCES AND DIMENSIONS OF ILLIQUIDITY

Amihud, Mendelson and Pedersen (2005: 270) stated that illiquidity in assets mostly arise due to:

o   Exogenous transaction costs;
o   Demand pressure and inventory risk;
o   Private information; and
o   Search friction.

Exogenous transaction costs, such as brokerage fees, settlement costs or taxes are incurred every time a security is traded. In the presence of such transaction costs, continuous trade will incur infinite transaction costs, and even a small transaction cost can dramatically decrease the frequency of trade (Jang, Koo, Liu & Loewenstein, 2007: 2329).

Demand pressure arises because not all market participants are present in the market at all times. Therefore, if a market participant needs to sell a stock quickly, no natural buyers may be available. As a result, the seller may sell to a market maker who buys in anticipation of being able to later lay off the position. This market maker, being exposed to the risk of price changes while he holds the asset in inventory, must be compensated for inventory risk (Amihud *et al.*, 2005: 291).

There is also the possibility that the counterparty of a trade may possess private information (with regard to the fundamentals of the company or the order flow in the stock) which can lead to a loss when trading with a more informed counterparty. Therefore, if there are traders who possess private information and uninformed traders become aware of this, the uninformed investor will choose not to trade, which will restrict liquidity (Liu,

2006: 633). Lastly, search friction refers to the difficulty of locating a counterparty that is willing to trade a particular stock, or a large quantity of a given stock. Search friction is particularly relevant in over-the-counter markets in which there is no central marketplace (Lagos & Rocheteau, 2008: 2).

Liu (2006) identified a further two possible reasons for illiquidity in a market. Firstly, it is suggested that liquidity will become an issue when the economy is in, or expected to go in, a recessionary state. In a recessionary state, risk-averse investors will prefer to invest in less risky and more liquid assets. This is in line with Hicks' (1967) "liquidity preference" notion, which suggests that investors hold assets to facilitate adjustments to change in economic conditions. It is also in line with Chordia, Sarkar and Subrahmanyam (2005), who showed that stock market liquidity is associated with monetary policy, and with Eisfeldt (2002), who modelled endogenous fluctuations in liquidity along with economic fundamentals such as productivity and investment. Secondly, Liu (2006: 634) suggested that companies themselves can cause illiquidity in their stocks. When the probability of default of a company is high, or when there is, for example, a poor management team, investors will not be interested in holding these shares.

When analysing the sources of market liquidity, one enters the realm of market microstructure theory (Hibbert, Kirchner, Kretzschmar, Li & McNeil, 2009: 6). Microstructure theory is concerned with how a market's transactional properties affect the price formation process and furthermore reflects the dimensions of market liquidity. Kyle (1985: 1317) identified the three main dimensions of liquidity to be *tightness, depth* and *resilience*. The relationship among these three dimensions of liquidity and price is shown graphically in Figure 2.1. Tightness refers to low transaction costs, such as the difference between buy and sell prices. Amihud and Mendelson (2006: 20) defined depth as the order size at the best quoted price, which is the largest size that does not incur a price impact cost above the bid-ask spread. Resilience is the speed with which the prices bounce back to equilibrium following a large trade.
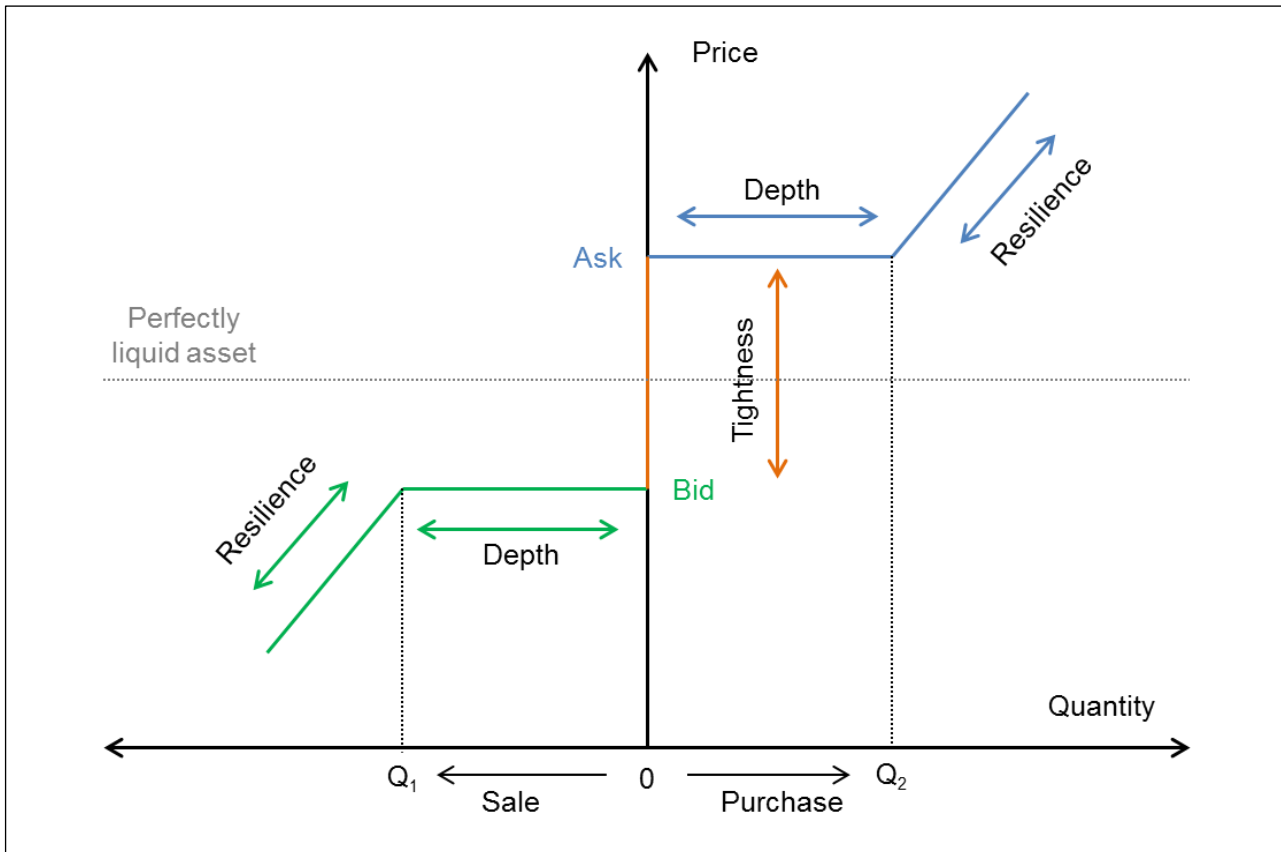
Figure 2.1: Dimensions of market liquidity

Source: Adapted from Bervas, 2006: 65.

As can be seen, a perfectly liquid asset will have a tightness of zero (in other words no transactional costs such as a bid-ask spread), an infinite depth (no order size would be big enough to influence the price) and instantaneous resilience (following a trade, the stock prices will revert back to equilibrium instantly).

A further two dimensions of liquidity were identified by Sarr and Lybek (2002: 5), namely *immediacy* and *breadth*. Immediacy represents the speed with which an order can be executed and settled. Immediacy thus reflects, among other things, the efficiency of the trading, clearing and settlement systems. Breadth, furthermore, refers to orders being large in volume, which together with depth leads to minimal trade impact on prices in the market.

According to Sarr and Lybek (2002: 8) the dimensions of liquidity should be used as the basis for determining how to measure liquidity. However, they found that no single measure has the ability to explicitly measure tightness, depth, resilience, immediacy and

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breadth. The next section sheds some light on the common liquidity measures employed in research.

2.3   LIQUIDITY MEASURES

While it is easy to understand the rationale behind liquidity, it has proven far more difficult to measure. Sarr and Lybek (2002) identified four categories of liquidity measures which aim to capture the five dimensions of liquidity as identified in Section 2.2: transaction cost measures, volume-based measures, price-based measures and market-impact measures. These categories are discussed below under separate headings. It should be noted that this section aims to introduce the most widely-used measures in each of the categories. However, given the scope of the research, many more measures and variations employed in academic research such as the weighted order value, the relative odds ratio and the Martin-index were omitted.

2.3.1   Transaction cost measures

Transaction costs can be either explicit (direct trading costs) or implicit (price-impact and search and delay costs). According to Amihud and Mendelson (2006: 20), direct trading costs include exchange fees, taxes and brokerage commissions, whereas price-impact costs reflect the price allowance that buyers and sellers make when trading a security (a discount when selling and a premium when buying). Resilience reflects the extent of bearing large-order flow in one direction without affecting the market price and for smaller trades the bid-ask spread represents the cost that a 'round trip' buy-and-sell transaction will incur. However, for larger trades the cost will exceed the bid-ask spread and increase with the order size. Depth can then be defined as the order size at the best quoted price, which is the largest size that does not incur a price impact cost above the bid-ask spread. Lastly, Amihud and Mendelson (2006: 20) suggested that search and delay costs are incurred when a trader searches for better prices than those quoted in the market or wishes to reduce the price-impact costs.

The introduction of automated trading systems led to more detailed order book data from which order-based liquidity measures can be calculated. An order-based measure, such as the bid-ask spread, represents the cost that an investor must incur in order to trade immediately (price impact and search and delay costs) as well as the direct trading costs (Aitken & Comerton-Forde, 2003: 47). The bid-ask spread is therefore often used in

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research (such as Amihud & Mendelson,1986; 1989; Eleswarapu & Reinganum,1993), as the preferred measure of liquidity. A dealer's (or any trader's) bid price is the price at which he or she is willing to buy, whereas the ask price is the price at which he or she is willing to sell a specified quantity of a stock (Maginn, Tuttle, Pinto & McLeavey, 2007: 641).

Figure 2.2 indicates the average bid-ask spread for large-cap US stocks, the equity volatility index (VIX), and the interest rate spread between the London Interbank Offered Rate (LIBOR) and US Treasury bills (TED) from July 2006 to July 2009.
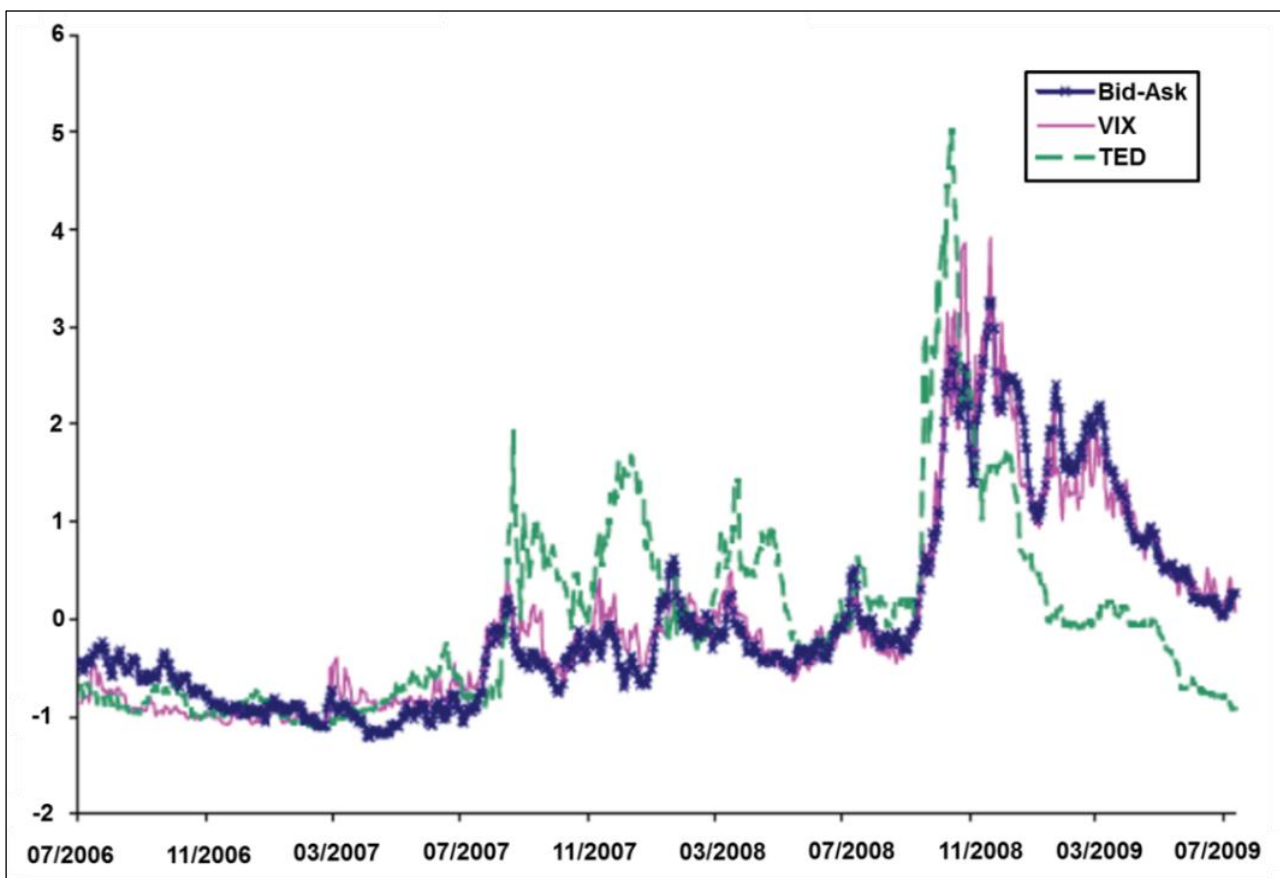
Figure 2.2: Average bid-ask spread for large-cap US stocks – effects of the 2008 crisis

Source: Damodaran, 2010: 34.

Note the surge in the average bid-ask spread starting in September 2008 through the end of the liquidity crisis in December 2008 suggesting that in periods of low liquidity the bid-ask spread will increase, leading to a negative relationship between liquidity and the bid-ask spread.

The bid-ask spread, however, requires a lot of microstructure data that is not readily available in many emerging stock markets and even when available, the data does not cover very long periods of time (Amihud, 2002: 32). According to Brennan and Subrahmanyam (1996: 442), the quoted bid ask-ask spread is a noisy measure of illiquidity in that many large trades occur outside the spread. The bid-ask spread is therefore effective and accurate in determining liquidity costs for small investors, but for large institutional investors, however, it may underestimate the true cost of trading and hence overestimate the liquidity status that should be assigned to the stock (Aitken & Comerton-Forde, 2003: 47). Furthermore, the bid-ask spread only takes into account the effect of liquidity on price and gives no indication with regard to depth (Hamon & Jacquillat, 1999: 371).

2.3.2   Volume-based measures

Volume-based measures are most useful in measuring depth (ample orders) and breadth (large orders). These measures are simple to calculate and the data used is readily available, even in most emerging markets. Volume-based measures, often referred to as trade-based measures, have widespread acceptance among market professionals. However, they have the inherent limitation that they make use of *ex post* rather than *ex ante* information (Aitken & Comerton-Forde, 2003: 47). Volume-based measures, such as trading volume, speed of trades, and the turnover ratio, are commonly used as measures of liquidity in empirical studies and are therefore discussed next.

Trading volume, as used in Brennan *et al*. (1998) and Chen *et al*. (2010) can be calculated by means of the following equation:

$$V_{i,t} = \sum P_{i,t} \times Q_{i,t}$$ ...(Eq 2.1)

Where: $V_{i,t}$ =   Rand volume traded of stock *i* in month *t*;

$P_{i,t}$, $Q_{i,t}$ =   prices and quantities traded of stock *i* in month *t*.

Trading volume is traditionally used to measure the existence of numerous market participants and transactions. This measure can, however, be given more meaning by relating it to the outstanding volume of the stock under consideration (Sarr & Lybek, 2002: 12). This results in the turnover ratio as used by Datar, Naik and Radcliffe (1998) and by the World Federation of Exchanges (2012) as a proxy for liquidity.

The turnover ratio can be calculated by means of the following equation:

$$T_{i,t} = \frac{V_{i,t}}{S_{i,t} \times P_{i,t}}$$ ...(Eq 2.2)

Where: $T_{i,t}$ =   turnover ratio of stock *i* in month *t*;

$V_{i,t}$ =   Rand volume traded of stock *i* in month *t*;

$S_{i,t}$ =   number of issued ordinary shares in month *t*;

$P_{i,t}$ =   average closing price over month *t*.

If the turnover ratio is low, one can expect the average holding period of the specific stock to be longer. Amihud and Mendelson (1986) found that stocks with higher bid-ask spreads have relatively longer expected holding periods. Therefore, turnover is negatively related to the spread and should be positively related to liquidity.

Next, Gabrielsen, Marzo and Zagaglia (2011: 6) identified the conventional liquidity ratio as one of the most frequently-used liquidity measures in empirical analysis. This ratio measures the traded volume needed to induce a stock price change of one per cent. The liquidity ratio ($LR_{i,t}$), for stock *i* can be determined by means of the following equation:

$$LR_{i,t} = \frac{\sum_{t=1}^{T} P_{i,t} V_{i,t}}{\sum_{t=1}^{T} |PC_{i,t}|}$$ …(Eq 2.3)

Where: $P_{i,t}$ =   price of asset *i* on day *t*;

$V_{i,t}$ =   volume traded of stock *i* on day *t*;

$|PC_{i,t}|$ =   absolute percentage price change over a fixed time interval.

A high ratio indicates that large volumes of trades have little influence on price. Thus, the higher the ratio, the higher the liquidity of stock *i* will be.

Lastly, Amihud (2002) proposed another measure called the illiquidity ratio (ILLIQ) defined as the average absolute return of a stock divided by its trading volume. This measure is similar to the conventional liquidity ratio in that it relates volume to price change.

The monthly illiquidity ratio is obtained from the following equation:

$$\text{ILLIQ}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} |r_{i,d,t}| / v_{i,d,t}. \qquad\qquad\qquad \text{...(Eq 2.4)}$$

Where: $r_{i,d,t}$ =   the absolute return for stock *i* on day *d* in month *t*;

$v_{i,d,t}$ =   trading volume for stock *i* on day *d* in month *t*;

$D_{i,t}$ =   the number of days with available data for stock *i* in month *t*.

The illiquidity ratio is limited in its ability to measure liquidity in that it is usually obtained based on average price changes and average trading volumes from the past. Therefore it does not account for price changes due to the sudden arrival of a large trade. Furthermore it does not distinguish whether price fluctuations are due to the lack of liquidity or the arrival of new information (Chai, Faff & Gharghori, 2010: 182). The illiquidity measure therefore provides a rough measure of the price impact. However, unlike order-based measures such as the bid-ask spread, the illiquidity ratio relies on data widely available even in those markets that do not report specialised information (Gabrielsen *et al.*, 2011: 11).

Volume-based measures, being *ex post* measures (indicating what has been traded in the past), rather than *ex ante* (forward looking) measures, however, often lead to critique. Volume-based measures are also particularly challenging when analysing small stocks in that these measures fail to indicate the liquidity costs associated with an immediate transaction (Aitken & Comerton-Forde, 2003: 47). Finally, trading volume may change significantly over time depending on trading patterns. Therefore volatility of turnover should also be taken into consideration (Sarr & Lybek, 2002: 12).

Volume-based measures, as discussed above, are all influenced by the prices of transactions in the market. Bernstein (1987: 60) suggested that prices will change in response to temporary variations in supply and demand, but that they will also change as a result of additional information entering the market and the subsequent more permanent shift in the equilibrium value of a stock. Price changes, as a result of new information entering the market, should not be confused with stock liquidity. Therefore, a criticism of volume-based measures is that they do not make a distinction between transitory and permanent price changes (Sarr & Lybek, 2002: 14).

2.3.3   Price-based measures

As discussed in Section 2.3.2, there is a need for an underlying structural model which can distinguish between short- and long-term price changes. Bernstein (1987: 61) supported this statement by suggesting that measures of liquidity when no new information is entering the market must be more relevant than measures of liquidity when new information leads to new equilibrium values.

The market efficiency coefficient (MEC) also called the variance ratio, as proposed by Hasbrouck and Schwartz (1988), is one of the most widely-used price-based measures in literature (Gabrielsen *et al.*, 2011: 14) This measure exploits the fact that price movements are more continuous in liquid markets, even if new information is affecting equilibrium prices.

To calculate the MEC, the following equation applies:

$$\text{MEC} = \frac{\text{Var}(R_t)}{T \times \text{Var}(r_t)} \qquad\qquad \text{...(Eq 2.5)}$$

Where: $\text{Var}(R_t)$ = variance of the logarithm of long-period returns;

$\text{Var}(r_t)$ = variance of the logarithm of short-period returns;

T = number of short periods in each longer period.

Resilience measures how long the market will take to return to its 'normal' level after absorbing a large order. If an asset is resilient, the asset price should have a more continuous movement and thus low volatility caused by trading. The MEC relates the volatility of short-term price movements to the volatility of longer-term price movements where a resilient asset will have an MEC ratio close to one.

Alternative price-based measures include vector auto regression econometric techniques. These techniques are employed to study the transmission channel of shocks across markets as is employed by studies such as Chung, Han and Tse (1996) and Hasbrouck (2002). However, as with other econometric techniques, Sarr and Lybek (2002: 17) argued against the use of these measures due to their lack of operational ease.

2.3.4   Market-impact measures

As mentioned in Section 2.3.2, volume-based measures generally do not distinguish between temporary price changes and permanent ones due to new information entering the market. Therefore, market movement, as a result of new information entering the market should ideally be extracted (Sarr & Lybek, 2002: 17). The capital asset pricing model (CAPM) provides an avenue to extract market movement. Systematic risk, risk that cannot be diversified away, is captured in the beta of a stock. Unsystematic risk, risk specific to the stock in question, remains after removing the systematic risk.

Hui and Heubel (1984) suggested the market-adjusted liquidity measure where the following CAPM equation applies:

$$R_i = \alpha + \beta R_m + u_i \qquad\qquad ...(Eq\ 2.6)$$

Where: R_i =   daily return on the ith stock;

α =   intercept term;

R_m =   daily market return; and

β =   regression coefficient, represents systematic risk;

u_i =   regression residuals or specific risk.

The variance of the regression residual ($u_i{}^2$) is then related to its volume traded:

$$u_i{}^2 = y_1 + y_2 V_i + e_i \qquad\qquad ...(Eq\ 2.7)$$

Where: $u_i{}^2$ =   squared residual;

y_1 , y_2 =   intercept term and slope respectively;

V_i =   daily percentage change in Rand volume traded;

e_i =   residual.

The intrinsic liquidity is determined by y_2. The smaller the coefficient value, the smaller is the impact of trading volume on the variability of the asset price, and the more liquid is the asset. Thus, the smaller the coefficient, the more breadth is prevalent in the market.

Liquidity can be seen as a multidimensional risk factor and therefore existing measures inevitably demonstrate a limited ability to capture liquidity risk fully and they might have

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been inaccurate even in the specific dimension they aim to capture (Liu, 2006: 632). The weighting and normalisation to create one single proxy for liquidity is found to be very challenging, if not impossible (Sarr & Lybek, 2002: 41). For this study, in line with Chen *et al.* (2010; 2013), a volume-based approach including Rand trading volume and stock turnover was followed.

The volume-based approach was appropriate for this study in view of the following:
o   The smallest stocks in the market were omitted from the study (volume-based measures are often criticised when applied to small stocks);
o   The study needed to be applicable to large institutional investors (order-based measures such as the bid-ask spread often underestimate the true cost associated with trades from large investors); and
o   The data for these specific measures was obtainable in the South African equity market for the period under review.

2.4   LIQUIDITY RESEARCH

Piqueira (2008: 2) stated the evolvement of liquidity research in the following order: firstly, the focus primarily fell on the effect of liquidity levels on the cross-section of expected stock returns. Next, the focus shifted towards the time-series properties of aggregate liquidity measures, suggesting the existence of predictability and commonality in liquidity. Lately, motivated by the time-series evidence, the systematic component of liquidity has been investigated as a potential source of priced risk. The review of literature in the rest of this section, in a similar manner, distinguishes between cross-sectional tests, studies of the effect of changes in aggregate liquidity over time and studies that focus on the effects of liquidity risk (rather than the level of liquidity) on stock prices.

2.4.1   The liquidity effect on the cross-section of expected returns

Evidence of a relationship between stock return and stock liquidity in the US equity market is introduced by Amihud and Mendelson (1986) in their seminal work: *Asset pricing and the bid-ask spread*. In this study, using the bid-ask spread as a measure of liquidity, a market was modelled with rational investors differing in their expected holding periods. What they found was an increase in average portfolio risk-adjusted returns as a function of the bid-ask spread persisting after controlling for company size. The introduction of the clientele effect, whereby investors with longer investment time horizons invest in higher

spread stocks, leads to higher-spread stocks being less spread sensitive, giving rise to a concave return-spread relationship. This is because the longer the investment holding period, the lower is the required compensation for a given increase in the spread.

Amihud and Mendelson (1986: 224) concluded that the liquidity effect is not an indication of market inefficiency, but rather a rational response by an efficient market to the existence of the spread. Amihud and Mendelson (1989; 2006) further proposed that the effect of liquidity on stock returns is larger than what would be naively expected. This is due to the fact that the costs of illiquidity are incurred repeatedly, every time the asset is traded. These costs are therefore additive and do not cancel out.

Eleswarapu and Reinganum (1993) also using the bid-ask spread as a measure for liquidity found the liquidity effect to be mainly limited to the month of January. However, Eleswarapu (1997), using the bid-ask spread as a measure of liquidity, found a consistent significant effect of the relative spread for both January and non-January months. Numerous other studies such as Brennan and Subrahmanyan (1996), Datar *et al.* (1998) and Brennan *et al.* (1998) confirmed that in the US stock market liquidity levels have an effect on the cross-section of expected stock returns which is not limited to the month of January.

Brennan and Subrahmanyan (1996) brought together diverse empirical techniques from asset pricing and market microstructure research to examine the return-liquidity relation. To measure liquidity they used intra-day transaction data to estimate both the variable (trade-size-dependent) and the fixed costs of transacting. Unlike Amihud and Mendelson (1986), who used the simple capital asset pricing model to adjust returns for risk, they further refined their study by using the three-factor model developed by Fama and French (1992). They found a significant relationship between stock return and stock liquidity after adjusting for the Fama-French risk factors and the stock price level.

Datar *et al.* (1998) supported the notion of a liquidity premium by using the turnover rate as a measure for liquidity. They found evidence suggesting that liquidity plays a significant role in explaining the cross-sectional variation in stock returns persisting even after controlling for company size, the book-to-market ratio and the company beta. Similarly, Brennan *et al.* (1998), using two different specifications of the factor model employed to adjust for risk: the principal components approach of Connor and Korajczyk (1988), and

the characteristic-factor-based approach of Fama and French (1993), found a strong negative relationship between stock returns and trading volume as a measure of liquidity.

Bank, Larch and Peter (2010), followed the approach of Amihud (2002) who argued that the effect of illiquidity on stock returns can be decomposed into expected and unexpected illiquidity. Using five measures of liquidity, in an attempt to determine the relationship between illiquidity and returns for the German market, they found individual stock returns to be positively related to expected illiquidity, but negatively related to unexpected illiquidity.

Furthermore, Hu (1997), using turnover as a measure for liquidity, found the cross-section of stock returns to be negatively related to stock turnover on the Tokyo stock exchange.

Where all the previously mentioned studies focus on stock returns, Loderer and Roth (2005) estimated the effect of illiquidity, measured by the bid-ask spread, on stock prices for the Swiss equity market. After controlling for company growth, dividends, risk and size they found the larger the spread, the lower the price-earnings (P/E) ratio. Using volume as a measure for liquidity they found similar results.

In the Australian equity market, Chan and Faff (2003) as well as Marshall and Young (2003), using the bid-ask spread, turnover rate, and amortised spread (the bid-ask spread adjusted for trading volume) as measures of liquidity, found liquidity to be negatively related to stock returns. This suggests that more liquid assets yield lower returns than their less liquid counterparts. Chan and Faff (2003) found that this occurrence persists even after controlling for well-known factors such as value/growth, size, beta and momentum. However, Clayton, Dempsey and Veeraraghavan (2008) found no such relationship, stating that idiosyncratic risk dominates liquidity as an explanation of stock returns.

Rouwenhorst (1999) examined the individual stock returns of 20 emerging markets (excluding South Africa) over a ten-year period and found no relation between the average stock return and stock liquidity as measured by turnover. However, Amihud *et al.* (2005: 301) suggested that this study did not control for other variables, in that it only compared return between a portfolio of high liquidity stocks and a portfolio of low liquidity stocks, and that the test period might have been too short to yield meaningful results. In a similar approach, Muller and Ward (2013) compared the performance of high liquidity portfolios relative to low liquidity portfolios in the South African equity market over a 27-year period

from 1985 to 2011. What they found is a liquidity premium for the initial part of the study, but that the liquidity premium diminished over the last nine years.

In the emerging market space most studies focus on liquidity on an aggregate market level. The effect of aggregate market liquidity on stock returns and the time-series properties associated with aggregate liquidity measures are therefore discussed next.

2.4.2 Time-series properties of aggregate liquidity measures

Amihud *et al.* (2005: 304) suggested that if liquidity levels have an influence on stock prices/returns, changes in liquidity should change asset prices/returns (*ceteris paribus*). Among others, the time-series effect of market-wide changes in liquidity on stock prices in the US equity market was examined by Amihud (2002), Jones (2002) and Pástor and Stambaugh (2003). On an aggregate market level, Amihud (2002) using the average daily ratio of absolute stock return to dollar volume across US stocks, showed that over time, expected aggregate market illiquidity positively affects *ex ante* stock excess return, suggesting that expected stock excess return partly represents an illiquidity premium. Similarly, Pástor and Stambaugh (2003) found that expected stock returns are related cross-sectionally to the sensitivities of returns to fluctuations in aggregate liquidity, whereas Jones (2002) found the time-series variation in aggregate liquidity to be an important determinant of conditional expected stock market returns.

Bekaert *et al.* (2003) suggested that, given the cross-sectional and temporal variation in the liquidity of emerging equity markets, these markets provide an ideal setting to examine the effect of liquidity on expected stock return. Jun *et al.* (2003: 1) found average stock returns over 27 emerging countries (including South Africa) to be positively correlated with aggregate market liquidity as measured by the turnover ratio, trading value and the turnover-volatility multiple. These results hold in both cross-sectional and time-series analyses, and are quite robust even after controlling for world market beta, market capitalisation and the price-to-book ratio.

In studying the time-series properties of aggregate liquidity measures in the US equity market, Chordia, Roll and Subrahmanyam (2001) found measures of liquidity, such as the bid-ask spread or trading activity, to be highly volatile and negatively serially dependent over time. They further found strong day-of-the-week effects in liquidity measures, a decrease in liquidity measures in bear markets and depth and trading activity to increase

prior to major macro-economic announcements. Jones (2002) found the bid-ask spread of stocks to be cyclical and that time-series variation in aggregate liquidity is an important determinant of conditional expected stock market returns. Huberman and Halka (2001) focused on four measures of liquidity and found these measures to vary over time. However, cross-sectionally, the temporal variation has a common component and is positively correlated with return and negatively correlated with volatility.

In the emerging market space, Hearn and Piesse (2009) found liquidity measured by the Liu (2006) multidimensional measure and proportion of zero returns, to be strongly related to the degree of economic integration between the local market and the wider global capital market. Stahel (2005) analysed aggregate market liquidity for a sample of 18 developed and emerging markets including South Africa. The results suggest that aggregate market liquidity is cross-sectionally determined by the country level, and corresponding global level of variables such as return, return volatility, interest rates, and portfolio flows.

2.4.3   Liquidity as a source of priced risk

The studies reviewed in Section 2.4.1 examined the effects of liquidity levels on stock returns. Since liquidity varies over time, as documented in Section 2.4.2, it stands to reason that liquidity risk should also be priced. In this regard, Pástor and Stambaugh (2003) found expected return to be an increasing function of the stocks' sensitivity to market-wide liquidity shocks, in other words that liquidity risk is priced in the US equity market. Liu (2006) measured liquidity as the standardised turnover-adjusted number of zero daily trading volumes over the prior 12 months. The study found a significant liquidity premium robust to the CAPM and the Fama-French three-factor model showing that liquidity is an important source of priced risk. This liquidity premium is robust to size, book-to-market, turnover, low price, and past intermediate-horizon returns.

Keene and Peterson (2007) examined the role of liquidity in asset pricing using a time-series asset pricing model. By employing six different measures for liquidity they found that liquidity is priced and explains a portion of returns even after controlling for size, book-to-market and momentum. Acharya and Pederson (2005) used a liquidity adjusted capital asset pricing model, and found a stock's required return to depend on its expected liquidity as well as on the covariance of its own return and liquidity with the market return and liquidity.

Bekaert *et al.* (2003) employed a similar methodology to Acharya and Pederson (2005), to determine the pricing of liquidity risk in 19 emerging markets excluding South Africa. They found that local market risk is not priced, but that the price of local liquidity risk is positive and significant.

Hearn *et al.* (2010), using a measure for liquidity derived from Amihud (2002), analysed four emerging market countries including South Africa. After sorting all shares in the sample based on size and liquidity, they on average found that illiquidity is a priced and a consistent characteristic in the average emerging market size-liquidity portfolios. They found that the market risk premium, and premiums attributed to size and illiquidity are important factors in pricing asset returns, but that size has greater overall explanatory power than that of illiquidity. When specifically addressing the South African equity market as a whole, however, they found no statistical significance for either illiquidity or the size effect.

Similarly, Reisinger (2012) found that liquidity (as measured by four different proxies) does not have a significant effect on stock returns, while size, value and momentum are found to be significant to a certain extent. This finding remains robust, irrespective of the type of liquidity measure used. In Malaysia, Ahmed (2009), using trading volume as a measure for liquidity, found that liquidity, together with the Fama-French factors, does play a role in explaining stock returns on the Kuala Lumpur Stock Exchange. However, none of the second moment variables proxying liquidity appeared to be statistically significant.

This section set out the evidence of the effect of liquidity levels on stock prices and returns, the changes in aggregate market liquidity and liquidity as a risk factor affecting stock returns. In the next section the evolvement of liquidity in the South African equity market is addressed.

2.5   EQUITY MARKET LIBERALISATION

Lin (2010: 3) defined equity market liberalisation as: "a decision by a country's government to allow foreigners to purchase shares in that country's stock market". Such liberalisation is then expected to benefit emerging countries in that it is associated with more international capital flows towards the specific country. In other words, opening up a country to foreign investment would increase liquidity in the stock market of this country.

In South Africa, the year 1995 marks some significant changes in the equity market. After the ending of *apartheid* in 1994, the subsequent period was characterised by financial market liberalisation in the form of opening up markets to foreign institutional investment (Hearn *et al.*, 2010: 490). This restoration of international contact led to large inflows of capital from other countries, which consisted largely of portfolio and shorter-term investments (Chauhan, 2012: 113).

As can be seen in Figure 2.3, employing foreign financial investment (blue line) as a percentage of gross domestic product (GDP), it appears that foreign investment in South Africa had increased in the post-*apartheid* era to 10.29 per cent in 1999. However, this was followed by a decline to 3.12 per cent in 2000, as a result of the developed market recession affecting the European Union during 2000 and 2001, and the United States during 2002 and 2003. After 2003 there was once again an increase in foreign financial investment as percentage of GDP to 11.41 per cent before retracting again due to the global financial crisis of 2008.
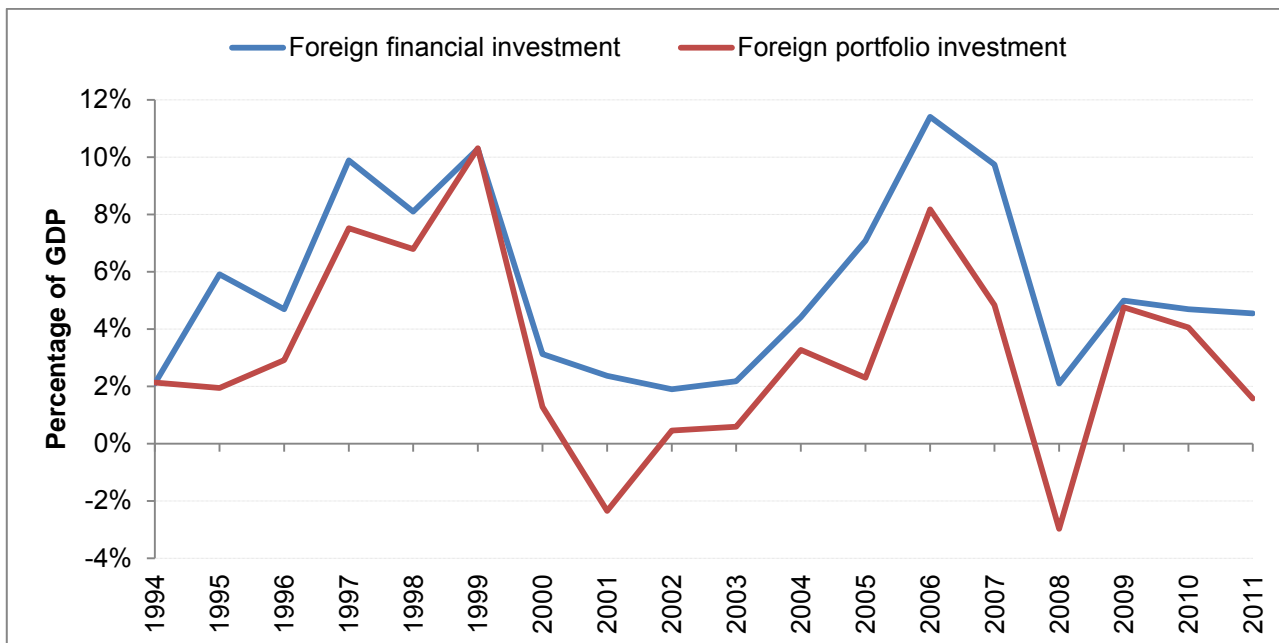
Figure 2.3: Foreign financial and foreign portfolio investment as percentage of GDP

Data source: South Africa Reserve Bank (SARB), 2011.

While foreign financial investment is a useful measure, this indicator includes trade credits, loans, currency, deposits as well as direct investment flows to South Africa. Therefore it can be beneficial to focus solely on foreign portfolio investment, the investment in stocks and bonds, as a percentage of GDP, as shown in Figure 2.3 (red

line). This indicator provides a better picture with regard to the increase in inflows toward the stock and bond market in South Africa in the post-*apartheid* era. Similar to the foreign financial investment, foreign portfolio investment increased from 2.14 per cent in 1994 to 10.31 per cent in 1999. From 2000 to 2001 the inflow, however, crashed to a negative -2.35 per cent indicating a net outflow of foreign portfolio investment funds. After 2003 there is once again an increase in portfolio financial investment as percentage of GDP to 8.18 per cent before retracting again due to the global financial crisis of 2008.

Besides opening up the market to foreign investment other reforms that further contributed to the equity market liberalisation in South Africa include the move towards an electronic trading system and the introduction of formal legislation to ensure international levels of corporate governance (Hearn *et al.,* 2010: 490). Furthermore, prior to 1994, only member stockbrokers were permitted to act, in a single capacity, when trading equities on the JSE. These brokers, often refusing to do business with small investors, led to few South Africans having the opportunity to participate and benefit from the free enterprise system (Mkhize & Msweli-Mbanga, 2006: 83).

In line with the US and London having deregulated their markets in 1976 and 1986 respectively, the JSE started its own restructuring programme in 1995. This programme, commonly known as the 'Big Bang' of 1995, moved the JSE from a membership limited to natural persons, to a membership being open to all. For the first time financial institutions were able to become members of the JSE (De Beer & Keyser, 2007). This led to the introduction of a system of dual capacity trading permitting stockbrokers to act as agent as well as principal, that is, essentially to buy and sell shares on behalf of their clients whilst simultaneously holding packages of shares in which they themselves could deal. This led to negotiable commissions with the fixed brokerage fee system being abolished. With negotiable commissions, competition for clients between brokering firms intensified, resulting in lower transaction costs for investors (Mkhize & Msweli-Mbanga, 2006: 83).

The equity market liberalisation period in South Africa led to increased liquidity and turnover in the South African equity market (De Beer & Keyser, 2007). As can be seen in Figure 2.4, liquidity (measured by trading value and turnover velocity) of listed shares on the JSE indicates sharp and significant increases post-1995. The turnover velocity is the ratio between the Electronic Order Book (EOB) volume traded of domestic shares and their market capitalisation.
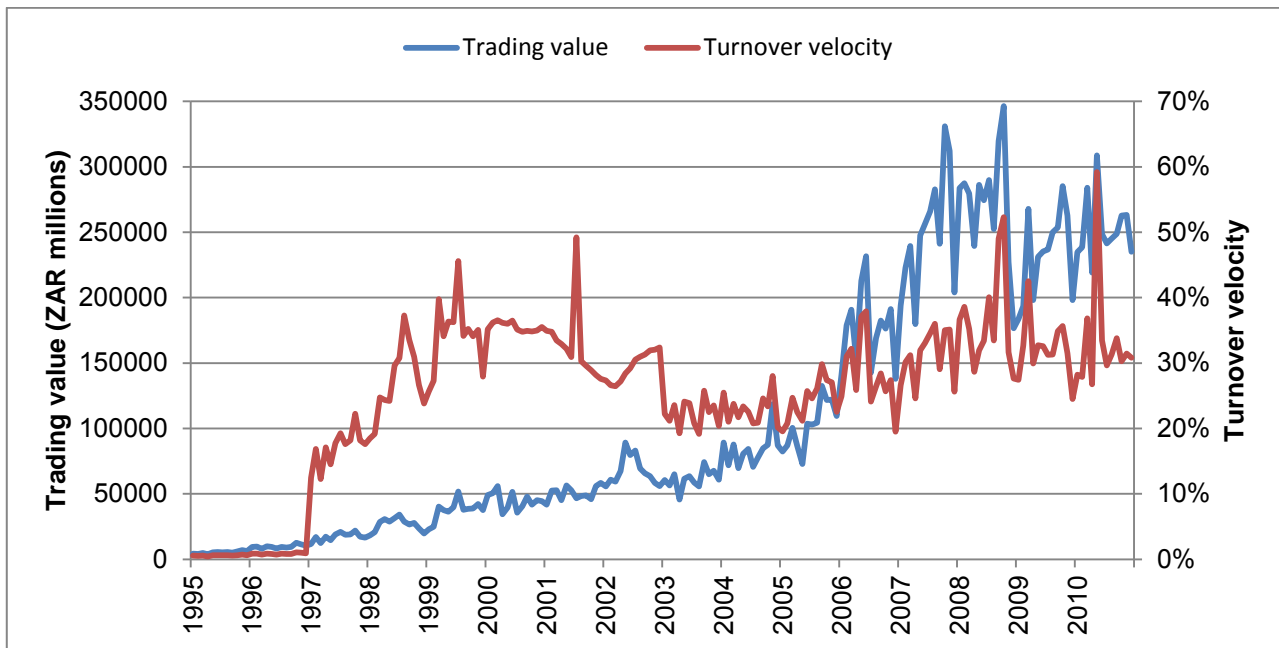
Figure 2.4: Trading value and turnover velocity of listed shares on the JSE

Data source: World Federation of Exchanges, 2012.

Although the South Africa market is now found to be economically and financially integrated with most of the major developed markets (Lamba & Otchere, 2001: 201), liquidity seemed almost non-existent pre-1995. Therefore this study chose to focus on the period starting from 1996 only.

2.6   SUMMARY AND CONCLUSION

This chapter provided an in-depth discussion of the sources of illiquidity, dimensions of liquidity and the proxies used to measure liquidity. It was stated that illiquidity in a market is mainly due to exogenous transaction costs such as brokerage fees, demand pressure and inventory risk due to not all market participants being present in the market at all times, private information held by a certain party to a trade, search friction relating to the time it takes to find a counterparty, the state of the economy and factors within the company itself.

In analysing the sources of illiquidity the researcher entered the realm of market microstructure theory, concerning the market's transactional properties and their effect on the price formation process. The price formation process reflects the dimensions of market liquidity which were defined as tightness, depth, resilience, immediacy and breadth. Tightness refers to low transaction costs, depth to the order size at the best quoted price

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and resilience to the speed with which a price will revert back to equilibrium following a large trade. Immediacy refers to the speed with which an order can be executed, and breadth, to many orders in a market.

Four categories of liquidity measures, which aim to capture the five dimensions of liquidity, were identified: transaction cost measures, volume-based measures, price-based measures and market-impact measures. However, no single measure was found to have the ability to explicitly capture tightness, depth, resilience, immediacy and breadth. Nonetheless, the researcher continued this chapter by introducing the most widely-used measures of liquidity in research.

Next, an extensive overview with regard to the evidence of the effect of liquidity levels on stock prices and returns, the changes in aggregate market liquidity and liquidity as a risk factor affecting stock returns were provided. Evidence of liquidity levels affecting stock returns in the US equity market was found to be well documented. Numerous studies attested to the outperformance of less liquid stocks relative to more liquid stocks cross-sectionally in this market. In the emerging market space, however, limited research is found. Research on liquidity in emerging markets seemed to focus on liquidity at an aggregate market level, therefore a focus on the effect of aggregate market liquidity on stock returns was deemed appropriate. In this regard, studies found average stock returns to be positively correlated with aggregate market liquidity in the US as well as some emerging markets such as South Africa. Lastly, as a risk factor, liquidity seemed to be a priced variable in both developed and emerging markets, creating a better understanding of the return generating process of stocks. However, in the South African market specifically, little support was found for this argument.

In conclusion, this chapter provided an outline of the evolvement of liquidity in the South African equity market often referred to as the South African equity market liberalisation. It is seen that post-1995, the subsequent period was characterised by a significant increase in equity market liquidity due to the opening up of markets to foreign investment, the move towards an electronic trading system and the introduction of formal legislation to ensure international levels of corporate governance.

CHAPTER 3
RESEARCH METHODOLOGY

Research is formalised curiosity. It is poking and prying with a purpose. It is a seeking that he who wishes may know the cosmic secrets of the world and that they dwell therein.

Hurston, 1942: 143.

3.1   INTRODUCTION

This chapter focuses on the research methodology of the study. It starts with an elaborate discussion of the research process that was followed in order to achieve the research objectives. The research process was structured in the form of six steps, which included various aspects such as planning the research design, data gathering, data processing and data analysis. The latter part of this chapter will focus on reliability and validity to ensure the trustworthiness of the research results.

3.2   THE RESEARCH PROCESS

For this study, the research process illustrated in Figure 3.1 was employed. This chapter now proceeds with a detailed discussion of each step of the research process.

Step 1
Problem discovery and definition

Step 2
Planning the research design

Step 3
Sampling

Step 4
Data gathering

Step 5
Data processing and analysis

Step 6
Conclusions and reporting research findings

Figure 3.1: The research process

Source: Adapted from Zikmund, Ward, Lowe, Winzar and Babin, 2011: 16.

3.3   STEP 1: PROBLEM DISCOVERY AND DEFINITION

The research process begins with problems or opportunities faced, which prompt the need for a decision. It is important to accurately identify such problems or opportunities as it sets the direction for the research that follows. In research, the adage: "a problem well defined is a problem half solved" emphasises the importance of an orderly definition of the research problem. If the diagnosis of the problem or opportunity is weak, the research may also lead to an insufficient solution (Cant, Gerber-Nel, Nel & Kotzé, 2005: 40).

According to Zikmund (2003: 94), defining a research problem involves the following interrelated legs:

o   Ascertain the decision maker's objectives;

o   Understand the background of the problem;

o   Isolate and identify the problem;

o   Determine the unit of analysis;

o   Determine the relevant variables; and

o   State the research objectives and research hypotheses.

The first step of the research process now proceeds with a discussion of each of these interrelated legs.

3.3.1   Ascertain the decision maker's objectives

As stated in Chapter 1, individual and institutional investors alike are continuously searching for investment strategies that can yield consistent and superior returns. In the case of this study, the focus fell on liquidity being a possible risk factor affecting stock returns and the ability of investors (the decision makers) to enhance risk-adjusted returns by incorporating a liquidity style into passive portfolio strategies.

3.3.2   Understand the background of the problem

Exploratory research is a preliminary research activity that can narrow the scope of the research topic and transform ambiguous problems into well-defined research objectives. According to Coldwell and Herbst (2004: 36), the aims of exploration are the development of hypotheses and not their actual testing. The researcher can obtain insight into the problem by employing a technique from one of the four basic categories available: previous research, pilot studies, case studies, and experience surveys (Zikmund, Babin, Carr & Griffin, 2010: 62). In this study, the analysis of previous research (as presented in Chapter 2) was employed.

3.3.3   Isolate and identify the problem

Through exploration, researchers can develop concepts more clearly, establish priorities, develop operational definitions and improve the final research design (Coldwell & Herbst, 2004: 10). From the exploratory research conducted it was possible to identify and define the research problem as presented in Section 1.3.

3.3.4   Determine the unit of analysis

The unit of analysis is the 'what' or 'whom' under investigation in the study. In this study the unit of analysis was the return associated with the different portfolio strategies and intersection group portfolios under investigation. A detailed discussion on the different portfolio strategies and intersection group portfolios can be found in Section 3.7.1.

3.3.5   Determine the relevant variables

The unit of analysis is determined by identifying the key variables in the study. A variable is anything that can vary or change from one instance to another. A constant, in contrast to a variable, is something that does not change (Zikmund *et al.*, 2010: 118). To address the specific problem, researchers must include all the relevant variables to be studied. Similarly, variables redundant to the study should be omitted (Zikmund, 2003: 97).

From the research problem the researcher was able to identify the variables that would have an influence on the single-stock returns, on the construction of the portfolio strategies and intersection group portfolios, on the return generated by these portfolios and on the measures to be used in assessing the risk-adjusted performance of the portfolio strategies employed.

After the researcher had ascertained the decision maker's objectives, understood the background, identified the problem and determined the unit of analysis and the variables, the researcher can proceed to the last leg in Step 1 of the research process. In this regard a discussion of the research objectives and research hypotheses now follows.

3.3.6   State the research objectives and research hypotheses

From Chapter 2 it became evident that the liquidity effect in the South African equity market remains largely unexplored. To the researcher's knowledge, for the South African equity market, any attempt to determine whether liquidity is a risk factor affecting stock return is scarce, whereas the effect of a liquidity bias in portfolio formation strategies seems almost non-existent. Therefore the primary objective of this study was to determine whether liquidity is a risk factor affecting stock returns in the South African equity market. Subsequently, as a secondary objective, the study aimed to explore whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral 'style index' strategies.

From the objectives of a study the researcher is able to logically derive formal hypotheses. These hypotheses are then empirically tested by applying statistics (Zikmund *et al.*, 2010: 41). For all research hypotheses employed in this study the five per cent level of significance was considered. As a primary objective this study aimed to determine if liquidity affects stock returns in the South African equity market. As mentioned in Chapter 1, liquidity is likely to be correlated with other variables such as size. Therefore, this study firstly examined liquidity as a residual effect measured independently of other variables such as the market premium, size and book-to-market ratio. The null hypothesis in this regard was that liquidity has no significant effect on stock returns after controlling for the market premium, size and book-to-market factors. To determine statistical significance the following hypotheses applied for the nine intersection group portfolios analysed:

$H_{0,1:}\ \beta_{LIQ(Small/Low)} = 0;$ $H_{A,1:}\ \beta_{LIQ(Small/Low)} \neq 0.$

$H_{0,2:}\ \beta_{LIQ(Small/Med)} = 0;$ $H_{A,2:}\ \beta_{LIQ(Small/Med)} \neq 0.$

$H_{0,3:}\ \beta_{LIQ(Small/High)} = 0;$ $H_{A,3:}\ \beta_{LIQ(Small/High)} \neq 0.$

$H_{0,4:}\ \beta_{LIQ(Mid/Low)} = 0;$ $H_{A,4:}\ \beta_{LIQ(Mid/Low)} \neq 0.$

$H_{0,5:}\ \beta_{LIQ(Mid/Med)} = 0;$ $H_{A,5:}\ \beta_{LIQ(Mid/Med)} \neq 0.$

$H_{0,6:}\ \beta_{LIQ(Mid/High)} = 0;$ $H_{A,6:}\ \beta_{LIQ(Mid/High)} \neq 0.$

$H_{0,7:}\ \beta_{LIQ(Large/Low)} = 0;$ $H_{A,7:}\ \beta_{LIQ(Large/Low)} \neq 0.$

$H_{0,8:}\ \beta_{LIQ(Large/Med)} = 0;$ $H_{A,8:}\ \beta_{LIQ(Large/Med)} \neq 0.$

$H_{0,9:}\ \beta_{LIQ(Large/High)} = 0;$ $H_{A,9:}\ \beta_{LIQ(Large/High)} \neq 0.$

β_{LIQ} was found by regressing intersection group portfolio excess return $(RP_t - Rf_t)$ on the monthly residual liquidity factor $(e_{LIQ,t})$, which is free from the influence of the market premium, size and book-to-market factors, by means of the following regression equation:

$$RP_t - Rf_t = A + \beta_{LIQ}(e_{LIQ,t}) + e_t \qquad \qquad \text{…(Eq 3.1)}$$

If the null hypothesis did not hold, the researcher would concur that there is a statistically significant effect of liquidity on portfolio return after controlling for the market premium, size and book-to-market factors.

Next, the study examined liquidity as a risk factor taking into account the Fama-French three-factor model factors, namely the market premium, size and book-to-market. In this instance liquidity was used in its original form and not as a residual specifically to address whether the inclusion of a liquidity factor improves the ability of the asset pricing model to capture shared variation in stock returns. To determine statistical significance, the following hypotheses were employed:

$H_{0,10}$: $R^2_{(LIQ\ included)} \leq R^2_{(LIQ\ excluded)}$;

$H_{A,10}$: $R^2_{(LIQ\ included)} > R^2_{(LIQ\ excluded)}$.

As indicated previously, $R^2_{(LIQ\ included)}$ was the coefficient of determination for the regression model including liquidity as a risk factor, and $R^2_{(LIQ\ excluded)}$ the coefficient of determination for the regression model excluding liquidity as a risk factor. If the null hypothesis did not hold, the researcher would concur that the inclusion of liquidity as a risk factor has a statistically significant improvement on the ability of the Fama-French asset pricing model to capture shared variation in stock returns.

As a secondary objective, the study aimed to explore whether incorporating a liquidity style into passive portfolio strategies yielded enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral 'style index' strategies. In this regard two liquidity-biased, one pure-liquidity and two liquidity-neutral portfolio strategies were constructed, tracked and the risk-adjusted performance analysed using a range of well-known financial ratios and formulas. Given the nature of the problem at hand, the researcher did not deem the use of hypotheses necessary for the secondary objective of this study.

3.4   STEP 2: PLANNING THE RESEARCH DESIGN

The research design can be seen as the master plan that stipulates the methods followed when collecting and analysing the relevant data. The objectives determined in Step 1 of the research process are included in the design to ensure that the data collected is appropriate for solving the particular research problem at hand (Zikmund *et al.,* 2010: 64).

According to Collis and Hussey (2003: 10), researchers generally choose a research design from one of four broad categories, namely exploratory, descriptive, analytical or predictive research designs. Exploratory research designs can be used when research questions are vague or when little theory is available. Being discovery-oriented, these research designs do not test specific research hypotheses. Exploratory research was utilised in the first step of the research process in an endeavour to isolate and identify the research problem.

Descriptive research designs are structured and designed to measure the characteristics described in the research problem. Unlike exploratory research, descriptive research is employed to describe a situation. This is generally done by providing measures of an event or activity, such as measures of central tendency or measures of dispersion (Hair, Wolfinbarger Celsi, Money, Samouel & Page, 2011: 147). Analytical (or explanatory) research extends the descriptive approach to suggest or explain why or how something is happening. The major aim of explanatory research is thus to identify the existence of causal relationships between variables (Collis & Hussey, 2003: 11). Since this study did not investigate existing cause-and-effect relationships, it did not make use of an analytical research design.

Lastly, predictive research aims to forecast the likelihood that particular phenomena will occur in given circumstances. Predictive research often incorporates quantitative regression analysis that allows the predicting of a particular outcome by simultaneously addressing a number of independent predictor variables (Moore, Neville, Murphy & Connolly, 2010: 61).

For the primary objective of this study, a predictive research design was employed. However, for the secondary objective, given the nature of the research problem, a descriptive research design without the use of formal hypotheses was deemed appropriate.

Research designs are either cross-sectional or longitudinal in nature. A cross-sectional research design provides and statistically summarises data for a specific point in time. A longitudinal research design, however, describes data over a certain time period. In contrast to a cross-sectional research design, a longitudinal research design requires data to be collected from the same sample over multiple periods of time. This research design

is appropriate when the research objective is affected by how variables vary over time (Hair *et al.*, 2003: 150-151). For this particular study, longitudinal data was employed.

After the researcher has determined the appropriate research design to be used in the study, the next step is to determine the appropriate sampling technique.

3.5   STEP 3: SAMPLING

Hair *et al.* (2003: 165) stated that a representative sample is obtained by following a set of well-defined procedures:

o   Define the target population;
o   Choose the sample frame;
o   Select the sampling method;
o   Determine the appropriate sample size; and
o   Implement the sampling plan.

The target population is the complete group of objects or elements relevant to the specific research project. These objects or elements are relevant since they possess the data the research project is designed to collect (Hair *et al.*, 2003: 165). In this regard, the target population of the study consisted of all listed stocks on the JSE from December 1995 to December 2012.

A sample frame is a comprehensive list of the elements from which a sample can be drawn (Hair *et al.*, 2003: 166). The constituents of the FTSE/JSE ALSI were chosen as the sample frame for the study since these companies best reflect the truly investable universe of stocks available to institutional investors. The FTSE/JSE ALSI represents 99 per cent of the FTSE/JSE Africa headline indices' constituents, based on full market capitalisation (before adjusting for free-float) (FTSE/JSE, 2010: 9). The remaining one per cent of companies, called fledglings, was excluded from the study. Figure 3.1 illustrates how the constituents of the FTSE/JSE Africa headline indices are determined.

Eligible Companies	
All Share (99%)	A liquidity screen is used to determine eligibility,
Top 40	
Mid Cap (41-100)	Thereafter, the remaining companies are ranked by their full market capitalisation,
	The top 99 per cent of market capitalisation (the FTSE/JSE ALSI) are separated into top-cap, mid-cap and small-cap indices,
Small Cap	
	Lastly, the indices are set up by applying free-float market capitalisation weightings.
Fledgling (1%)	

Figure 3.2: FTSE/JSE Africa headline indices' constituents

Source: FTSE/JSE, 2010: 9.

The year-end constituents of the FTSE/JSE ALSI since December 2002 were obtained from the JSE website. The FTSE/JSE Africa Index Series replaced the JSE Actuaries indices on 24 June 2002 and therefore, the constituents of the backdated FTSE/JSE ALSI were collected from the JSE directly. Fortunately, in a joint initiative, FTSE and the JSE created this index dating back to July 1995 based on the new rules for constructing indices of the FTSE/JSE Africa Index Series (Johannesburg Stock Exchange, [S.a.]: 7). For a company to have been included in the sample frame, it must have had a free-float factor of more than 15 per cent per period in compliance with the FTSE/JSE ground rules. It has to be mentioned that this rule was applied to the specific constituent data obtained from the JSE directly (constituent data from December 1995 to December 2001). The dataset used from December 2002 excluded companies with free-float factors below 15 per cent.

The year-end FTSE/JSE ALSI constituents for each year were used as the basis for developing the sample frame for the following year. In other words the FTSE/JSE ALSI constituents of December 1995 were the basis for developing the sample frame for 1996.

Once a sample frame has been determined the researcher can proceed to selecting a sampling method. According to Hair et al. (2011: 167), traditional sampling methods can be

divided into two broad categories: *probability* and *non-probability*. In probability sampling each unit of the target population has a known probability of being selected into a sample. This is the preferred method of sampling if possible, because it allows the researcher to infer unbiased generalisations upon the population of interest. In non-probability sampling, however, the inclusion or exclusion of certain units are left to the discretion of the researcher. For both the primary and secondary objectives of this study, non-probability sampling techniques were employed.

In non-probability sampling, the units of a sample are chosen without considering their probability of occurrence. The four main techniques in non-probability sampling are *convenience*, *judgement*, *quota*, and *snowball* sampling (Zikmund *et al.*, 2010: 401). A convenience sample results when the more convenient units are chosen from the target population. It is thus the sampling method that is the easiest and cheapest to conduct, but it is also the least reliable (Coldwell & Herbst, 2004: 81). Judgement and quota sampling are purposive sampling techniques in that the sample selected conforms to certain criteria that the researcher wishes to analyse (Coldwell & Herbst, 2004: 81). In judgement sampling the researcher uses his/her own judgment to select a sample that fulfils a specific purpose, such as ensuring that all units chosen have a certain specified characteristic. In quota sampling, to improve the sample's representativeness, the researcher uses relevant characteristics to stratify the sample (Zikmund *et al.*, 2010: 401). Lastly, in snowball sampling the existing study subjects recruit future study subjects. Thus the sample group appears to grow like a rolling snowball. In this study a judgement sampling technique, in which the researcher selects a sample based on his or her judgment about some characteristic required of the sample, was used.

For the two objectives, two different samples were deemed appropriate. For the primary objective, determining whether liquidity is a risk factor affecting stock returns in the South African equity market, all companies in the sample frame with the necessary data were included. To be included a company must have had available data regarding its annual Rand trading volume, earnings per share, year-end number of shares outstanding, and monthly stock price and dividend yield, for the preceding year.

Table 3.1 illustrates the evolvement of the sample frame and Table 3.2 the evolvement of the sample for the 17 years analysed.

Table 3.1: Sample frame: 1996 to 2012

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Companies in FTSE/JSE ALSI	278	205	240	275	239	195	161	161	154	160	157	159	159	163	157	166	164
Companies excluded (Free-float constraints)	6	4	4	6	2	2	0	0	0	0	0	0	0	0	0	0	0
Companies in Sample Frame	272	201	236	269	237	193	161	161	154	160	157	159	159	163	157	166	164

Table 3.2: Sample: 1996 to 2012

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Companies in Sample Frame	272	201	236	269	237	193	161	161	154	160	157	159	159	163	157	166	164
Companies excluded (Data constraints)	22	22	30	56	51	7	3	6	5	9	4	3	8	8	3	5	5
Companies in Sample	250	179	206	213	215	186	158	155	149	151	153	156	151	155	154	161	159

For the secondary objective, exploring whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral 'style index' strategies, a further rule for inclusion applied. Only companies that represented at least 0.05 per cent of the total market capitalisation of the overall market index (FTSE/JSE ALSI) were selected. This was done in an endeavour to select a refined sample which has sufficient capacity to absorb meaningful investment.

The JSE is a highly-concentrated market, dominated by only a couple of large companies (Kruger & van Rensburg, 2008: 5). As a result there is a significant number of very small firms (based on market capitalisation), which do not provide sufficient investable capacity to an institutional investor. As can be seen in Figure 3.3, at December 2012, in excess of 20 per cent of the FTSE/JSE ALSI was represented by only two companies.

More than 50 per cent of the market capitalisation is concentrated within ten stocks. Additionally, constituents of the FTSE/JSE top 40 index which represents the biggest 40 stocks in the market according to market capitalisation, represent 84.5 per cent of the overall market index. Hence, the remaining 15.5 per cent of the index consists of 120 shares, of which a significant number are very small firms (by market capitalisation). It is difficult for an institutional investor to invest in such small firms given the significant investable capacity required.
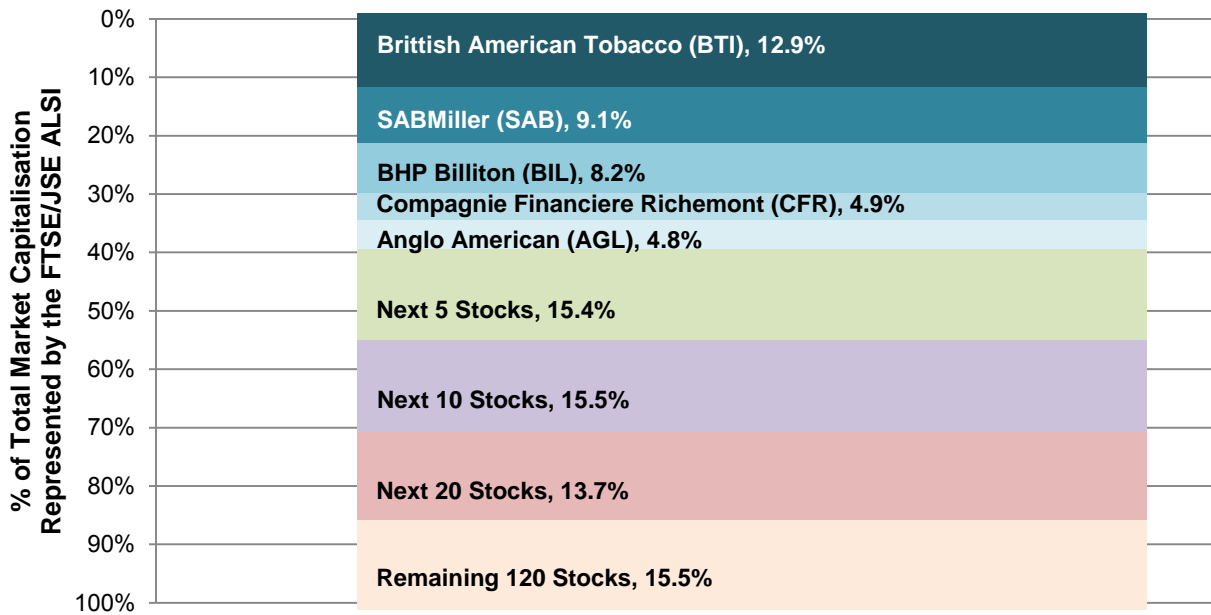
Figure 3.3: Distribution of market capitalisation weights (December 2012)

Source: Johannesburg Stock Exchange, 2012.

Excluding those companies that represented less than 0.05 per cent of the market index makes for a more realistic strategy that institutional investors should be able to apply. However, applying this rule of inclusion places a limitation on the study in that a large number of companies (constituents) are omitted from the study. The number of companies in this refined sample and the number of companies omitted each year can be seen in Table 3.3.

Table 3.4 indicates the size of the sample and refined sample together with the percentage of the FTSE/JSE ALSI market capitalisation included for the primary and secondary objectives of this study. As indicated, both the sample and the refined sample (mostly) represented in excess of 90 per cent of the FTSE/JSE ALSI market capitalisation.

Table 3.3: Refined Sample: 1996 to 2012

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Companies in Sample	250	179	206	213	215	186	158	155	149	151	153	156	151	155	154	161	159
Companies excluded (0.05% limitation)	74	40	47	66	79	66	49	42	35	42	39	41	35	38	43	45	45
Companies in Refined Sample	176	139	159	147	136	120	109	113	114	109	114	115	116	117	111	116	114

Table 3.4: Sample / Refined Sample size

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Companies in Sample	250	179	206	213	215	186	158	155	149	151	153	156	151	155	154	161	159
FTSE/JSE ALSI % included in Sample	92.0	94.2	92.9	95.1	93.8	96.7	99.1	99.1	98.9	95.9	96.6	95.7	99.5	99.8	99.3	99.3	99.5
Companies in Refined Sample	176	139	159	147	136	120	109	113	114	109	114	115	116	117	111	116	114
FTSE/JSE ALSI % included in Refined Sample	89.9	92.9	91.6	93.6	92.2	95.3	97.9	98.2	98.0	94.8	95.6	94.6	98.5	98.9	98.1	98.3	97.7

Focusing only on those companies that are listed at the end of the period under review would have exposed the study to survivorship bias. It was thus important to include those companies that delisted during the period under investigation. By including both listed and delisted companies in the study the researcher aimed to reduce the apparent persistence in the performance of portfolio strategies and group formations that arises due to excluding delisted companies (Brown, Goetzmann, Ibbotson & Ross, 1992: 576).

After the researcher defined the target population, chosen the sample frame, selected the sampling method and determined the appropriate sample size, the last procedure is to implement the sampling plan.

3.6   STEP 4: DATA GATHERING

In this step of the research process the actual collection of data takes place. As stated in Chapter 1, data can be classified as either primary or secondary data. Since the data, primarily obtained from the McGregor BFA (Pty) Ltd (2012) database, existed prior to this study, the data used can be classified as secondary data. Primary research was, however, deemed necessary since the data obtained from the secondary research had to be adjusted to a usable format. The following sections present the data employed for the primary and secondary objectives of this study.

3.6.1   Liquidity as a risk factor

For the primary objective, sorting the sample stocks into size and liquidity terciles, a measure of size and liquidity was required for each stock. As a measure of size, the researcher used the company's free-float market capitalisation weight in the sample. The market capitalisation of each stock was retrieved from the McGregor BFA (Pty) Ltd (2012) database. The free-float factor for each stock was obtained from the JSE directly for the period before 2002 and from the JSE website thereafter.

As a proxy of liquidity, the researcher used the turnover measure. As stated in Section 2.3.2, turnover is relatively market capitalisation neutral as it effectively measures how many times the total number of free-float shares outstanding of a specific company were traded during a year. The Rand volume traded, number of issued ordinary shares and average monthly closing price for each stock were obtained from the McGregor BFA (Pty) Ltd (2012) database.

After sorting the stocks into size and liquidity terciles, nine size/liquidity intersection group portfolios were constructed. For each intersection group portfolio the researcher had to determine the monthly holding period return. In this regard the researcher obtained monthly price data and dividend yields from the McGregor BFA (Pty) Ltd (2012) database. Liquidity was then tested as an explanatory risk factor of the portfolio excess return while controlling for the market premium, size and book-to-market factors. To control for these factors the researcher had to gather data on a market portfolio proxy, an appropriate risk-free rate and factor-mimicking portfolios based on size and book-to-market ratios. The risk-free rate and market portfolio data are discussed in Section 3.6.3 and Section 3.6.4 respectively. To construct the factor mimicking portfolios based on size (return of a portfolio of small stocks minus the return of a portfolio of large stocks), and on book-to-market (value/growth) (return of a portfolio of high book-to-market ratio stocks minus the return of a portfolio of low book-to-market ratio stocks), market capitalisation and book-to-market ratios for all stocks in the sample frame were sourced from the McGregor BFA (Pty) Ltd (2012) database.

3.6.2   Portfolio strategies

For the secondary objective, the weight of a company within the pure-liquidity portfolio was dependent on the Rand volume traded for the company during the previous year. The weight of a company within a liquidity-neutral portfolio was dependent on the company's year-end free-float market capitalisation or annual positive earnings. Lastly, the weight of a company within a liquidity-biased portfolio was dependent on the company's year-end free-float market capitalisation or annual earnings as well as the liquidity of the specific stock using the volume traded as a measure of liquidity. Free-float factors were once again obtained from the JSE, whereas market capitalisation, Rand volume traded and annual earnings were sourced from McGregor BFA (Pty) Ltd (2012).

Once the portfolio strategies were constructed, in line with the primary objective of this study, the researcher had to determine the monthly holding period return of each portfolio strategy. In this regard, the researcher once again obtained monthly price data and dividend yields from the McGregor BFA (Pty) Ltd (2012) database. The holding period return of each portfolio strategy was then analysed on a risk-adjusted basis by means of risk-adjusted performance measures. For the risk-adjusted performance measures, the researcher had to further obtain data on an appropriate risk-free rate and a market

portfolio proxy. The decisions on a risk-free rate and market portfolio proxy are discussed under separate headings below.

3.6.3   Risk-free rate

The risk-free rate is a rate that has no default risk and no correlation with other investments (Bodie, Kane & Marcus, 2003: 137). Although there is general consensus that government securities ought to be employed as proxies for the risk-free rate, diverse views exist as to whether long- or short-term rates should be employed (Hirt & Block, 2003: 607). Academic studies commonly use a short-term Treasury bill rate, whereas practitioners favour a long-term rate. Practitioners do so for two reasons: firstly, as a long-term rate is consistent with the goal of estimating a long-run cost of equity, and secondly, as it is less volatile than a short-term rate (Cornell, Hirshleifer & James, 1997: 13).

In South Africa, Correia and Uliana (2004: 71) proposed another measure for the risk-free rate, namely the negotiable certificate of deposit (NCD) rate. They argued that this rate is more applicable in the South African setting given the effect of historic government regulations on the liquidity and pricing of government securities. Several studies such as Meyer (1998), Von Wielligh and Smit (2000) and Akinjolire and Smit (2003) used the NCD rate as a proxy for the risk-free rate in recognition of this distortion. Similar to these studies, the NCD rate was employed as the risk-free rate in this study. The NCD rate was sourced from the Bureau for Economic Research (BER) (2010) of Stellenbosch University.

3.6.4   Market portfolio

Firstly, in line with academic and practitioner application, the FTSE/JSE ALSI was employed as a proxy for the market portfolio in this study. However, Correira and Ulliana (2004: 66) pointed out that using the FTSE/JSE ALSI as a market proxy is seriously flawed. The main concern regarding the use of the FTSE/JSE ALSI relates to its skewed nature in favour of mining and commodity stocks. The question which becomes evident is then: Which index or combination of indices is the most appropriate proxy for the market index in South Africa?

Bowie and Bradfield (1993: 6) first addressed this question, suggesting that a combination of the JSE Actuaries Financial and Industrial Indices (predecessors of the present day FTSE/JSE Financial and Industrial Indices) ought to be employed as a proxy for the

market index. They justified their argument by stating that many investors reward mining shares (and more particularly gold shares) as representing a different type of risk and hence a different market altogether. As suggested by Campbell (1979) and Gilbertson and Goldberg (1981: 40), Bowie and Bradfield (1993) found an evident segmentation between the Mining and Industrial sectors on the JSE. This suggested that stocks should be priced to compensate investors for bearing the risk of the two indices separately.

The research by Van Rensburg and Slaney (1997: 1) on this topic revealed that using the JSE Actuaries All Gold and Industrial Indices provided the best explanation of the return generating process on the JSE and ought to be employed as a proxy for the market portfolio. In 2002, Van Rensburg (2002: 83) updated their 1997 results due to the reclassification of the JSE sector indices that occurred in March 2000. In this successive study it was found that the new Financial-Industrial (J250) and Resources (J000) indices could be employed as observable proxies for the first two principal components. Consequently, it was suggested that these indices replace the JSE Actuaries All Gold and Industrial Indices in future applications.

In this study, the FTSE/JSE Financial Industrial (J250) index and FTSE/JSE Resource 10 (J210) index were employed as a further proxy for the market portfolio. The FTSE/JSE Resources (J000) index, as suggested by Van Rensburg (2002), was discontinued in 2006, due to the implementation of new indices based on the Industry Classification Benchmark (ICB) developed by the global index companies FTSE Group and Dow Jones (Maltz, 2005). The reason behind this discontinuation stemmed from the fact that the FTSE/JSE Resource 20 (J210) index included the same shares as the FTSE/JSE Resources (J000) index. It was therefore decided that the FTSE/JSE Resource 20 (J210) index was representative of this sector in the market. This index later changed to include only ten companies and subsequently led to the name change to FTSE/JSE Resource 10 (J210) index. Data on both the FTSE/JSE Financial Industrial (J250) index and FTSE/JSE Resource 10 (J210) index was obtained from the McGregor BFA (Pty) Ltd (2012) database.

Once all the data was gathered, the researcher proceeded to the data processing and analysis step of the research process.

3.7   STEP 5: DATA PROCESSING AND ANALYSIS

Once the data is gathered the researcher needs to firstly process the data and secondly analyse the processed data (Cant *et al.*, 2003: 54). Data processing refers to the process of converting raw data to a reduced form which is appropriate for analysis and interpretation (Coldwell & Herbst, 2004: 96). The data collected for this specific study was quantitative in nature. Therefore, quantitative research, which infers and resolves problems by using numbers, was employed to achieve the objectives of the study (Coldwell & Herbst, 2004: 15). The data processing for the primary and secondary objectives is now discussed followed by the analysis of the processed data.

3.7.1   Data processing

For the primary objective each stock in the sample had to be allocated a size and liquidity value. For size, each stock was allocated its free-float market capitalisation weight in the sample at year-end. The following equation applied:

$$\text{Size}_i = \frac{\text{MC(FF)}_i}{\text{MC(FF)}} \qquad\qquad\qquad \text{…(Eq 3.2)}$$

Where: Size_i =   size measure for stock *i*;

MC(FF)_i =   free-float market capitalisation of stock i at year-end;

MC(FF) =   free-float market capitalisation of all stocks in the sample at year-end.

As a measure for liquidity, each stock was allocated its turnover value. For each specific stock, turnover measures how many times the number of shares outstanding (adjusted for free-float) was traded in the market during the year. The following equation applied:

$$T_i = \frac{V_i}{S_i \times P_i} \qquad\qquad\qquad \text{...(Eq 3.3)}$$

Where: T_i =   annual turnover rate of stock *i*;

V_i =   annual Rand volume traded of stock *i* during the year;

S_i =   number of issued ordinary shares (adjusted for free-float) at year-end;

P_i =   average monthly closing price over year.

Once each stock in the sample was allocated a size and liquidity value, the stocks were independently sorted into size and liquidity terciles. The researcher then took the intersections of the two terciles to form nine intersection group portfolios. To test the influence of liquidity on the portfolio returns a measure of portfolio return was required. The portfolio return was calculated as the equal weighted holding period return of the stocks in the portfolio. The method used to determine stock returns is explained in more detail in Section 3.8.1.

As a secondary objective, the researcher aimed to explore whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral 'style index' strategies. In line with Chen *et al.* (2010), this study focused on 'passive' investment strategies, in the sense that they are designed to take advantage of certain easily observable stock attributes. Most passive investment strategies are based on market capitalisation. Arnott, Hsu and Moore (2005), however, suggested that fundamentals weighted, non-capitalisation-based strategies (based on a fundamental variable such as earnings, sales/revenue, book values, and dividends) can consistently provide higher returns and lower risks than their traditional capitalisation weighted counterparts. In this regard, an earnings weighted strategy was included as a pure value or fundamental indexation strategy in which the market valuation of a stock does not play a role in determining the stock's portfolio weight (Chen *et al.*, 2010: 7). Earnings was chosen as the fundamental variable to focus on because, firstly, sales/revenues and book values are not always comparable across different industries. Secondly, increasingly more companies today choose to pay low or no dividends which unnecessarily disqualifies too many stocks (Ramorwa, 1). The earnings factor is therefore more comparable across industries and many more companies have positive earnings than have positive dividends (Chen *et al.*, 2010: 8).

Next, the researcher included a liquidity bias in the earnings weighted and market capitalisation strategies in an endeavour to take advantage of the liquidity premium, whilst retaining the benefits associated with indexing. Including a liquidity bias in these strategies gave rise to the earnings-based liquidity strategy and market capitalisation-based liquidity strategy. Lastly, a pure-liquidity strategy, favouring high liquidity stocks was included in the study in an endeavour to determine whether it is viable to hold highly-traded or 'popular' stocks. Each portfolio strategy was constructed at year-end and held for the next 12 months. After 12 months the stocks under review were re-analysed and the portfolio

strategy was rebalanced. A detailed discussion on the formation of each of these strategies now follows.

To construct each portfolio strategy, it was assumed that there are N stocks in the sample. For stock n and time t, $E_{n,t}$ denoted the annual preceding 12 month positive earnings of the stock, $C_{n,t}$ its year-end free-float market capitalisation, and $V_{n,t}$ the total Rand trading volume for the preceding 12 months. For the N stocks in the sample, E_t, was the sum of all positive annual earnings earned, C_t, the total free-float market capitalisation at year-end and V_t, the total Rand volume traded for the preceding 12 months. Earnings for each company ($E_{n,t}$) were the average annual earnings per share (EPS) multiplied by the number of ordinary shares outstanding at the portfolio formation date. Whereas the free-float market capitalisation was intended to focus on a company's tradable size, earnings represented the total earnings of the company. Therefore, unlike market capitalisation, earnings were not adjusted with the stock's free-float factor.

Equations 3.4, 3.5 and 3.6 were applicable in this regard:

$$E_t = \max\{E_{1,t},0\} + \max\{E_{2,t},0\} + \ldots + \max\{E_{N,t},0\} \quad\quad \text{...(Eq 3.4)}$$

$$C_t = C_{1,t} + C_{2,t} + \ldots + C_{N,t} \quad\quad \text{...(Eq 3.5)}$$

$$V_t = V_{1,t} + V_{2,t} + \ldots + V_{N,t} \quad\quad \text{...(Eq 3.6)}$$

To account for outliers (extreme values which are assumed to be spurious because of their extremity), all inputs ($E_{1,t} \ldots E_{N,t}$; $C_{1,t} \ldots C_{N,t}$; $V_{1,t} \ldots V_{N,t}$) were winsorised at the five per cent and 95 per cent levels. In this regard, rather than omitting extreme data points, winsorisation replaced extreme values by certain outer boundary values. All data below the 5th percentile was set to the 5th percentile and all data above the 95th percentile was set to the 95th percentile. The construction applied for each portfolio strategy now follows.

3.7.1.1 *Market capitalisation strategy*

The weight assigned to each stock was equal to the stock's free-float market capitalisation divided by the total free-float market capitalisation of all stocks in the sample. The portfolio weight for stock n was then equal to $C_{n,t}/C_t$.

3.7.1.2 Earnings weighted strategy (fundamental index strategy)

The weight assigned to each stock was equal to the stock's preceding 12-month positive earnings divided by the total positive preceding 12-month earnings of all stocks in the sample. Companies with negative or no earnings for the prior year were thus excluded from the study. The portfolio weight for stock *n* was then equal to $E_{n,t}/E_t$.

3.7.1.3 Volume weighted strategy (pure-liquidity strategy)

The weight assigned to each stock was equal to the stock's preceding 12-month total Rand volume traded divided by the total Rand volume traded of all stocks in the sample. The portfolio weight for stock *n* was then equal to $V_{n,t}/V_t$.

3.7.1.4 Earnings-based liquidity strategy

For this strategy a positive earnings weight was assigned to each stock, but it was biased with a negative volume weight relative to the earnings weight. For each stock the earnings weight $E_{n,t}/E_t$ and volume weight $V_{n,t}/V_t$ were calculated in the same manner as for the earnings and volume weighted strategies. For each stock the volume-to-earnings (V/E) ratio ($V_{n,t}/E_{n,t}$) indicated the volume of trading for each Rand of earnings during a year. If the stock's V/E ratio equalled the sample's V/E ratio it was assigned its earnings weight.

$$\text{If: } \frac{V_{n,t}}{E_{n,t}} = \frac{V_t}{E_t} \rightarrow \text{stock's liquidity-biased portfolio weight} = \frac{E_{n,t}}{E_t}$$

If the stock were traded frequently, measured in total rand volume traded, the liquidity portfolio weight was proportionally lower than its earnings weight.

$$\text{If: } \frac{V_{n,t}}{E_{n,t}} > \frac{V_t}{E_t} \rightarrow \text{stock's liquidity-biased portfolio weight} < \frac{E_{n,t}}{E_t}$$

On the other hand, if the stock traded less than the market average, the liquidity portfolio weight was proportionally higher than its earnings weight.

$$\text{If: } \frac{V_{n,t}}{E_{n,t}} < \frac{V_t}{E_t} \rightarrow \text{stock's liquidity-biased portfolio weight} > \frac{E_{n,t}}{E_t}$$

More specifically, as per personal communication (Theart, 2011) with Mr Chen of Chen *et al.* (2010; 2013), the earnings weight of each stock was adjusted to its portfolio weight as follows:

$$\text{Stock's liquidity-biased portfolio weight} = \frac{E_{n,t}}{E_t} + \left(\frac{E_{n,t}}{E_t} - \frac{V_{n,t}}{V_t} \right)$$

If the whole expression resulted in a negative value, the weight was forced to zero and all remaining positive weights were proportionally adjusted to add up to 100 per cent again.

3.7.1.5 *Market Capitalisation-Based Liquidity Strategy*

Similar to the earnings-based liquidity strategy, this study also used market capitalisation as the basis from which to define a liquidity bias. For this strategy, $C_{n,t}/C_t$, was defined as the stock's market capitalisation weight after adjusting for free float. If the stock's volume-to-market capitalisation (V/C) ratio, $(V_{n,t}/C_{n,t})$, equalled the sample V/E ratio (V_t/C_t) the stock was assigned its market capitalisation weight.

$$\text{If: } \frac{V_{n,t}}{C_{n,t}} = \frac{V_t}{C_t} \rightarrow \text{stock's liquidity-biased portfolio weight} = \frac{C_{n,t}}{C_t}$$

If the stock traded frequently, the liquidity portfolio weight was proportionally lower than its market capitalisation weight.

$$\text{If: } \frac{V_{n,t}}{C_{n,t}} > \frac{V_t}{C_t} \rightarrow \text{stock's liquidity-biased portfolio weight} < \frac{C_{n,t}}{C_t}$$

On the other hand, if the stock traded less than the market average, the liquidity-biased portfolio weight was proportionally higher than its market capitalisation weight.

$$\text{If: } \frac{V_{n,t}}{C_{n,t}} < \frac{V_t}{C_t} \rightarrow \text{stock's liquidity-biased portfolio weight} > \frac{C_{n,t}}{C_t}$$

More specifically, the market capitalisation weight of each stock was adjusted to its portfolio weight as follows:

$$\text{Stock's liquidity-biased portfolio weight} = \frac{C_{n,t}}{C_t} + \left(\frac{C_{n,t}}{C_t} - \frac{V_{n,t}}{V_t} \right)$$

As with the earnings-based liquidity strategy, if the whole expression resulted in a negative value, the weight was forced to zero and all remaining positive weights were proportionally adjusted to add up to 100 per cent again.

A major shortcoming of this approach was that the market capitalisation of a company may have already incorporated a liquidity premium (Chen *et al.*, 2010: 9). Nonetheless, this strategy was included in the study.

Each portfolio strategy was constructed and held for the next 12 months. After 12 months the stocks under review were re-analysed and the portfolio strategy was rebalanced. The monthly portfolio return was calculated by appropriately weighting the holding period return of each of the constituent stocks in the portfolio. The method used for determining stock returns is explained in more detail in Section 3.8.1.

Once the data has been processed, the researcher could continue to analyse the processed data. Analysis of the data is discussed next.

3.7.2   Analysis of the data

Once the raw data has been reduced to an appropriate format, the researcher can continue with the analysis of the data. The purpose of data analysis is then to generate meaning from the collected data (Colwell & Herbst, 2004: 92). In this study, as a basis for further analysis, descriptive statistics were employed to summarise and present the analysed data. This was followed by regression analysis to determine whether liquidity as a risk factor affects stock return. Lastly, the risk-adjusted performance measures based on the five constructed portfolio strategies were analysed. This was done in an endeavour to determine whether liquidity-biased portfolio strategies realised enhanced risk-adjusted performance relative to the pure-liquidity and liquidity-neutral portfolio strategies. Descriptive statistics, regression analysis and the final analysis for both the primary and secondary objectives are discussed next under separate headings.

3.8   DESCRIPTIVE STATISTICS

Zikmund *et al.* (2010: 431) stated that descriptive statistics describe basic characteristics and summarise data in a straightforward and understandable manner. In this study, the researcher used numerical descriptive measures to summarise and present the data. The descriptive statistics presented in the study should provide a better understanding of the nature of the data and are important for the development of statistical inference (Keller, 2005: 90). In line with DeFusco *et al.* (2011), who explored four properties of return distributions, this section sets out the descriptive statistics with regards to the central

tendency, dispersion, skewness and kurtosis of the return distributions employed in this study.

3.8.1   Measurement of central tendency

In this study, monthly holding period returns (HPR) of different portfolio strategies and intersection group portfolios were analysed. To determine the HPR of a portfolio strategy or intersection group portfolio, the researcher had to appropriately weigh the individual HPRs of the stocks/companies under review.

The HPR expresses the change in the value of a stock for a one-month period. The following equation was used to determine the monthly HPR for each stock:

$$\text{HPRt} = \frac{P_t + \frac{DY_t}{12} - P_{t-1}}{P_{t-1}} \qquad\qquad \text{...(Eq 3.7)}$$

Where: HPRt   =   holding period return for month t;

P_t =   stock price at end of month t;

P_{t-1} =   stock price at end of month t-1;

DY_t =   annual dividend yield in month t.

When analysing the HPR of a portfolio strategy or intersection group portfolio it will likely yield high rates of return during some months and low rates or even negative rates of return during others. According to Reilly and Brown (2008: 10), it is therefore also necessary to determine a summary figure that can indicate the investor's typical experience, or the rate of return to be expected if the investment is held over some longer period of time.

The mean is a measure of central tendency that reflects all the values in the data set and is an appropriate figure to compare across different data sets (Coldwell & Herbst, 2004: 103). To determine such a summary figure this study made use of the annualised arithmetic average mean and annualised geometric average mean rate of return for the period under review. In each of these cases the monthly average mean return was determined, and subsequently annualised accordingly to provide an annual figure. These two measures are discussed separately below.

3.8.1.1 Arithmetic average mean rate of return

The arithmetic average mean return is simply the sum of the monthly returns divided by the number of months. This statistic, however, ignores compounding and therefore does not represent an equivalent single monthly rate for the year. This measure is useful since it does best in forecasting the return for the next month (Bodie *et al.*, 2003: 133).

The following equation determines the realised arithmetic average mean rate of return:

$$\bar{r}_{AMi} = \frac{\sum HPR_i}{n}$$
...(Eq 3.8)

Where: $\bar{r}_{AMi}$ = the monthly arithmetic mean rate of return of portfolio *i*;

$\sum HPR_i$ = the sum of portfolio *i*'s monthly holding period returns;

n = number of periods over which the investment is held.

To annualise the monthly arithmetic mean rate of return the determined value is simply multiplied by 12.

Although such an annual arithmetic average mean return does well in indicating the expected rate of return during a future single period, it is biased upward when attempting to measure the portfolio's long-term performance (Reilly & Brown, 2008: 10). The geometric average mean rate of return is therefore also employed as an alternative measure in this study.

3.8.1.2 Geometric average mean rate of return

The geometric average mean return is equal to the single per-period return that will give the same cumulative performance as the sequence of actual monthly returns. The geometric average mean return can be calculated by compounding the sequence of actual monthly returns and then finding the equivalent single per-period return (Bodie *et al.*, 2003: 133). This is a superior measure of the long-term mean rate of return because it indicates the compound rate of return based on the ending value of the investment (Reilly & Brown, 2008: 11). The following equation determines the realised geometric average mean rate of return:

$$\bar{r}_{GMi} = [\prod(1 + HPR_i)]^{\frac{1}{n}} - 1$$
...(Eq 3.9)

Where: $\bar{r}_{GMi}$ =   the monthly geometric mean rate of return of portfolio i;

$\prod(1 + HPR_i)$ =   the product of portfolio i's monthly holding period returns plus one, i.e.$(1+HPR_1)x(1+HPR_2)…(1+HPR_n)$;

n   =   number of periods over which the investment is held.

To annualise the monthly geometric mean return the following equation applies:

$$\text{annualised } \bar{r}_{GMi} = [1 + \bar{r}_{GMi}]^{12} - 1 \qquad\qquad \text{...(Eq 3.10)}$$

Where: annualised $\bar{r}_{GMi}$ =   the annual geometric mean of portfolio i;

$\bar{r}_{GMi}$ =   the monthly geometric mean rate of return of portfolio i.

The geometric average represents the compound rate of growth that equates the beginning value to the ending value for one unit of money initially invested. Therefore, in contrast to the arithmetic average, the geometric average does not introduce an upward bias in the calculated expected terminal value of the investment. Researchers analysing performance over multiple periods will therefore often include the geometric averages in their results as well (Stowe, Robinson, Pinto & McLeavey, 2010: 115).

3.8.2   Measurement of dispersion

According to Coldwell and Herbst, (2004: 104), it is likely that two data sets can have the same mean, but have very different distributions of values. Therefore a measure to determine the spread of values around the mean is further needed to accurately describe and summarise the data.

The variance and its related measure, the standard deviation, can be used as measures of the variability within a data set. These measures ultimately determine how far a set of numbers are spread out, describing how far the actual outcomes lie from the mean. The variance and standard deviation measures are now discussed.

3.8.2.1 Variance

The uncertainty (or risk) of an investment can be quantified as a function of the magnitudes of possible surprises (actual return being different from expected return). To summarise this risk with a single figure, the variance can be determined by the squared deviation between the historical values and the arithmetic mean value of a data set (Bodie *et al.*, 2003: 114). The variance is given by:

$$\text{Var}_i = \frac{\sum(r_t - \bar{r})^2}{n-1}$$ ...(Eq 3.11)

Where: Var_i = portfolio *i*'s variance;

r_t = actual return of portfolio in period *t*;

$\bar{r}$ = arithmetic mean rate of return on the portfolio;

n = total number of observations in the data set.

To annualise a monthly variance one can simply multiply the value by 12. The result of squaring deviations is that the variance has a dimension of squared percentages making it difficult to apply in a real-world sense. The standard deviation, as the square root of the variance, gives a value in the same dimension as expected return (percentage); therefore, the standard deviation is discussed next.

3.8.2.2 Standard deviation

According to Reilly and Brown (2008: 202), the standard deviation is one of the best-known measures of risk. It is a statistical measure that indicates the dispersion of returns around the expected value. The larger the standard deviation, the greater the uncertainty and risk regarding future expected returns. As the following equation implies, the standard deviation can be defined as the square root of the variance.

$$\sigma_i = \sqrt{\text{Var}_i}$$ ...(Eq 3.12)

Where: σ_i = portfolio *i*'s standard deviation;

Var_i = portfolio *i*'s variance.

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If the return of the underlying portfolio is measured on a monthly basis the standard deviation will provide a monthly figure as well. To annualise a monthly standard deviation one can simply multiply the value by $\sqrt{12}$.

3.8.3 Skewness

According to Maginn *et al.*, (2007: 556), skewness is a measure of asymmetry in the distribution of returns. All else equal, positive skewness is desirable when analysing stock returns. When a distribution is symmetrical, the skewness is zero. With a tail stretching to the right (larger values), it is skewed positively and with a tail stretching to the left (smaller values), it is skewed negatively. When skewness values are larger than one or smaller than minus one this indicates a substantially skewed distribution (Hair *et* al., 2011: 314). Mathematicians define skewness in terms of the second and third moments around the mean. This is done by means of the Fisher-Pearson coefficient of skewness. More recently, however, the use of the adjusted Fisher-Pearson standardised moment coefficient has become more popular (Doane & Seward, 2011: 6-7): The Fisher-Pearson standardised moment coefficient, used in this study as a measure of skewness, can be determined by means of the following formula:

$$S_i = \frac{n}{(n-1)(n-2)} \sum_{t=1}^{n} \left(\frac{r_t - \bar{r}}{S} \right)^3 \qquad \text{...(Eq 3.13)}$$

Where: S_i = The Fisher-Pearson standardised moment coefficient (skewness) of distribution *i*;

r_t = actual return of distribution in period *t*;

$\bar{r}$ = arithmetic mean rate of return on the distribution;

S = standard deviation of distribution;

n = total number of observations in the data set.

3.8.4 Kurtosis

Kurtosis evaluates a distribution's peakedness or flatness. Distributions where returns cluster in the center are peaked (leptokurtic) whereas distributions where returns are more widely distributed in the tails are flat (platykurtic). For a normal curve the kurtosis is three (mesokurtic). Kurtosis is often quoted in the form of excess kurtosis (kurtosis relative to the kurtosis of the normal distribution). When a distribution has excess kurtosis exceeding one

it is considered peaked whereas excess kurtosis of lower that minus one is considered flat (Hair *et al.,* 2011: 315).

Kurtosis can be determined by means of the following equation:

$$K_i = \frac{n(n+1)}{(n-1)(n-2)(n-3)} \sum_{t=1}^{n} \left(\frac{r_t - \bar{r}}{S}\right)^4 \qquad \text{...(Eq 3.14)}$$

Where: | | | |
|---|---|---|
| K_i | = | The kurtosis of distribution *i*; |
| r_t | = | actual return of distribution in period *t*; |
| $\bar{r}$ | = | arithmetic mean rate of return on the distribution; |
| S | = | standard deviation of distribution; |
| n | = | total number of observations in the data set. |

3.9 REGRESSION ANALYSIS

As can be seen in the next sections, regression analysis was employed for both the primary and secondary objectives of this study. In light thereof, the researcher deemed a discussion on regression analysis as essential. Regression analysis, as part of inferential statistics, may be used to summarise and explain the nature of the relationships between a dependent and the independent variables. It enables a researcher to develop a mathematical relationship amongst variables in order to predict the value of a single dependent variable (Y) from the knowledge of one or more independent variables $(X_{1\ldots n})$ (Levine & Stephan, 2009: 207; Hair *et al*., 2003: 177). Regression analysis can therefore be either simple or multiple.

Simple regression analysis examines how one variable (the dependent variable) is influenced by another variable (the independent variable), whereas multiple regression analysis examines how multiple independent variables influence the dependent variable (Keller, 2005: 627). Both single and multiple regression, utilising ordinary least squares (OLS) estimates, were employed in this study. The most basic form of a multiple regression model is the following:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n + e \qquad \text{...(Eq 3.15)}$$

Where: Y   =   dependent variable;

          β_0 =   intercept term;

          $\beta_{1\dots n}$ =   regression coefficient(s);

          $X_{1\dots n}$ =   independent variable(s);

          e   =   error term.

The purpose of a regression model is to explain Y in terms of X, holding other factors constant. For example, β_1 is the approximate change in Y for a one unit change in X_1, *ceteris paribus.* The intercept term (β_0) represents the y-axis intercept.

The data sets used in research analysis (and therefore regression analysis in this particular study) come in a variety of types. Whereas some econometric methods can be applied with little or no modification to many different kinds of data sets, the special features of some data sets must be accounted for (Wooldridge, 2009: 5). The most important data structures encountered in applied work include *cross-sectional data*, *time-series data* and *pooled cross sections* (panel data).

Whereas cross-sectional data consists of many units of a variable observed at a given point in time, time-series data consists of observations over time. The time dimension of time-series data makes it more difficult to analyse than cross-sectional data since observations can rarely be assumed to be independent over time. As the current period depends on the past periods, the data exhibits temporal ordering which makes it more difficult to analyse than cross-sectional data (Wooldridge, 2009: 8)

For regression, time-series data also requires alterations to the assumptions used under cross-sectional data, since the data no longer consists of a random sample of observations; instead it is one realisation of a stochastic process (Wooldridge, 2009: 341). According to Wooldridge (2009: 370-371), the time-series data employed in a study must conform to the Gauss-Markov Time Series Assumptions as used for statistical inference. These assumptions are as follows:

o **Assumption 1: Linearity in Parameters**
  The stochastic process $\{(X_{t1}, X_{t2}, \dots, X_{tk}, Y_t): t = 1, 2, \dots, n\}$ follows the linear model $Y_t = \beta_0 + \beta_1 X_{t1} + \beta_2 X_{t2} + \dots + \beta_k X_{tk} + \varepsilon_t$ where $\{\varepsilon_t: t = 1, 2, \dots, n\}$ is the sequence of errors or disturbances. Here, n is the number of observations (time periods).

o **Assumption 2: No Perfect Collinearity**

In the time-series process, no independent variable is constant or a perfect linear combination of the other.

o **Assumption 3: Zero Conditional Mean**

Given the independent variables for all time periods, the expected value of ε_t for each t, is zero. Mathematically, $E(\varepsilon_t|x) = 0$, t = 1,2, …, n. This implies that ε is uncorrelated with the independent variables in all time periods.

o **Assumption 4: Homoskedasticity**

Conditional on x, the variance of ε_t is the same for all t: $Var(\varepsilon_t|x) = Var(\varepsilon_t) = \sigma^2$, t = 1, 2, …, n. To test for heteroskedasticity (the lack of homoscedasticity) in the time series data of this study the Breusch-Pagan test was employed.

o **Assumption 5: No Serial Correlation**

Conditional on x, the error terms in two different time periods are uncorrelated: $Corr(t_t, n_s|x) = 0$, for all t ≠ s. To test for serial correlation in the time series data of this study the Durbin-Watson test statistic was employed. The Durbin-Watson test statistic tests the null hypothesis that the residuals from an ordinary least-squares regression are not autocorrelated against the alternative that the residuals follow an AR1 process. The Durbin-Watson statistic ranges in value from zero to four. A value near two indicates non-autocorrelation; a value toward zero indicates positive autocorrelation; a value toward four indicates negative autocorrelation (Durbin-Watson Significant Tables, 2012).

o **Assumption 6: Normality**

The errors ε_t are independent of x and are independently and identically distributed as Normal $(0, \sigma^2)$.

Assumptions 1 to 3 above establish unbiased OLS estimators, whereas Assumption 6 allows for exact statistical inference on any sample size (Wooldridge, 2009: 370-371). A further problem with time-series data is that it often displays non-stationarity (a trend, seasonality or a noticeable change in variability over time). Time-series stationarity is a statistical characteristic of the mean and variance of a series over time. If both the mean and variance are constant over time, then the series is said to be a stationary process (has no unit root), otherwise, the series is described as being a non-stationary process (has a

unit root). However, stationarity is required in regression analysis to draw meaningful conclusions (Matignon, 2005: 509). If the X and Y data-series in the regression are both non-stationary random processes (integrated), then modeling the X, Y relationship as a simple OLS relationship as in Equation 3.15 will only generate a spurious regression. It is, however, possible to control for the trend by regressing each variable in the model on the time variable. An advantage of such a de-trended series is that it better reflects the R^2, which is a measure of the amount of variance in the dependent variable explained by the independent variables considered by the model (Valle e Azevedo, 2011: 16). To test for non-stationarity in the time-series data of this study the Augmented Dickey-Fuller (ADF) test of time-series data was employed.

Determining whether liquidity as a risk factor affects stock returns, both multiple and simple regressions were performed by means of the statistical program, Statistica Version 11 (StatSoft Inc, 2012). The regression analysis, as employed for the primary objective of this study, is now discussed in more detail.

3.10   LIQUIDITY AS A RISK FACTOR

This study set out to determine whether liquidity is an important variable for capturing the shared time-series variation in stock returns after accounting for the market premium, size and book-to-market factors. Specifically, adapting the methodology employed by Keene and Peterson (2007), and Hearn *et al*. (2010), a liquidity-mimicking portfolio was added to the Fama and French (1993) three-factor model which accounts for market risk (market premium), size risk and value risk in an endeavour to determine the importance of liquidity in the context of other known time-series determinants of stock returns. As stated by Keene and Peterson (2007: 94), liquidity as an independent variable is likely to be highly correlated with other variables in the model, especially size. Therefore liquidity was examined both in its original form, and as a residual effect measure independent of the other variables.

In its original form, in line with Keene and Peterson (2007: 94) and Hearn *et al.* (2010: 8) liquidity was measured as a factor-mimicking portfolio (LIQ), between the average returns generated by the three low liquidity portfolios (small, medium and large size) and the average returns generated by the three high liquidity portfolios (small, medium and large size): LIQ = (Low/Small + Low/Med + Low/Large)/3 - (High/Small + High/Med + High/Large)/3.

Next, to purge the effects associated with the market premium, size and book-to-market factors, the liquidity factor-mimicking portfolio (LIQ) was regressed on the market premium (MKT), and the factor-mimicking portfolios of the other two variables (SIZE and BM respectively). The size effect was measured as a factor-mimicking portfolio (SIZE), between the average returns generated by the three small stock portfolios (low, medium and high liquidity) and the average return on the three large size stock portfolios (low, medium and high liquidity): SIZE = (Small/Low + Small/Med + Small/High)/3 - (Large/Low + Large/Med + Large/High)/3.

The value effect was measured as a factor-mimicking portfolio (BM), between the returns generated by a portfolio consisting of a third of the companies with the highest book-to-market ratios minus the return on a portfolio consisting of the third of companies with the lowest book-to-market ratios from the same sample of stocks as used for the other factor-mimicking portfolios. The residuals obtained from the regression are then the measure of liquidity that is free from any influence from the market, size and book-to-market factors. The following multiple regression equation was employed in this regard:

$$\text{LIQ}_t = A + \beta_M \text{MKT}_t + \beta_S \text{SIZE}_t + \beta_B \text{BM}_t + e_{\text{LIQ},t} \qquad \text{...(Eq 3.16)}$$

Where:

LIQ_t	=	liquidity factor-mimicking portfolio return in month t;
A	=	intercept term;
$\beta_M \text{MKT}_t$	=	component of return related to market premium;
$\beta_S \text{SIZE}_t$	=	component of return related to stock size;
$\beta_B \text{BM}_t$	=	component of return related to stock book-to-market ratio;
e_{LIQ}	=	monthly residual liquidity factor.

To test for liquidity as a determinant of returns, the excess portfolio return of the nine intersection group portfolios were regressed against the liquidity residual from Equation 3.16. The following simple regression equation was employed in this regard:

$$\text{RP}_t - \text{Rf}_t = A + \beta_{\text{LIQ}}(e_{\text{LIQ},t}) + e_t \qquad \text{...(Eq 3.17)}$$

Where:

$\text{RP}_t - \text{Rf}_t$	=	portfolio return in excess of the risk-free rate in month t;
$\beta_{\text{LIQ}}(e_{\text{LIQ},t})$	=	component of return related to liquidity;

$$A , e_t \qquad = \qquad \text{intercept term and error term respectively.}$$

Next, the researcher examined liquidity as a risk factor in the presence of other factors known to affect returns. In this instance, liquidity was used in its original form and not as a residual specifically to address whether the inclusion of a liquidity factor improves the ability of the asset pricing model to capture shared variation in stock returns. In this regard, the first regression (as can be seen in Equation 3.18) included liquidity as a risk factor, whereas the second regression (as can be seen in Equation 3.19) was similar but with liquidity removed.

$$RP_t - Rf_t = A + \beta_L(LIQ)_t + \beta_M(MKT)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \qquad \text{...(Eq 3.18)}$$

$$RP_t - Rf_t = A + \beta_M(MKT)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \qquad \text{...(Eq 3.19)}$$

Where: $RP_t - Rf_t$ =   excess return on one of the nine intersection group portfolios over the risk-free rate;

$\beta_L(LIQ)_t$ =   the component of return related to liquidity risk;

$\beta_M(MKT)_t$ =   the component of return related to market risk;

$\beta_S(SIZE)_t$ =   the component of return related to size risk;

$\beta_B(BM)_t$ =   the component of return related to value risk;

A , e_t =   intercept term and error term respectively.

The R^2 value provides evidence of the combined ability of the independent variables to capture shared variation in stock returns and therefore the ability of these regressions to represent well-specified asset pricing models. A step-wise regression was employed to determine whether the inclusion of liquidity as a risk factor leads to statistically significant increases in the R^2 values obtained.

Multiple regression does not explicitly indicate the directed dependencies among the set of variables. In other words, liquidity as a risk factor can influence excess portfolio return either directly or indirectly through one of the other 'mediator' independent variables. In this regard, the market premium, size and book-to-market factors were analysed as mediation variables to the extent that these variables account for the relationship between the independent variable (liquidity factor) and the dependent variable (portfolio excess return) (Baron & Kenny, 1986: 1176). In this regard, rather than merely hypothesising a

direct relationship between the independent variable and the dependent variable, a mediational model hypothesises that the independent variable influences the mediator variable, which in turn influences the dependent variable (Bannon, 2008: 1). To indicate the effect of liquidity directly and via the other independent variables, a mediation path model was employed. A mediation path model seeks to detect and explain the process that underlies an observed relationship between the dependent and independent variable via the other explanatory variables in the model. A mediation path model is interpreted in the same manner as a regression model in that the coefficients obtained indicate the influence of the independent variables (directly or via the mediation variables) on the dependent variable (Kidd, 2013).

The secondary objective of this study was to explore whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to the pure-liquidity and liquidity-neutral 'style index' strategies. In this regard the researcher constructed, tracked and analysed the portfolio strategies using a range of well-known financial ratios and formulas. The risk-adjusted performance measures employed in this regard are discussed next.

3.11   RISK-ADJUSTED PERFORMANCE ANALYSIS

The monthly HPR return for the five portfolio strategies was determined as part of descriptive statistics to analyse the performance of each portfolio strategy. Looking at performance alone, however, is inadequate since it does not take into account the risk exposure that led to the specific performance. Therefore the use of risk-adjusted performance measures was deemed appropriate.

In this section a number of risk-adjusted performance measures are presented. These measures can be employed to evaluate the historic risk and return profile of different portfolio strategies. Firstly, the Sharpe and Sortino ratios are presented. These measures, according to Padgette (1995: 174), are *market independent* performance measures as they only require a fund's return series for calculation.

Thereafter this section proceeds with a brief overview of the Capital Asset Pricing Model (CAPM). The CAPM serves as the basis for the next risk-adjusted performance measures to be presented, namely the single-factor Jensen's alpha, the Information ratio and the

Treynor ratio. These measures, according to Padgette (1995: 174) are *market dependent* measures as they evaluate a fund's performance relative to a broad market index.

Lastly, given the problems associated with the market dependent measures, an alternative asset pricing theory suggested by Ross (1976: 341), namely the arbitrage pricing theory (APT) is introduced. In particular, the Van Rensburg and Slaney (1997: 1) application of this model, applicable in a South African context, is presented.

3.11.1 The Sharpe ratio

The Sharpe ratio was introduced by William F. Sharpe in 1966 (Sharpe, 1966). Initially termed the reward-to-variability ratio, it was soon referred to as the Sharpe Index, the Sharpe measure or the Sharpe ratio (Sharpe, 1994: 49). In its 47 years of existence it has undergone some refinements and augmentations but the basic concept remained intact. Today it is the industry standard and most widely-used method for calculating risk-adjusted returns (Maginn *et al.*, 2007: 632).

The Sharpe ratio rests upon the Markowitz mean-variance paradigm. Therefore the Sharpe ratio firstly assumes the one-period portfolio return to be normally distributed and secondly, that the mean and standard deviation of the distribution are sufficient statistics to evaluate risk-adjusted returns of a portfolio (McLeod & Van Vuuren, 2004: 15).

Originally intended by Sharpe to be used as an *ex ante* measure of risk-adjusted performance, the Sharpe ratio has been widely implemented as an *ex post* measure to record and rank historic portfolio performance as well. As can be seen in Equation 3.20 the *ex post* Sharpe ratio compares the performance associated with risk taking (the return in excess of the risk-free rate) with the total risk of the portfolio (as measured by the portfolio standard deviation).

$$\text{Sharpe}_i = \frac{\bar{r}_i - \bar{r}_f}{\sigma_i} \qquad \qquad \text{...(Eq 3.20)}$$

Where: $\bar{r}_i$ =   the annualised arithmetic average mean rate of return of portfolio *i*;

           $\bar{r}_f$ =   the mean annualised rate of return of a risk-free asset;

           σ_i =   the annualised standard deviation of the rate of return of portfolio *i*.

A main criticism of the Sharpe ratio holds that in using the standard deviation as a measure of volatility leads to a non-directionally biased adjustment for risk. The Sharpe ratio, in other words, penalises a portfolio for periods of extraordinary high performance which is not only acceptable, but highly desirable by investors. To respond to this limitation the Sortino ratio was developed.

3.11.2 The Sortino ratio

Sortino and Van der Meer (1991: 28) argued that the use of the standard deviation as a measure of risk (as is the case with the Sharpe ratio) is seriously flawed. The standard deviation measures the risk associated with achieving the mean return and is often totally unrelated to the risk associated with achieving unwanted returns. In this regard the standard deviation makes no distinction between 'good' and 'bad' volatility (Sortino & Price 1994: 61).

As can be seen in Equation 3.21, the Sortino ratio has as numerator the difference between the return on the portfolio and some minimum acceptable return (MAR) level. If this MAR level is the risk-free rate, the numerator will be the same as for the Sharpe ratio. The denominator, however, only accounts for 'bad' volatility by using the downside deviation (DD) as a measure of risk (Sortino & Price 1994: 62). The downside deviation thus measures the risk associated with not achieving the MAR level.

$$\text{Sortino}_i = \frac{\overline{r_i} - \overline{\text{MAR}}}{\text{DD}_i} \qquad\qquad ...(\text{Eq } 3.21)$$

Where: $\overline{r_i}$ =   the annualised arithmetic average mean rate of return of portfolio *i*;

$\overline{\text{MAR}}$ =   the minimum acceptable return level;

DD_i =   the annualised downside deviation of the rate of return of portfolio *i*.

The downside deviation computes volatility using only the rate of return points below the MAR level. In this study the downside deviation (DD) was calculated using the following equation:

$$\text{DD} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\text{HPR} - \text{MAR})^2 f(t)} \qquad\qquad ...(\text{Eq } 3.22)$$

$f(t) = 1$ if HPR $<$ MAR

$f(t) = 0$ if HPR $\geq$ MAR

Where: DD   =   monthly downside deviation of portfolio strategy;

HPR   =   monthly holding period return of portfolio strategy;

MAR   =   minimum acceptable return level;

n   =   the number of months under study.

To annualise the monthly downside deviation the value is simply multiplied by $\sqrt{12}$.

According to Kaplan and Knowles (2004: 3), the MAR level can be stated as any value equal to or above zero. Therefore a constant value equal to or above zero per cent, the risk-free rate or even the inflation rate could be used. For the purpose of this research, the MAR value was set at zero as rational investors frown upon negative fund returns.

The Sharpe and Sortino ratios presented together can provide a more detailed picture of the risk-adjusted performance of portfolio strategies than either will in isolation. The Sharpe ratio, however, is better grounded in financial theory and analytically more tractable (Maginn *et al.,* 2007: 633)

3.11.3   The single-factor CAPM Jensen's alpha

To explain this measure adequately a brief overview of the CAPM's characteristics is necessary. The CAPM is generally attributed to the works of Sharpe (1964), Lintner (1965a; 1965b), and Mossin (1966). French (2003), however, suggested that the work of Jack L. Treynor also deserves credit due to his unpublished manuscripts: *Market Value, Time, and Risk* (1961) and *Toward a Theory of Market Value Risky Assets* (1962).

The CAPM describes the relationship between the risk and expected return of individual stocks or portfolios and although the CAPM does not fully withstand empirical tests, it has become a cornerstone of modern financial economics and played a pivotal role in the development of quantitative investment management. Equation 3.23 is referred to as the CAPM and states that the expected return of a portfolio has two components: firstly, the risk-free rate, r_f, and secondly, the expected excess return on the market portfolio

$(E(r_m) - r_f)$. This last mentioned component is called the market risk premium (DeFusco, McLeavey, Pinto & Runkle, 2004: 404-405).

$$E(r_i) = r_f + \beta_i(E(r_m) - r_f) \qquad \qquad \text{...(Eq 3.23)}$$

Where: $E(r_i)$ =   the expected return for portfolio *i;*

r_f =   the risk-free rate;

β_i =   the beta coefficient of portfolio *i;*

$(E(r_m) - r_f)$ =   the market premium.

The CAPM states that the expected return of portfolio i, $E(r_i)$, is a linear function of its beta, (denoted by the Greek symbol, β), which measures the portfolio's sensitivity to movement in the market portfolio (DeFusco *et al.*, 2004: 404). It can be seen then, that the expected risk premium of a portfolio, $(E(r_i) - r_f)$, could be shown to be proportional to the market risk premium, $(E(r_m) - r_f)$.

Portfolio performance is often evaluated based on the achievement of a positive alpha (positive excess risk-adjusted returns). To use the CAPM as a method of risk adjustment it is transformed into the form of an index model. An index model is useful since it firstly makes use of realised, not expected returns, and secondly, since it makes use of actual portfolios, such as the All-Share Index, rather than the theoretical market portfolio as is the assumption with the above-mentioned CAPM.

To move from a model cast in expectations to a realised-return framework, the following simple regression equation in realised excess returns holds:

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + e_i \qquad \qquad \text{...(Eq 3.24)}$$

Where: $r_i - r_f$ =   the realised excess returns over the risk-free rate for portfolio *i;*

α_i =   the *ex post* alpha- the portfolio's excess return if the market is neutral, that is, if the market's excess return, $(r_m - r_f)$,   is zero;

$\beta_i(r_m - r_f)$ =   the component of return due to movements in the overall market;

e_i =   the unexpected component due to unexpected events that are relevant only to this portfolio.

When comparing Equations 3.23 and 3.24, one can see that the CAPM predicts the α_i to be zero for all portfolios. This should, however, be seen in the light of the fact that the CAPM is a statement about expected returns of a fairly priced security. From an *ex post* perspective it is unsurprising that some portfolios would have done better or worse than expected. Jensen (1968: 381) showed that if a portfolio manager can consistently select undervalued stocks, the portfolio will indeed earn a higher premium than that implied by the CAPM. Such a portfolio manager will yield a positive random error term because the actual returns for the portfolio will exceed the expected returns implied by the CAPM. Jensen (1968: 383) demonstrated that consistent positive differences (superior performance) will bring about a positive intercept (positive alpha), whereas consistent negative differences (inferior performance) will give rise to a negative intercept (negative alpha). This measure of *ex post* alpha is closely related to the Treynor measure which is discussed next.

3.11.4 The Treynor ratio

Like the Jensen alpha measure, the Treynor measure relates a portfolio's realised excess returns to the systematic risk of the portfolio. It thus implicitly assumes a completely diversified portfolio where the systematic risk is the relevant risk measure. Such circumstances call for the use of a beta-based risk adjustment (Bodie *et al.,* 2003: 689). The calculation for the Treynor ratio is provided in the following equation:

$$\text{Treynor}_i = \frac{\bar{r}_i - \bar{r}_f}{\beta_i} \qquad\qquad\qquad ...(\text{Eq 3.25})$$

Where: $\bar{r}_i$ =   the mean annualised rate of return of portfolio *i*;

$\bar{r}_f$ =   the mean annualised rate of return of a risk-free asset;

β_i =   the beta coefficient of portfolio *i.*

The beta coefficient is a standardised measure of the relative risk of a portfolio compared to the market. Portfolios that are riskier than market portfolio will have a beta coefficient greater than one, whereas a portfolio that is less risky than the market portfolio will have a coefficient lower than one (Strong, 2008: 601). This measure is standardised in that it

relates the covariance between the portfolio strategy and the market portfolio to the variance of the market portfolio.

To calculate the beta coefficient of a portfolio, the following equation applies:

$$\beta_i = \frac{Cov_{i,m}}{\sigma_m^2}$$ ...(Eq 3.26)

Where: β_i = the beta coefficient of portfolio i;

$Cov_{i,m}$ = the covariance between the return on the portfolio and the market;

σ_m^2 = the variance of the market portfolio.

3.11.5 The Information ratio

As discussed in Sections 3.11.1 and 3.11.4 the Sharpe and Treynor ratios alike express portfolio return as a differential return in excess of the risk-free rate. These risk-adjusted performance measures would therefore represent the results of a self-financing strategy where the long position in the portfolio is financed through borrowing at the risk-free rate. According to Maginn *et al.* (2007: 770), however, there is no reason for insisting on appraising performance in the context of borrowing at the risk-free rate. The Information ratio therefore assesses the investor's ability to generate a portfolio return in excess of that of a comparison or benchmark portfolio relative to the variability of that excess return (Reilly & Brown, 2008: 1051). The Information ratio (IR) is given by the following equation:

$$IR_i = \frac{\overline{r_i} - \overline{r_B}}{\sigma_{ER}}$$ ...(Eq 3.27)

Where: $\overline{r_i}$ = the mean annualised rate of return of portfolio i;

$\overline{r_B}$ = the mean annualised return for the fund's benchmark index;

σ_{ER_i} = the standard deviation of portfolio i's excess return.

The numerator of the Information ratio is often referred to as the active return of the portfolio whereas the denominator is referred to as the portfolio's active risk. From this perspective the Information ratio measures the reward earned per incremental unit of risk created by deviating from the benchmark's holdings (Maginn *et al.,* 2007: 770). According

to Goodwin (1998: 35), a key assumption of this ratio is that the benchmark roughly matches the systematic risk of the specific portfolio. Therefore, the Information ratio is most useful when the benchmark has been carefully chosen to match the style of portfolio strategy under investigation.

Reilly and Brown (2008: 1052) indicated that if excess portfolio returns are estimated with historical data using the same single-factor regression model used to compute Jensen's alpha, the Information ratio can be simplified to:

$$IR_i = \frac{\alpha_i}{\sigma_e} \qquad \qquad \text{...(Eq 3.28)}$$

Where: α_i =   the single-factor CAPM Jensen's alpha;

           σ_e =   the standard error of the regression.

Market dependent risk-adjusted performance measures, such as the Jensen's alpha, Treynor ratio and Information ratio, all have an inherent weakness in that they require the use of a proxy for the market portfolio (Roll, 1977: 130; 1978: 1053). Roll (1980: 5) refers to this problem as the benchmark error. The CAPM stipulates that the market portfolio should include all risky assets in the economy on a value-weighted basis. Theoretically the selection of a market portfolio is straightforward. Empirically, however, the selection is very difficult as investors can among others include foreign stocks and bonds, real estate, options, art, stamps and coins in their proxy for the market portfolio (Reilly & Brown, 2008: 257).

Due to the difficulty in obtaining a return series reflecting all available risky assets in the economy, a practical compromise is to use the rate of return on a broad index of stocks, such as the S&P500 Index in the USA or the FTSE/JSE ALSI in South Africa. Both these indices, however, are limited to domestic stocks and do not truly reflect all available risky assets in the market.

Due to the criticism regarding the use of CAPM-based risk-adjusted performance measures this section now concludes with an alternative multi-factor measure based on Arbitrage Pricing Theory (APT).

3.11.6 The multi-factor APT Jensen's alpha

The CAPM has been one of the most frequently-used financial economic theories ever developed. Many empirical studies, however, criticise amongst others the dependence on a single risk factor (excess return to the market portfolio) and a market portfolio of risky assets that is not available (Reilly & Brown, 2008: 270).

One particularly compelling challenge to the efficacy of the CAPM is research results suggesting the possibility of developing profitable trading strategies even after adjusting for risk as measured by beta. Typical of these studies were the findings of Banz (1981), indicating that portfolios consisting of low market capitalisation stocks outperformed large market capitalisation stock portfolios on a risk-adjusted basis, and Basu (1977), documenting low price-earnings stocks to outperform high price-earnings stocks. More recently the work of Fama and French (1992) also showed stocks with high book value-to-market price ratios ('value' stocks) tend to outperform those with a low book value-to-market price ratios ('growth' stocks) on a risk-adjusted basis. Studies such as these led the financial economists to believe that there was something wrong with the way the single factor CAPM measured risk (Reilly & Brown, 2008: 270).

In the mid-1970's Ross (1976; 1977) developed the Arbitrage Pricing Theory. In contrast to the CAPM, the APT is relatively intuitive, requires only limited assumptions, and allows for multiple dimensions of investment risk. The problem that arises from the APT, however, is identifying the appropriate risk factors to be included in the model. According to Reilly and Brown (2008: 280), two general approaches have been employed in the factor identification process. Firstly, risk factors can be macro-economic in nature, such as the model developed by Chen, Roll and Ross (1986), which includes risk factors, such as changes in the inflation rate, monthly growth rate in US industrial production and unanticipated changes in the bond credit spread. Secondly, risk factors can be micro-economic in nature using certain characteristics of the underlying sample of stocks. A typical example of this approach is the Fama and French (1992) approach which, in addition to the excess return on a stock market portfolio (as specified in the CAPM), defined two additional micro-economic risk factors:

$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + \beta_{i,S}SMB + \beta_{i,B}HML + e_i \qquad \qquad \text{...(Eq 3.29)}$$

Where: SMB   =   return of portfolio of small-cap stocks less the return of a portfolio of large-cap stocks;

       HML   =   return of a portfolio of high book-to-market ratio stocks less the return of a portfolio of low book-to-market ratio stocks;

       β_{iS} , β_{iB} =   portfolio sensitivity to each of the risk factors.

More specifically SMB aims to capture the risk associated with company size whereas HML is intended to capture the risk between investing in 'value' vs 'growth' companies. This three-factor model was later extended to a four-factor model by Carhart (1997) who included a factor for momentum as well.

Van Rensburg and Slaney (1997: 1) developed a two-factor APT model using the JSE Actuaries All Gold and Industrial indices applicable to the South African equity market. This model grew out of concern regarding the suitability of the FTSE/JSE ALSI as a proxy for the market index in South Africa (Correia & Uliana 2004: 67). In a successive study, Van Rensburg (2002) found that the new Financial-Industrial (J250) and Resources (J000) indices could be used as observable proxies for the above-mentioned two principal components. The two-factor APT model is specified by means of the following multiple regression:

$$r_i - r_f = \alpha_i + \beta_{i,F}(R_F - r_f) + \beta_{i,R}(R_R - r_f) + e_i \qquad \text{...(Eq 3.30)}$$

Where: $r_i - r_f$ =   the risk premium of fund *i*;

       α_i =   the *ex post* alpha- the portfolio's excess return;

       $R_F - r_f$ =   the risk premium of the Financial-Industrial index;

       $R_R - r_f$ =   the risk premium of the Resources index;

       $\beta_{i,R}$ & $\beta_{i,F}$ =   portfolio sensitivity to each of the risk factors;

       e_i =   the unexpected component due to unexpected events that are relevant only to this portfolio.

For the two-factor arbitrage theory model, in this study, the FTSE/JSE Financial Industrial (J250) index and FTSE/JSE Resource 10 (J210) index were employed. As stated in Section 3.6.4 the FTSE/JSE Resource 10 (J210) index is a suitable replacement for the

FTSE/JSE Resources (J000) index after its discontinuation in 2006. In 2001 Von Wielligh and Smit (2001: 120) extended this model to a three-factor APT model, but found that the majority of the cross-sectional variation in returns could be explained by the two-factor Van Rensburg and Slaney APT model. The two-factor Van Rensburg and Slaney APT model was therefore applied in this study.

3.12   RELIABILITY AND VALIDITY

Cant *et al.* (2003) stated that the trustworthiness of any research study is dependable on the reliability and validity of the measurement tools employed. Therefore, the measurement tools should yield consistent results (reliability) and should measure what they intend to measure (validity). Reliability and validity will now be discussed in more detail.

3.12.1 Reliability

Reliability refers to the extent to which a measuring instrument produces consistent results if repeated. Reliability is thus an indicator of a measures internal consistency (Zikmund *et al.*, 2010: 301). The procedures used to ensure that measurements are reliable include test-retest reliability, equivalent form reliability and internal consistency reliability (Cant *et al.*, 2003: 235).

The measurement tools that were employed for this study (the proxies for size and liquidity) were consistent with the measurement tools of previous empirical studies on similar topics. The use of these measures could, therefore, be seen as indication of its reliability.

3.12.2 Validity

Validity refers to the extent to which a measuring instrument measures what is actually wished to be measured (Zikmund, 2003: 301). The two types of validity to be concerned with are internal validity and external validity.

3.12.2.1 Internal validity

This form of validity refers to whether the manipulation of the independent variables influenced the observed effects on the dependent variables (Malhotra, 2010: 254). It is therefore concerned with inferences regarding the relationships between variables

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(Coldwell & Herbst, 2004: 40). In other words, internal validity suggests that the instruments really measured what was attempted to be measured in the study.

Internal validity consists of three forms (Cant *et al.,* 2005: 235–236):

o **Content validity:** refers to the subjective agreement among professionals that a measurement instrument accurately reflects what it proposes to measure.

o **Criterion validity:** reflects the ability of the measurement instrument to correlate with other measures of the same construct.

o **Construct validity:** implies that the empirical evidence generated by a measurement instrument is consistent with the theoretical logic about the concepts. It therefore measures the extent to which a measure behaves in a theoretically sound manner.

As mentioned, the measurement instruments used in this study were based on previous empirical studies which showed that these measures do behave in a theoretically sound manner. Construct validity as well as content validity was, thus, used to test internal validity for this study.

3.12.2.2 External validity

This form of validity refers to the generalisability of the research results (Coldwell & Herbst, 2004: 41). According to Coldwell and Herbst (2004: 41), the two dominant approaches to provide evidence for a generalisation are:

o **Sampling model:** A simple random sample is selected from the population the researcher wants to generalise to. The findings based on this sample can then be generalised back to the population.

o **Proximal similarity:** A framework developed to identify other places and times that are similar to the study at hand. The results of a study can then be generalised to these other circumstances identified.

The constituents of the FTSE/JSE ALSI were chosen as the sample frame for the study. The FTSE/JSE ALSI represents 99 per cent of the market capitalisation of all listed stocks on the JSE. As indicated in Section 3.5 the sample and refined sample mostly represented in excess of 90 per cent of the sample frame market capitalisation. These samples,

therefore, included the majority of the target population market capitalisation. This means that the findings can be fairly safely generalised to the rest of the South African equity market and perhaps even to some other emerging markets.

3.13   STEP 6: CONCLUSIONS AND REPORTING RESEARCH FINDINGS

The last step of the business research process is preparing the research report. This report is an important component of the research process because it summarises and communicates the research findings (Hair *et al.*, 2011: 32). A report on the findings of this particular study is provided in the next chapter.

3.14   SUMMARY AND CONCLUSION

In this chapter, the focus was placed on the methodology of the study. Firstly an elaborate discussion of the research process (consisting of six steps) was provided. It is imperative that a well-structured research process is followed in a research project since it conveys a step-by-step plan as to how the primary and secondary objectives of a study will be reached.

The sample frame for the primary and secondary objectives of this study consisted of all the constituents of the FTSE/JSE ALSI with a free-float factor of more than 15 per cent. For the primary objective, determining whether liquidity is a risk factor affecting stock returns in the South African equity market, all stocks in the sample frame with the necessary prior-year data were included. For the secondary objective, assessing the relative risk-adjusted performance of liquidity-biased portfolio strategies a further rule for inclusion applied. The sample for the secondary objective consisted of all companies with a FTSE/JSE ALSI representation of more than 0.05 per cent. This was done in an endeavour to select a sample which has sufficient capacity to absorb meaningful investment which is required for institutional investment.

For both the primary and secondary objectives, descriptive statistics were required. Descriptive statistics, based on the constructed portfolio strategies and size/liquidity intersection group portfolios, indicate the nature of the data set and include the measurement of central tendency, measurement of dispersion and measurement of skewness and kurtosis. The descriptive statistics were followed by the regression analysis, in an endeavour to achieve the primary objective, which provided statistical evidence to

describe the nature of the relationship between liquidity and portfolio return. Lastly, the researcher introduced the risk-adjusted performance measures to be analysed in assessing the relative risk-adjusted performance of liquidity-biased portfolio strategies in an endeavour to achieve the secondary objective of the study.

In the next chapter the research findings of this study are presented.

CHAPTER 4
RESEARCH RESULTS

It ain't the things we don't know that get us in trouble. It's the things we know that ain't so.

Artemus Ward in Zikmund et al., 2010: 5.

4.1   INTRODUCTION

This chapter provides the research results obtained by following the steps of the research process. The chapter sets out with a detailed discussion on the data processing and the numerical descriptive statistics employed. This is followed by the application of the regression analysis and lastly, it concludes with the most pertinent results of the study.

4.2   DATA PROCESSING

After all the relevant data for the primary and secondary objectives of this study had been collected (Step 4 of the research process), the researcher was in a position to process the raw data and convert it to a reduced form, which was appropriate for analysis and interpretation.

For the primary objective, each stock in the sample had to be allocated a size and liquidity measure at year-end. In line with Chen *et al.* (2013), the year-end free-float market capitalisation weight was used as a proxy for size (see Section 3.7.1 Equation 3.2) and prior-year turnover (see Section 3.7.1 Equation 3.3) as a proxy for liquidity. Once these measures were allocated, independently sorted liquidity and size terciles were formed at the end of each December. The intersections of the two independent sets of terciles were then used to produce nine intersection group portfolios to be held for the following year. Note that the portfolios were constructed at year-end and held for the next 12 months. Hence the first portfolios were constructed based on the trading information on the last trading day of December 1995 and held for the 12 months of 1996. After 12 months the strategies were re-balanced. The last portfolios were therefore constructed based on the trading information on the last trading day of December 2011 and held for the 12 months of 2012.

Table 4.1 reports the average values of the different sorting measures for each intersection group portfolio. The values reported are the summed annual average values (for the different sorting measures respectively) divided by 17 (the number of years under study).

Table 4.1: Average values of sorting measures

Size tercile	Turnover tercile	Average Market Capitalisation weight	Averages Turnover
Small-cap	Low	0.11%	19.75%
	Medium	0.09%	47.79%
	High	0.06%	162.45%
Mid-cap	Low	0.21%	21.07%
	Medium	0.21%	48.19%
	High	0.20%	139.16%
Large-cap	Low	1.76%	21.01%
	Medium	1.93%	50.30%
	High	1.44%	134.26%

In contrast to the finding of Keene and Peterson (2007) for the US, there is no apparent positive relation between size and liquidity in the South African equity market. In other words, high (low) liquidity stocks do not necessarily equal a larger (smaller) average size. In all three size terciles (small-cap, mid-cap and large-cap) low liquidity portfolios consist of larger-sized stocks than high liquidity portfolios. Similarly, in the high liquidity tercile, small-cap portfolios consist of significantly higher turnover stocks than that of the large-cap portfolios. However, this pattern is not prevalent in the mid-cap and large-cap terciles.

In addition, the annual average, minimum and maximum number of stocks in each size/liquidity intersection group portfolio is presented in Table 4.2.

Table 4.2: Number of stocks in each intersection group portfolio

Size tercile	Turnover tercile	Average Number of Stocks over the Research Period	Minimum Number of Stocks over the Research Period	Maximum Number of Stocks over the Research Period
Small-cap	Low	25	12	32
	Medium	20	12	33
	High	16	7	30
Mid-cap	Low	21	18	28
	Medium	21	15	32
	High	27	7	34
Large-cap	Low	12	1	35
	Medium	17	12	24
	High	15	4	31

As shown in Figure 4.1 there has been an overall increase in market-wide liquidity levels as represented by the nine size/liquidity intersection group portfolios. On average, over the period under review, the turnover associated with high turnover portfolios increased from 48.17 per cent to 108.99 per cent, whereas the turnover associated with low and medium turnover portfolios respectively increased from 3.97 per cent to 24.95 per cent and from 12.43 per cent to 50.19 per cent (secondary axis). Overall, when combining the above-mentioned figures, turnover within the FTSE/JSE ALSI constituents increased from 21.50 per cent to 61.38 per cent over the period under review. These figures are significantly higher than those turnover figures suggested by Correia, Flynn, Iliana and Wormald (2010: 13) who reported on all stocks listed on the JSE. This suggests that the FTSE/JSE ALSI, representing the largest stocks in the market, also represents the most liquid stocks in the South African equity market.
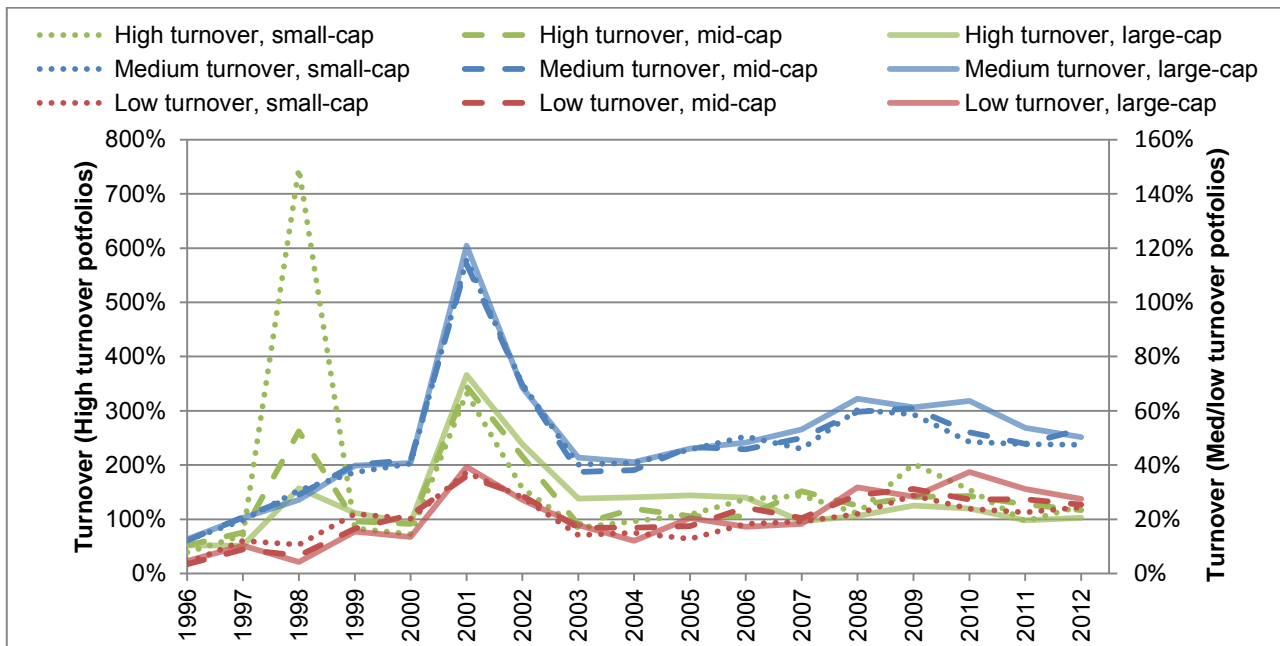
Figure 4.1: Average turnover of intersection group portfolios

The spikes observed in Figure 4.1 can be explained by the initial surge in trading during periods of financial crisis. The increase as observed in 2008 reflects the general downturn in developed country financial markets that led fund managers to transfer holdings out of emerging markets to less risky investments. Similarly this is observed in 1997 following the 1997 Asian currency crisis, and in 2000 following the depreciation of the Rand (Hearn *et al.*, 2010). It is interesting to relate this figure to the change in foreign financial and foreign portfolio investment as indicated in Chapter 2. When comparing Figure 2.3 and Figure 4.1, similar significant movements are observed. Therefore, the initial surge of trading in periods of financial crisis as indicated in Figure 4.1 relates to periods of decreases in foreign financial and portfolio investment (as percentage of GDP) as indicated in Figure 2.3.

For the secondary objective, Table 4.2 indicates the number of stocks included in each portfolio strategy for the period under review. As can be seen the market capitalisation strategy and volume weighted strategy consisted of all stocks in the sample as identified in Section 3.5. The earnings weighted strategy, in line with Chen *et al.* (2010), consisted of a lower number of stocks since only those companies with positive prior-year earnings were included. Lastly, given the weighting technique of the liquidity-biased portfolio strategies as discussed in Sections 3.7.1.4 and 3.7.1.5, those stocks with a negative weighting were forced to a weight of zero and excluded from the strategy.

The market capitalisation-based liquidity strategy, on average, includes more than 80 per cent of the market capitalisation strategy shares. In 11 out of the 17 years it includes in excess of 90 per cent of the market capitalisation strategy shares. However, the earnings-based liquidity strategy is based on a significantly lower number of shares than the earnings weighted strategy. In the first four years under review less than 70 per cent of the shares are included in the liquidity-biased portfolio strategy. In only three years does the earnings-based liquidity strategy include in excess of 90 per cent of the earnings weighted strategy shares. The number of companies excluded from the earnings-based liquidity strategy is therefore of concern. The relative performance of the earnings-based liquidity strategy can therefore not exclusively be attributed to the liquidity factor included in this portfolio. It is possible that the performance is due to the different composition of shares under review. However, keeping this limitation in mind, the researcher decided to include the earnings based strategies in the data analysis of this study.

Table 4.3: Number of companies in respect of different portfolio strategies

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
Companies in sample	176	139	159	147	136	120	109	113	114	109	114	115	116	117	111	116	114
Market capitalisation strategy	176	139	159	147	136	120	109	113	114	109	114	115	116	117	111	116	114
Market capitalisation-based liquidity strategy	140	120	136	133	128	102	92	108	107	102	106	109	106	104	104	112	106
Earnings weighted strategy	176	139	159	147	136	116	106	109	108	103	109	109	112	111	106	109	110
Earnings-based liquidity strategy	120	95	108	93	111	99	92	102	95	90	97	98	95	100	93	84	88
Volume weighted strategy	176	139	159	147	136	120	109	113	114	109	114	115	116	117	111	116	114

The overall decline in the number of stocks included in each portfolio strategy for the period 1996 to 2012 is in line with the overall decline in the number of listed stocks on the JSE for the same period. Figure 4.2 indicates the total number of stocks listed on the JSE (blue line) and the number of stocks in the FTSE/JSE ALSI (red line) for the period.
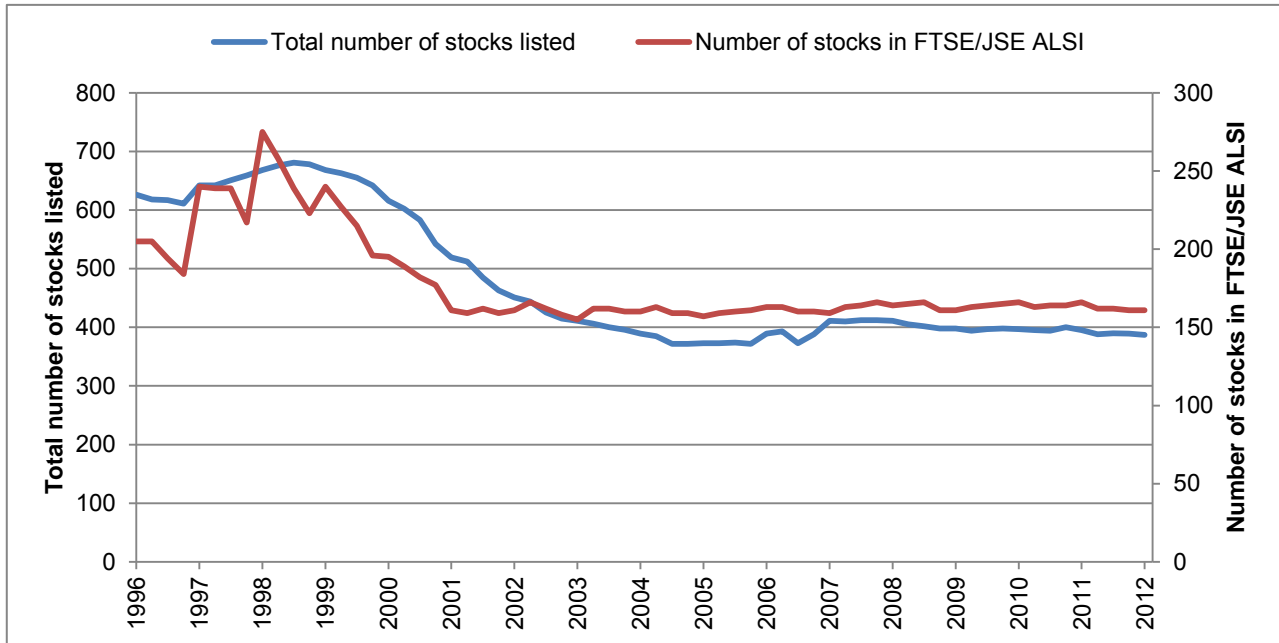
Figure 4.2: Number of JSE listed and FTSE/JSE ALSI stocks

Source: JSE, 2012; World Federation of Exchanges, 2012.

With 638 companies listed at the end of 1995, the JSE took the number one position among emerging markets based on market capitalisation. It has, however, lost this position due to the increased number of de-listings since then (Mabhunu, 2004: 15). Although there has been no improvement in the JSE's world ranking according to market capitalisation, there has been a significant improvement in its ranking based on market activity based on the value of shares traded and share turnover velocity (World Federation of Exchanges, 2012).

Once the raw data had been reduced to an appropriate format the analysis of the data could be continued. In this regard numerical descriptive statistics were used to summarise and present the processed data. The descriptive statistics for the primary and secondary objectives of this study are now presented.

4.3   DESCRIPTIVE STATISTICS

Descriptive statistics summarise data in order to successfully describe important aspects of large data sets. This is done in an endeavour to transform raw data into usable information (DeFusco *et al.*, 2011). In line with DeFusco *et al.* (2011), who explored four properties of return distributions, this chapter provides the descriptive statistics with regard to the central tendency, dispersion, skewness and kurtosis. Firstly, as measures for central tendency, the annualised arithmetic and annualised geometric average mean rates of return were employed. Secondly, to measure the dispersion around the mean, the variance and standard deviation measures were employed. Lastly, skewness and excess kurtosis were employed to evaluate asymmetry and the relative incidence of returns clustered near the mean returns respectively.

4.3.1   Liquidity as a risk factor: Explanatory risk factors

For the primary objective of this study the effect of liquidity was analysed as a residual effect (independent of other explanatory factors) and in its original form in the presence of the other explanatory factors. Liquidity was measured as a factor-mimicking portfolio (LIQ) between the return of a portfolio consisting of low liquidity stocks minus the return on a portfolio consisting of high liquidity stocks. The three other explanatory factors addressed was the market premium (MKT) (return on the market portfolio minus the risk-free rate), size (SIZE) (return of a portfolio of small stocks minus the return of a portfolio of large stocks) and book-to-market (BM) (return of a portfolio of high book-to-market ratio stocks minus the return of a portfolio of low book-to-market ratio stocks). As a proxy for the market portfolio the FTSE/JSE ALSI, FTSE/JSE Financial Industrial and FTSE/JSE Resource 10 indices were employed. Table 4.4 provides the descriptive statistics of the liquidity factor and other explanatory factors as employed in the time-series regression models.

Table 4.4: Descriptive statistics: Explanatory risk factors

Factors	Geometric mean	Arithmetic mean	Variance	Standard deviation	Skew-ness	Excess kurtosis[a]
Market Premium (MKT) (ALSI)	3.68%	5.70%	33.46	5.78%	-0.85	3.77
Market Premium (MKT) (FTSE/JSE Financial Industrial)	3.64%	5.61%	32.05	5.66%	-1.27	6.69
Market Premium (MKT) (FTSE/JSE Resource 10)	4.75%	8.33%	61.29	7.83%	-0.07	0.77
Size (SIZE)	-6.00%	-5.47%	11.59	3.40%	-0.30	1.16
Book-to-market (BM)	7.92%	8.29%	10.99	3.32%	0.54	1.16
Liquidity (LIQ)	2.25%	2.68%	7.63	2.76%	-0.34	1.20

(a) Excess kurtosis relative to the normal distribution (in excess of three)

4.3.1.1 Explanatory risk factors: Measurement of central tendency

The annualised geometric and arithmetic mean rates of return indicate the average market premium of the FTSE/JSE ALSI, FTSE/JSE Financial Industrial and FTSE/JSE Resource indices. As indicated the highest return above the risk-free rate was obtained by the FTSE/JSE Resource 10 index. The size factor is a factor mimicking portfolio indicating a return obtained from entering a long position in small stocks and a short position in large stocks. This factor mimicking portfolio yields negative mean rates of return indicating that large stocks outperformed small stocks over the period under review. This result is in line with Muller and Ward (2013: 7) who found that there is no small size premium over the period December 1984 to December 2012 when comparing the returns of the largest 40 companies (comparable to the FTSE/JSE Top 40 index) with the companies ranked 101 to 160 based on market capitalisation (comparable to the FTSE/JSE Small-cap index). The book-to-market and liquidity factors both yield positive returns indicating that low liquidity stocks outperformed high liquidity stocks and that high book-to-market stocks outperformed low book-to-market stocks.

4.3.1.2 Explanatory risk factors: Measurement of dispersion

Low levels of variance and standard deviation are observed over all explanatory factors. This is due to the method in which the factors were constructed: a long position in one dimension and a short position in the other. Therefore the variability between the two

positions largely cancels out. The highest variability is observed it the FTSE/JSE Resource 10 market premium measure.

4.3.1.3 *Explanatory risk factors: Skewness and Kurtosis*

As indicated in Section 3.8.3, Hair *et al.* (2011: 314) stated that skewness values larger than one or smaller than minus one indicate a substantially skewed distribution. Most of the explanatory factors indicate slight negative skewness, indicating more observations fall below the mean rate of return. The market premium based on the FTSE/JSE Financial Industrial index is the only factor, however, to be considered substantially skewed.

With regard to kurtosis, Hair *et al.* (2011: 315) stated that a distribution with excess kurtosis (relative to the normal distribution) exceeding one is peaked whereas a distribution with excess kurtosis lower than minus one is flat. All factors except the FTSE/JSE Resource 10 market premium indicate peaked distributions. This suggests that the explanatory factor observations mostly cluster near the mean rates of return.

4.3.2   Liquidity as a risk factor: Intersection group portfolios

Furthermore, for the primary objective of this study, the excess portfolio return of nine size/liquidity intersection group portfolios was regressed on the liquidity factor and other explanatory factors known to affect stock returns. The numerical descriptive statistics applicable to the intersection group portfolios are presented in Table 4.5.

Table 4.5: Descriptive statistics: Intersection group portfolios

Size tercile	Turnover tercile	Geometric mean	Arithmetic mean	Variance	Standard deviation	Skew- ness	Excess kurtosis[a]
Small-cap	Low	13.56%	14.45%	321.46	17.93%	-1.07	4.96
	Medium	10.42%	11.80%	365.47	19.12%	-0.51	0.76
	High	1.15%	3.59%	481.37	21.94%	-0.38	0.96
Mid-cap	Low	14.75%	15.72%	369.50	19.22%	-0.52	5.42
	Medium	12.40%	13.79%	400.44	20.01%	-0.64	2.66
	High	15.00%	16.26%	439.13	20.96%	-0.23	1.52
Large-cap	Low	10.52%	11.95%	372.85	19.31%	-0.53	3.15
	Medium	16.12%	17.23%	426.86	20.66%	-0.72	4.80
	High	12.94%	14.22%	396.85	19.92%	-0.27	0.43

 (a) Excess kurtosis relative to the normal distribution (in excess of three)

4.3.2.1 Intersection group portfolios: Measurement of central tendency

Over the period under review, across the small-cap tercile, the low-turnover portfolio earned an annualised geometric (arithmetic) mean rate of return of 13.56 per cent (14.45 per cent), whereas the high-turnover portfolio earned 1.15 per cent (3.59 per cent). This difference produces a liquidity return spread of 12.41 per cent (10.86 per cent) within the small-cap tercile. This would suggest that size does not capture liquidity and that the liquidity effect (where low liquidity stocks outperform high liquidity stocks) holds. However, for the mid-cap and large-cap portfolios, low turnover and high turnover portfolios yield similar returns, indicating that the liquidity effect diminishes in these terciles. This is in contrast to the findings of Chen *et al.* (2010: 25) who indicated that the liquidity effect in the US stock market decreases as one move from small-cap to large cap-portfolios, but that it remains significant even in the large-cap portfolios.

4.3.2.2 Intersection group portfolios: Measurement of dispersion

The variance and standard deviation statistics in Table 4.5 indicate similar risk profiles for the nine intersection group portfolios. In line with Chen *et al.* (2010), across all size terciles the low turnover portfolios yield the lowest standard deviations. This can be explained by the measure of dispersion employed. Standard deviation measures the variability of the underlying asset price movements. Therefore it would be expected that low turnover portfolios with lower levels of trading will have more stable underlying asset prices reducing the standard deviation measures in these portfolios.

4.3.2.3 Intersection group portfolios: Skewness and Kurtosis

Only one intersection group portfolio (small-cap, low turnover) can be classified as substantially negatively skewed. This means that the distribution of returns of the small-cap, low turnover portfolio has a tail stretching to the left. Upon closer inspection the skewness of this specific intersection group portfolio can be attributed to outliers formed during years of financial crises: 1998, 2000 and 2008. All nine intersection group portfolios display positive kurtosis with six portfolios considered to have peaked (leptokurtic) distributions.

4.3.3   Risk-adjusted performance analysis

For the secondary objective of this study the performance of two liquidity-biased portfolio strategies, one pure-liquidity and two liquidity-neutral portfolio strategies were analysed.

This was done in an endeavour to determine whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance. The numerical descriptive statistics of the five portfolio strategies are presented in Table 4.6.

Table 4.6: Descriptive statistics: Portfolio strategies

Portfolio Strategy	Geometric mean	Arithmetic mean	Variance	Standard deviation	Skew-ness	Excess kurtosis[a]
Market Capitalisation Strategy	14.91%	16.00%	407.14	20.18%	-0.47	2.65
Market Capitalisation-Based Liquidity Strategy	15.84%	16.79%	391.75	19.79%	-0.63	3.28
Earnings Weighted Strategy	13.96%	15.06%	380.48	19.51%	-0.45	1.68
Earnings-Based Liquidity Strategy	13.59%	14.66%	364.32	19.09%	-0.81	1.86
Volume Weighted Strategy	13.55%	14.99%	466.27	20.99%	-0.20	2.09
FTSE/JSE ALSI	14.41%	15.55%	412.16	20.30%	-0.79	3.52

(a) Excess kurtosis relative to the normal distribution (in excess of three)

4.3.3.1 Portfolio strategies: Measurement of central tendency

Firstly, from the annualised geometric and arithmetic average mean rates of return it becomes evident that the market capitalisation-based strategies outperform the earnings and volume weighted strategies over the period 1996 to 2012. This is in contrast to the findings of Chen *et al.* (2010: 28) who found significant outperformance of earnings strategies over market capitalisation strategies in the US stock market. Secondly, unlike the findings by Chen *et al.* (2010), only the market capitalisation strategy is enhanced when including a liquidity bias, whereas the earnings-based liquidity strategy provides lower mean rates of return than the earnings weighted strategy. As mentioned in Section 4.2, this result should be interpreted with caution. The earnings-based liquidity strategy suffers from a substantially lower number of shares than that of the earnings weighted strategy. The underperformance of the earnings-based liquidity strategy can therefore not exclusively be attributed to the liquidity factor included in this strategy. Lastly, the pure-liquidity volume weighted strategy underperforms both the market capitalisation-

based and earnings-based strategies. Thus, investing in highly-traded or 'popular' stocks does not pay in the South African equity market.

Figure 4.3 indicates the cumulative total return (where all dividends are reinvested) of an initial R100 investment on the last trading day of December 1995 over a 17-year period.
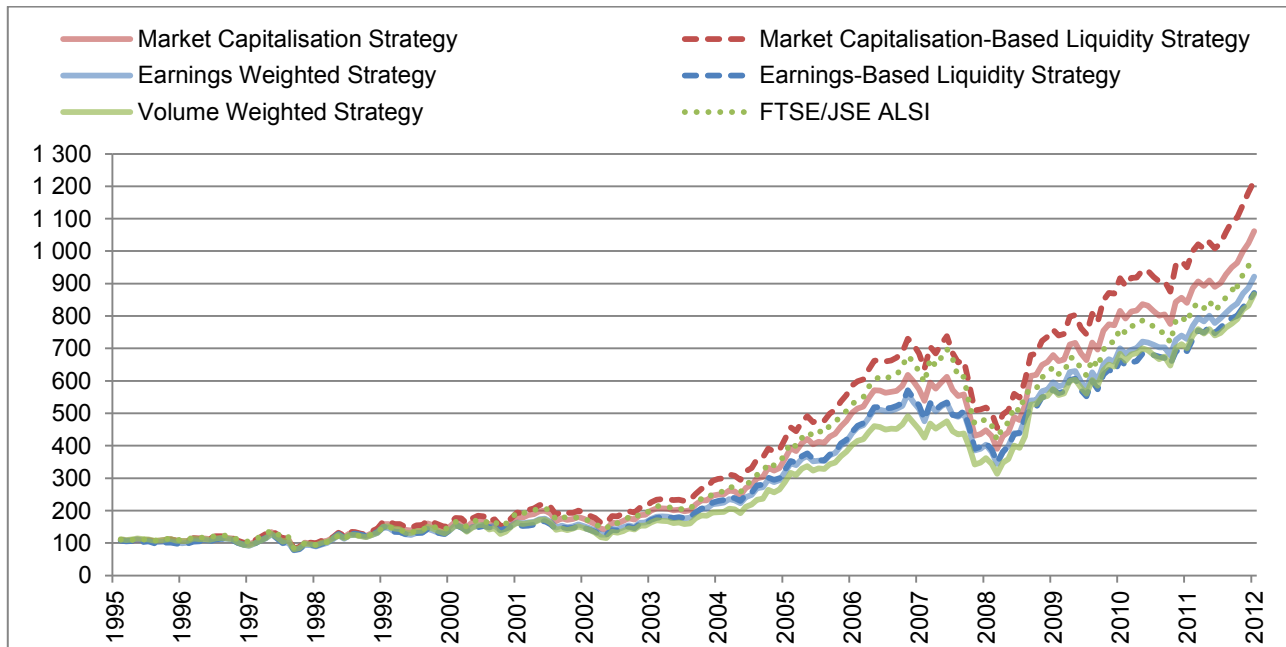
Figure 4.3: Cumulative investment return of portfolio strategies

Not surprisingly, the market capitalisation-based liquidity strategy does the best, followed by the market capitalisation strategy. The volume weighted strategy, earnings weighted strategy and earnings-based liquidity strategy all underperform the FTSE/JSE ALSI based on cumulative performance. The market capitalisation strategy, which in theory should yield similar returns to that of the FTSE/JSE ALSI, returns slightly better results. This is firstly due to the winsorisation of market capitalisation values in an endeavour to reduce the effect of outliers. Secondly, it is due to the market capitalisation strategy only being rebalanced at year-end, whereas the FTSE/JSE ALSI is rebalanced (or reconstituted) quarterly (FTSE/JSE, 2013).

Figure 4.4 indicates the annualised geometric mean rates of return of each portfolio strategy for each individual year under review. It is interesting to note how the earnings-based strategies outperform the market capitalisation-based strategies during the Asian financial crisis during 1997 to 1998 and the global financial crisis of 2008. This is in line with the findings of Kang (2012) who found that fundamentals weighted, non-capitalisation-

based strategies outperform market capitalisation weighted strategies in periods of financial crisis.
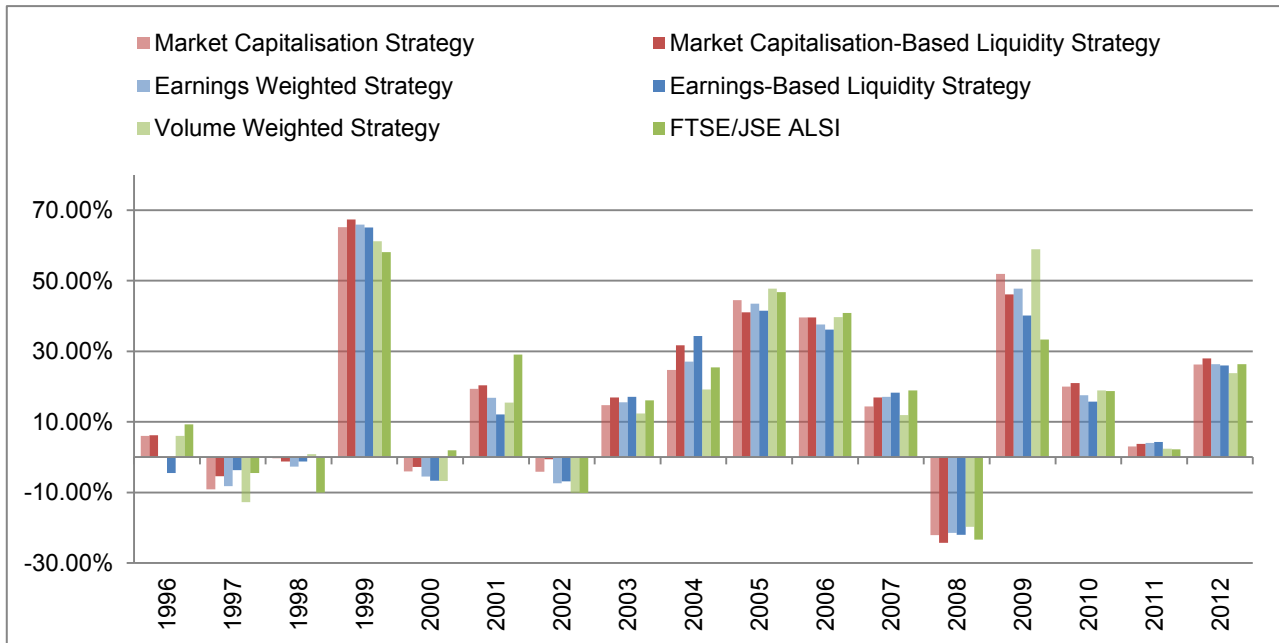
Figure 4.4: Annualised geometric mean rates of return of portfolio strategies

4.3.3.2 Portfolio strategies: Measurement of dispersion

The variance and standard deviation statistics in Table 4.6 indicate very similar risk profiles for the five portfolio strategies. The largest variation in dispersion is within the volume weighted strategy. This could be attributed to the highly-traded nature of the stocks within this strategy. The volume weighted strategy favours popular 'hot' stocks which leads to a great deal of price movement within these assets. In line with the findings of Chen *et al.* (2011), both the market capitalisation and earnings-based liquidity strategies have lower variation in dispersion than their liquidity-neutral counterparts. Therefore, including a liquidity bias, thereby tilting portfolio weights towards lower turnover stocks, reduces volatility and lowers the risk as measured by standard deviation.

4.3.3.3 Portfolio strategies: Skewness and Kurtosis

None of the portfolio strategies can be classified as substantially skewed with all strategies only exhibiting minimal degrees of negative skewness. With regard to kurtosis, however, all strategies display peaked distributions. In other words, all strategies have distributions where the observations are clustered near the mean.

Once the descriptive analysis has been performed, transforming the raw data into a form which makes it easy to understand and interpret, the inferential analysis can be developed. In this study, to achieve the primary and secondary objectives, regression analysis was employed. This chapter now continues with an introduction to the regression analysis methods as employed in the study and concludes with the final results.

4.4　　REGRESSION ANALYSIS

As stated in Chapter 3, regression analysis summarises and explains the nature of the relationships between dependent and independent variables. It furthermore enables a researcher to predict the value of a single dependent variable (Y) from the knowledge of one or more independent variables ($X_{1...n}$) (Levine & Stephan, 2009: 207; Hair *et al.*, 2003: 177). The validity of regression analysis depends on several assumptions concerning the model. For this study, in line with Wooldridge (2009: 370-371), the time-series data employed had to conform to the Gauss-Markov Time Series Assumptions. The following assumptions, as discussed in Section 3.9, were applicable:

o　　Assumption 1: Linearity in Parameters;

o　　Assumption 2: No Perfect Collinearity;

o　　Assumption 3: Zero Conditional Mean;

o　　Assumption 4: Homoskedasticity;

o　　Assumption 5: No Serial Correlation; and

o　　Assumption 6: Normality.

As suggested by Chatterjee and Hadi (2013: 97), Assumption 1, Assumption 3 and Assumption 6 were checked and confirmed for all parameters by means of a normal probability plot of the standardised residuals of the model. For normality, the ordered residuals had to be approximately the same as the ordered normal scores. Assumption 2 was confirmed by means of analysing the correlation between the different independent variables in the model. Data was further tested for the presence of heteroskedasticity (the lack of homoscedasticity) and serial correlation. To test for the presence of heteroskedasticity, the Breusch-Pagan test was employed. In the event of significant heteroskedasticity, autoregressive conditional heteroskedasticity (ARCH) and generalised autoregressive conditional heteroskedasticity (GARCH) models were employed to correct for heteroskedasticity in the residuals. To test for serial correlation in the time series data of this study the Durbin-Watson test statistic was employed. The Durbin-Watson test

statistic tests the null hypothesis that the residuals from an ordinary least-squares regression are not autocorrelated against the alternative that the residuals follow an AR(1) process. The Durbin-Watson statistic ranges in value from zero to four. A value near two indicates non-autocorrelation. In the event of serially correlated error terms, autoregressive (AR) modelling techniques were employed to account for the presence of serial correlation. This was done by modelling appropriate AR models of the order one, AR(1), to the residuals.

Lastly, the Augmented Dickey-Fuller test was utilised to test for the stationarity of data. Time series stationarity is a statistical characteristic of the mean and variance of a series over time. If both the mean and variance are constant over time, then the series is said to be a stationary process (has no unit root); otherwise, the series is described as being a non-stationary process (has a unit root). If the X and Y data-series in the regression are both non-stationary random processes (integrated), then modeling the X, Y relationship as a simple OLS relationship will only generate a spurious regression. If the X or Y data-series was found to have a unit root, thus indicating that individually they are non-stationary, the ΔY and ΔX (differenced) were tested to determine if they exhibited a linear trend over time. If the differenced variables were found not to have a unit root and thus exhibit a linear trend over time, the residuals of regressing Y on X were tested for stationarity through the Augmented Dickey-Fuller test. If the residuals of the regression were found not to have a unit root and are therefore stationary, it was concluded that the Y and X variables are co-integrated which indicates that the linear relationship between Y and X is too strong to be coincidence. If this was not the case, the data was detrended to control for the trend by regressing each variable in the model on the time variable.

4.5   LIQUIDITY AS A RISK FACTOR

To test for liquidity as a determinant of returns, the excess portfolio return of the nine intersection group portfolios was regressed against the liquidity residual. Because the nine regressions make use of purged residuals as the independent variable, the results showed the effect of liquidity independent of the market premium, size and book-to-market factors.

As shown in Table 4.7, the coefficients of low turnover portfolios have the tendency to have a positive relation with returns, whereas the coefficients of high turnover portfolios have a negative relation with returns. This is because of the manner in which the liquidity factor was formed; low liquidity minus high liquidity.

Table 4.7: Regressions of the residual liquidity factor

Size tercile	Turnover tercile	Intercept (A)	*t*-Statistic (A)	Coefficient (β_{LIQ})	*t*-Statistic (β_{LIQ})	*p*-Value (β_{LIQ})	F-Statistic
Small-cap	Low	0.004	1.095	0.627	4.627	0.000**	21.43**
	Medium	0.002	0.419	0.353	2.349	0.020*	5.52*
	High	-0.005	-1.194	-0.533	-3.143	0.002**	9.88**
Mid-cap	Low	0.005	1.304	0.667	4.597	0.000**	21.14**
	Medium	0.003	0.807	0.267	1.698	0.091	2.88
	High	0.005	1.258	-0.316	-1.925	0.056	3.71
Large-cap	Low	0.002	0.458	0.554	3.742	0.000**	14.01**
	Medium	0.006	1.461	0.203	1.243	0.215	1.55
	High	0.004	0.900	-0.303	-1.934	0.055	3.74

Notes: The following regression equation was conducted: $RP_t - Rf_t = A + \beta_{LIQ}(e_{LIQ,t}) + e_t$; where RP_t is return on different intersection group portfolios.

** Significant at the 1% level

* Significant at the 5% level

This study finds statistical significance of the coefficients in low turnover portfolios and small stock portfolios. The F-statistics indicate that the employed model was suitable in these intersection group portfolios. Therefore, as indicated in Table 4.8, the researcher could reject $H_{0,1}$, $H_{0,2}$, $H_{0,3}$, $H_{0,4}$ and $H_{0,7}$ at the five per cent level of significance. This suggests that there is a statistically significant effect of liquidity on portfolio return after controlling for the market premium, size and book-to-market factors in small stock and low liquidity portfolios only.

Table 4.8: Hypotheses testing $H_{0,1-9}$

Size tercile	Turnover tercile	Null Hypothesis	Decision
Small-cap	Low	$H_{0,1}$	Reject
	Medium	$H_{0,2}$	Reject
	High	$H_{0,3}$	Reject
Mid-cap	Low	$H_{0,4}$	Reject
	Medium	$H_{0,5}$	Fail to Reject
	High	$H_{0,6}$	Fail to Reject
Large-cap	Low	$H_{0,7}$	Reject
	Medium	$H_{0,8}$	Fail to Reject
	High	$H_{0,9}$	Fail to Reject

Notes: See Section 3.3.6 for a discussion on nine hypotheses employed.

Next, the effect of liquidity on returns was examined in the context of other factors known to affect returns: the market premium, size and book-to-market. In this instance liquidity was used in its original form and not as a residual specifically to address whether the inclusion of a liquidity factor improves the ability of the Fama-French three-factor asset pricing model to capture shared variation in stock returns. In this regard, the first regression equation (presented as Equation 3.18) included liquidity as a risk factor whereas the second regression equation (presented as Equation 3.19) was similar, but with liquidity removed.

Correia and Uliana (2004) cast doubt on suitability of the FTSE/JSE ALSI as a proxy for the market portfolio in South Africa mainly due to its skewed nature towards resources and mining companies. Therefore, based on the research of Van Rensburg (2002) (see Section 3.11.6), this part of the analysis employed two different proxies for the market portfolio: first the FTSE/JSE ALSI and thereafter the FTSE/JSE Financial Industrial (J250) and FTSE/JSE Resource 10 (J210) indices. Only the first model, employing the FTSE/JSE ALSI as a proxy for the market portfolio, however, was used to test the research hypothesis, $H_{0,10}$, as indicated in Section 3.3.6. The results of the regressions can be seen in Table 4.9 and 4.10 respectively.

Table 4.9: Regressions of liquidity and other explanatory factors (FTSE/JSE ALSI as market portfolio)

Size tercile	Turnover tercile	Eq	Intercept (A)	t-Statistic (A)	Coeffi-cient (βL)	t-Statistic (βL)	Coeffi-cient (βM)	t-Statistic (βM)	Coeffi-cient (βS)	t-Statistic (βS)	Coeffi-cient (βB)	t-Statistic (βB)	R^2
Small-cap	Low	1	0.002	1.098	0.627	8.842**	0.858	22.888**	0.819	13.937**	-0.002	-0.029	0.756
		2	0.004	1.565			0.755	18.000**	0.691	10.303**	-0.018	-0.257	0.660
	Medium	1	-0.000	-0.120	0.353	3.991**	0.872	18.656**	0.794	10.831**	0.087	1.177	0.668
		2	0.001	0.207			0.814	17.673**	0.722	9.801**	0.078	1.016	0.641
	High	1	-0.004	-1.471	-0.533	-5.884**	0.821	17.169**	0.887	11.812**	-0.044	-0.573	0.732
		2	-0.005	-1.822			0.909	18.484**	0.996	12.665**	-0.030	-0.362	0.685
Mid-cap	Low	1	0.001	0.365	0.667	6.950**	0.824	16.225**	0.296	3.722**	-0.016	-0.193	0.610
		2	0.002	0.853			0.714	13.310**	0.160	1.862	-0.033	-0.367	0.515
	Medium	1	0.001	0.449	0.267	2.851**	0.852	17.190**	0.323	4.155**	-0.149	-1.891	0.655
		2	0.002	0.678			0.808	16.853**	0.268	3.500**	-0.156	-1.946	0.641
	High	1	0.004	1.410	-0.316	-3.139**	0.795	14.936**	0.201	2.409*	-0.095	-1.127	0.636
		2	0.003	1.128			0.847	16.375**	0.266	3.216**	-0.087	-1.008	0.618
Large-cap	Low	1	-0.004	-1.557	0.554	6.590**	0.782	17.574**	-0.171	-2.456*	-0.064	-0.900	0.703
		2	-0.002	-0.917			0.691	14.838**	-0.285	-3.827**	-0.078	-1.004	0.638
	Medium	1	0.001	0.504	0.203	2.857**	0.934	24.920**	-0.095	-1.621	-0.020	-0.339	0.815
		2	0.001	0.732			0.901	24.839**	-0.137	-2.359*	-0.025	-0.421	0.807
	High	1	-0.001	-0.412	-0.303	-4.458**	0.846	23.569**	-0.144	-2.552*	0.058	1.018	0.818
		2	-0.001	-0.752			0.895	25.086**	-0.082	-1.432	0.066	1.106	0.799

Notes: The following regression equations were conducted:

$$RP_t - Rf_t = A + \beta_L(LIQ)_t + \beta_M(MKT)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \quad (Eq \ 1); \quad RP_t - Rf_t = A + \beta_M(MKT)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \quad (Eq \ 2),$$

where RP_t is the return on different intersection group portfolios.

**   Significant at the 1% level

*   Significant at the 5% level

Table 4.10: Regressions of liquidity and other explanatory factors (FTSE/JSE Financial Industrial and FTSE/JSE Resource 10 as market portfolio)

Size tercile	Turnover tercile	Eq	Intercept (A)	t-Statistic (A)	Coefficient (β_L)	t-Statistic (β_L)	Coefficient (β_F)	t-Statistic (β_F)	Coefficient (β_R)	t-Statistic (β_R)	Coefficient (β_S)	t-Statistic (β_S)	Coefficient (β_B)	t-Statistic (β_B)	R^2
Small-cap	Low	1	0.001	0.847	0.445	6.528**	0.115	4.442**	0.809	22.578**	0.814	15.486**	0.045	0.839	0.805
		2	0.003	1.380			0.041	1.587	0.825	20.968**	0.743	13.120**	0.057	0.967	0.762
	Medium	1	-0.001	-0.423	0.137	1.582	0.097	2.952**	0.856	18.810**	0.791	11.852**	0.146	2.128*	0.728
		2	-0.001	-0.262			0.074	2.503*	0.861	18.893**	0.769	11.735**	0.149	2.176*	0.724
	High	1	-0.004	-1.915	-0.804	-9.686**	0.020	0.640	0.878	20.113**	0.889	13.885**	0.037	0.567	0.804
		2	-0.006	-2.403*			0.154	4.498**	0.849	16.054**	1.018	13.385**	0.015	0.192	0.710
Mid-cap	Low	1	0.001	0.247	0.395	4.314**	0.019	0.548	0.870	18.061**	0.290	4.115**	0.062	0.853	0.694
		2	0.002	0.661			-0.047	-1.441	0.884	17.629**	0.227	3.153**	0.073	0.960	0.665
	Medium	1	0.001	0.222	0.062	0.702	0.090	2.678**	0.855	18.354**	0.331	4.852**	-0.080	-1.144	0.734
		2	0.001	0.296			0.080	2.642**	0.857	18.471**	0.322	4.817**	-0.079	-1.122	0.733
	High	1	0.003	1.328	-0.547	-5.613**	0.040	1.091	0.825	16.091**	0.203	2.698**	-0.022	-0.291	0.700
		2	0.002	0.706			0.132	3.689**	0.805	14.641**	0.290	3.673**	-0.037	-0.451	0.652
Large-cap	Low	1	-0.004	-2.272*	0.334	4.457**	0.049	1.731	0.825	20.910**	-0.160	-2.767**	0.015	0.247	0.797
		2	-0.003	-1.745			-0.007	-0.246	0.837	20.316**	-0.213	-3.605**	0.024	0.383	0.776
	Medium	1	0.001	0.395	-0.071	-1.164	0.064	2.787**	0.945	29.550**	-0.098	-2.097*	0.048	0.990	0.883
		2	0.000	0.278			0.076	3.671**	0.942	29.514**	-0.087	-1.895	0.046	0.950	0.882
	High	1	-0.002	-0.961	-0.475	-7.435**	0.123	5.056**	0.800	23.793**	-0.148	-2.993**	0.107	2.112*	0.860
		2	-0.003	-1.529			0.202	8.207**	0.783	20.649**	-0.071	-1.312	0.094	1.643	0.821

Notes: The following regression equations were conducted:

$$RP_t - Rf_t = A + \beta_L(LIQ)_t + \beta_F(MKT_F)_t + \beta_R(MKT_R)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \text{ (Eq 1)}; \quad RP_t - Rf_t = A + \beta_F(MKT_1)_t + \beta_R(MKT_2)_t + \beta_S(SIZE)_t + \beta_B(BM)_t + e_t \text{ (Eq 2)},$$

where RP_t is the return on different intersection group portfolios.

**   Significant at the 1% level

*   Significant at the 5% level

In both models, but for the second model to a lesser extent, the inclusion of liquidity leads to statistically significant liquidity coefficients. This suggests that liquidity has an explanatory power over portfolio returns. In the second model liquidity is only significant in the high and low liquidity terciles indicating a weaker liquidity effect than in the first model.

The market premium in the first model remains significant at the one per cent level across all intersection group portfolios. This suggests that the market premium factor based on the FTSE/JSE ALSI has explanatory power over portfolio excess returns. However, in this model, across all size terciles, the market premium coefficients for high liquidity portfolios decline when liquidity is included. This suggests that the inclusion of liquidity may weaken the effect of the market factor in high liquidity portfolios. However, this is not the case for low and medium liquidity portfolios. In the second model varying degrees of statistical significance is observed from the market premium based on the FTSE/JSE Financial Industrial index, and highly significant coefficients across all intersection group portfolios from the market premium based on the FTSE/JSE Resource 10 index. The inclusion of liquidity in this model similarly decreases the FTSE/JSE Financial Industrial market premium coefficients for high liquidity portfolios, but increases the FTSE/JSE Resource 10 market premium coefficients for high liquidity portfolios. This suggests that the inclusion of liquidity weakens the effect of the FTSE/JSE Financial Industrial market factor, but strengthens the effect of the FTSE/JSE Resource 10 factor in high liquidity portfolios.

In both models, the frequency of statistical significance of the size factor is considerably greater for small-cap portfolios than for mid-cap and large cap portfolios. This suggests that the size effect is statistically significant and large in the small-cap portfolios, but that this effect becomes weaker in the larger-cap portfolios. Across all size terciles, the size coefficients for high liquidity portfolios decline when liquidity is included. This suggests that the inclusion of liquidity may weaken the effect of size in high liquidity portfolios. The book-to-market factor, however, seems to explain very little of the time series variation in portfolio returns with very few coefficients in either of the models being statistically significant.

In both models the inclusion of a liquidity factor results in slightly lower values observed for the estimated intercepts in most cases. Although very few of the intercepts are statistically significant, non-zero intercepts remain, indicating continued missing risk factors. In both models, when analysing the coefficients of determination (R^2), it is evident that including

liquidity as a risk factor leads to a higher percentage of variation in the dependent variable than can be explained by the independent variables.

To determine whether $H_{0,10}$ (as stated in Section 1.3.1 and Section 3.3.6) could be rejected however, further statistical analysis was required. $H_{0,10}$ states that the inclusion of liquidity does not improve the ability of the asset pricing model to capture shared variation in stock returns. In this regard, the researcher performed a step-wise regression to determine whether the improvement of the coefficients of determination (R^2) after the inclusion of the liquidity factor was statistically significant or the result of chance. The regression results are presented in Table 4.11.

Table 4.11: Improvement in coefficient of determination (R^2)

Size tercile	Turnover tercile	FTSE/JSE ALSI as market portfolio			FTSE/JSE Financial Industrial and FTSE/JSE Resource 10 as market portfolio		
		R^2 (LIQ excl)	R^2 (LIQ incl)	*p*-value (change)	R^2 (LIQ excl)	R^2 (LIQ incl)	*p*-value (change)
Small-cap	Low	0.660	0.756	0.000**	0.762	0.805	0.000**
	Medium	0.641	0.668	0.000**	0.724	0.728	0.115
	High	0.685	0.732	0.000**	0.710	0.804	0.000**
Mid-cap	Low	0.515	0.610	0.000**	0.665	0.694	0.000**
	Medium	0.641	0.655	0.005**	0.733	0.734	0.484
	High	0.618	0.636	0.002**	0.652	0.700	0.000**
Large-cap	Low	0.638	0.703	0.000**	0.776	0.797	0.000**
	Medium	0.807	0.815	0.005**	0.882	0.883	0.246
	High	0.780	0.818	0.000**	0.821	0.860	0.000**

Notes:

**   Significant at the 1% level

*   Significant at the 5% level

The *p*-values obtained, indicate the statistical significance of the change between the R^2 value obtained from the regression model with liquidity excluded and the R^2 value obtained from the model with liquidity included. In the first model all coefficients of determination are enhanced by including liquidity by a statistically significant margin. In the second model only six of the nine coefficients of determination are enhanced by a statistically significant

margin. Only the first model, employing the FTSE/JSE ALSI as a proxy for the market portfolio, was used to test the research hypothesis. In this regard the null hypothesis ($H_{0,10}$) can be rejected and the study concludes that the inclusion of liquidity as a risk factor has a statistically significant improvement on the ability of the Fama-French three-factor asset pricing model to capture the shared variation in stock returns in the South African context.

As indicated in Chapter 3, the regression results (in Tables 4.9 and 4.10) do not explicitly indicate the directed dependencies among the set of independent variables. Therefore, the market premium, size and book-to-market factors were analysed as mediation variables to the extent that these variables account for the relationship between the independent variable (liquidity factor) and the dependent variable (portfolio excess return) (Baron & Kenny, 1986: 1176). The mediation path model in Figure 4.5 seeks to detect and explain the process that underlies the observed relationship between the dependent ($RP_t - Rf_t$) and independent variable (LIQ) via the other explanatory variables (MKT, SIZE, BM) in the model.

Each path in the mediation path model has a path coefficient indicating the independent variable (LIQ) effect on the dependent variables (excess portfolio return on intersection group portfolios) either directly or through the mediation variables (MKT, SIZE, BM) under analysis. Since this is a non-parametric model the output does not contain p-values to test the significance of the path coefficients. To test statistical significance bootstrapping had to be performed. Bootstrapping is effectively implemented by constructing a number of random samples from the original dataset (Kidd, 2013). From the bootstrapping a 95 per cent confidence interval for bootstrapping means can be established. If these confidence intervals do not overlap with 0, the coefficient is found to be statistically significant.

The path coefficients and bootstrapping results for each of the paths analysed are presented in Table 4.12. As indicated, liquidity has a significant direct effect and significant mediation effect through the market premium on all dependent variables. The book-to-market factor seems to have no mediating effect, whereas size has some degree of mediation in the smaller-sized terciles.

Table 4.12: Path coefficients and bootstrapping results

Path	Path Coefficient	Bootstrap Mean	95% Lower	95% Upper	Significance
LIQ -> Small-cap / Low Liquidity	0.33	0.33	0.25	0.41	significant
LIQ -> Small-cap / Medium Liquidity	0.17	0.18	0.08	0.27	significant
LIQ -> Small-cap / High Liquidity	-0.23	-0.23	-0.33	-0.15	significant
LIQ -> Mid-cap / Low Liquidity	0.33	0.33	0.22	0.43	significant
LIQ -> Mid-cap / Medium Liquidity	0.13	0.12	0.03	0.23	significant
LIQ -> Mid-cap / High Liquidity	-0.14	-0.15	-0.25	-0.06	significant
LIQ -> Large-cap / Low Liquidity	0.27	0.27	0.18	0.38	significant
LIQ -> Large-cap / Medium Liquidity	0.09	0.09	0.02	0.16	significant
LIQ -> Large-cap / High Liquidity	-0.14	-0.14	-0.20	-0.08	significant
LIQ -> MKT	-0.25	-0.26	-0.48	-0.02	significant
MKT -> Small-cap / Low Liquidity	0.95	0.94	0.86	1.03	significant
MKT -> Small-cap / Medium Liquidity	0.90	0.90	0.81	0.98	significant
MKT -> Small-cap / High Liquidity	0.74	0.74	0.60	0.86	significant
MKT -> Mid-cap / Low Liquidity	0.85	0.84	0.75	0.94	significant
MKT -> Mid-cap / Medium Liquidity	0.84	0.84	0.76	0.92	significant
MKT -> Mid-cap / High Liquidity	0.75	0.75	0.61	0.86	significant
MKT -> Large-cap / Low Liquidity	0.80	0.80	0.71	0.88	significant
MKT -> Large-cap / Medium Liquidity	0.90	0.90	0.82	0.96	significant
MKT -> Large-cap / High Liquidity	0.84	0.84	0.77	0.90	significant
LIQ -> SIZE	-0.15	-0.15	-0.31	0.02	not significant
SIZE -> Small-cap / Low Liquidity	0.53	0.53	0.41	0.66	significant
SIZE -> Small-cap / Medium Liquidity	0.48	0.49	0.38	0.59	significant
SIZE -> Small-cap / High Liquidity	0.47	0.47	0.37	0.57	significant
SIZE -> Mid-cap / Low Liquidity	0.18	0.18	0.08	0.29	significant
SIZE -> Mid-cap / Medium Liquidity	0.19	0.19	0.07	0.31	significant
SIZE -> Mid-cap / High Liquidity	0.11	0.11	0.01	0.21	significant
SIZE -> Large-cap / Low Liquidity	-0.10	-0.10	-0.21	0.01	not significant
SIZE -> Large-cap / Medium Liquidity	-0.05	-0.05	-0.14	0.03	not significant
SIZE -> Large-cap / High Liquidity	-0.08	-0.08	-0.16	0.00	not significant
LIQ -> BM	0.06	0.06	-0.11	0.24	not significant
BM -> Small-cap / Low Liquidity	0.00	0.00	-0.07	0.07	not significant
BM -> Small-cap / Medium Liquidity	0.05	0.05	-0.04	0.14	not significant
BM -> Small-cap / High Liquidity	-0.02	-0.02	-0.11	0.07	not significant
BM -> Mid-cap / Low Liquidity	-0.01	-0.01	-0.13	0.11	not significant
BM -> Mid-cap / Medium Liquidity	-0.08	-0.08	-0.19	0.01	not significant
BM -> Mid-cap / High Liquidity	-0.05	-0.05	-0.16	0.05	not significant
BM -> Large-cap / Low Liquidity	-0.04	-0.04	-0.13	0.05	not significant
BM -> Large-cap / Medium Liquidity	-0.01	-0.01	-0.09	0.07	not significant
BM -> Large-cap / High Liquidity	0.03	0.03	-0.04	0.10	not significant

Statistically significant paths are indicated on Figure 4.5 in dark black lines. It could thus be concluded that liquidity does not only have a significant direct effect on stock return, but also a significant indirect effect through the market premium factor and to a certain extent the size factor. More analysis based on this mediation path analysis is, however, required.
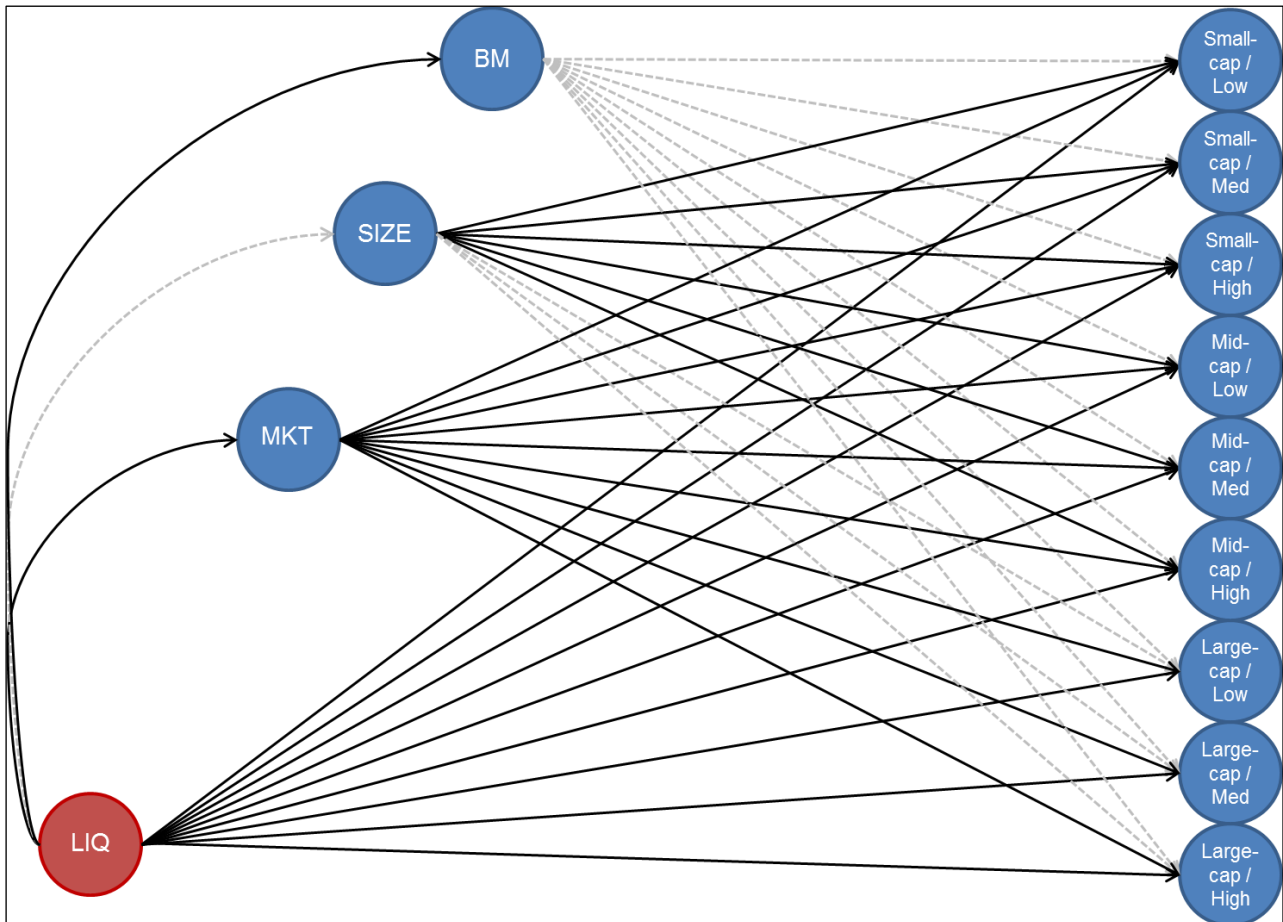
Figure 4.5: Mediation path model

4.6   RISK-ADJUSTED PERFORMANCE MEASURES

To give effect to the primary objective, as a secondary objective, it was explored whether incorporating a liquidity style into passive portfolio strategies can yield enhanced risk-adjusted performance relative to other pure-liquidity and liquidity-neutral passive 'style index' strategies. In this regard the risk-adjusted performance of two liquidity-biased, one pure-liquidity and two liquidity-neutral portfolio strategies was analysed using a range of market independent and market dependent risk-adjusted performance measures. The results with regard to these risk-adjusted performance measures are now presented.

4.6.1   Market-independent measures

Reilly and Brown (2008: 257) stated that the selection of a proxy for the market portfolio is very difficult as investors can theoretically include all assets in all asset classes. Even by only focusing on local stocks, it is difficult to proxy a portfolio that is representative of the return generating process of the market. It was therefore deemed necessary to include risk-adjusted performance measures that are not limited by choosing an appropriate proxy for the market portfolio. In this regard the Sharpe and Sortino ratios were employed.

The Sharpe ratio compares the performance associated with risk taking (the return in excess of the risk-free rate) with the total risk of the portfolio (as measured by the portfolio standard deviation). Sortino and Van der Meer (1991: 28), however, argued that the standard deviation measures the risk associated with achieving the mean return and is often totally unrelated to the risk associated with achieving unwanted returns. In this regard, the Sortino ratio rather compares the difference between the return and some minimum acceptable return (MAR) level with the 'unwanted' volatility of a portfolio by using the downside deviation as a measure of risk.

As shown in Table 4.12, the highest ranked portfolio based on both the Sharpe and Sortino ratios is the market capitalisation-based liquidity strategy. Therefore, including a liquidity bias in the market capitalisation strategy, leads to a better risk-adjusted performance ranking. In contrast to the market capitalisation strategies, the inclusion of a liquidity bias in the earnings weighted strategy results in a worse risk-adjusted performance ranking. Furthermore, as the descriptive statistics in Section 4.3.2 predicted, the earnings weighted strategies significantly underperform their market capitalisation counterparts on a risk-adjusted basis. The volume weighted strategy, favouring highly-traded stocks

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underperforms all other strategies based on the Sharpe and Sortino ratios, leaving it with the lowest risk-adjusted performance ranking.

Table 4.12: Sharpe and Sortino ratio results and rankings

Portfolio Strategy	Sharpe Ratio	Sharpe Rank	Sortino Ratio	Sortino Rank
Market Capitalisation Strategy	0.23	2	1.06	2
Market Capitalisation-Based Liquidity Strategy	0.31	1	2.10	1
Earnings Weighted Strategy	0.19	3	1.03	3
Earnings-Based Liquidity Strategy	0.17	4	1.00	4
Volume Weighted Strategy	0.15	5	0.98	5

4.6.2 Market-dependent measures

Market dependent measures evaluate a strategy's performance relative to the performance of a broad market index (Padgette, 1995: 174). Firstly, the CAPM Jensen's alpha, the Treynor ratio and the Information ratio based on the FTSE/JSE ALSI as proxy for the market portfolio are discussed. Next, based on numerous empirical studies criticising the use of a single risk factor (the market risk premium), the results of the APT Fama-French model including an additional two risk factors are presented. Lastly, based on the research of Correira and Ulliana (2004), indicating their concern with regards to the use of the FTSE/JSE ALSI as a proxy for the market portfolio, the results of the Van Rensburg and Slaney two-factor APT model are presented.

Table 4.13 indicates the results and relative rankings of the portfolio strategies based on the CAPM Jensen's alpha, the Treynor ratio and Information ratio. For all three measures, in line with the market independent risk-adjusted performance measures, the market capitalisation-based liquidity strategy has the highest ranking.

Table 4.13: CAPM Jensen's alpha, Treynor and Information ratio results and rankings

Portfolio Strategy	CAPM Jensen's alpha					Treynor Ratio	Infor- mation Ratio	Rank
	Intercept (α_i)	t- Statistic (α_i)	p- Value (α_i)	Coef. (β_i)	Adj R^2			
Market capitalisation strategy	0.048%	0.461	0.646	0.986	0.94	0.05	0.10	2
Market capitalisation-based liquidity strategy	0.116%	1.241	0.216	0.972	0.95	0.14	0.22	1
Earnings weighted strategy	-0.012%	-0.103	0.918	0.940	0.91	0.04	-0.08	3
Earnings-based liquidity strategy	-0.029%	-0.213	0.831	0.904	0.88	0.04	-0.12	4
Volume weighted strategy	-0.047%	-0.330	0.742	1.000	0.89	0.03	-0.12	5

Notes: The following regression equation was conducted for the CAPM Jensen's alpha measure: $r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + e_i$, where r_i is the return on different portfolio strategies.

** Significant at the 1% level

* Significant at the 5% level

The single-factor CAPM Jensen's alpha represents the average return on a portfolio strategy over and above that predicted by the Capital Asset Pricing Model (CAPM). As shown, only the market capitalisation-based strategies yield positive monthly alphas. Although it might seem that the market capitalisation-based and more specifically the market capitalisation-based liquidity strategy could yield outperformance on a risk-adjusted basis, these alphas are, however, not statistically significant at the one or five per cent level of significance based on the associated *t*-statistics and *p*-values. Constructing a portfolio based on these results should therefore be done with caution. In line with the CAPM Jensen's alpha, the Treynor and Information ratios both indicate the enhanced risk-adjusted performance of a liquidity bias in the market capitalisation-based strategy only.

Table 4.14 indicates the Fama-French APT model including an additional two risk factors to the market risk premium. In this regard the FTSE/JSE ALSI was still used as a proxy for

the market portfolio, but size and book-to-market ratios were included as additional risk factors in the model.

Table 4.14: The Fama-French APT model results and rankings

Portfolio Strategy	Fama-French							
	Intercept (α_i)	*t*-Statistic (α_i)	*p*-Value (α_i)	Coef (β_i)	Coef ($\beta_{i,S}$)	Coef ($\beta_{i,B}$)	Adj R^2	Rank
Market capitalisation strategy	0.057%	0.533	0.595	0.970	-0.047	-0.033	0.94	2
Market capitalisation-based liquidity strategy	0.115%	1.191	0.235	0.954	-0.064	0.027	0.95	1
Earnings weighted strategy	-0.038%	-0.302	0.763	0.943	-0.011	0.027	0.91	4
Earnings-based liquidity strategy	-0.063%	-0.444	0.657	0.912	-0.006	0.042	0.88	5
Volume weighted strategy	-0.018	-0.124	0.901	0.986	-0.027	-0.044	0.89	3

Notes: The following regression equation was conducted:
$$r_i - r_f = \alpha_i + \beta_i(r_m - r_f) + \beta_{i,S}SMB + \beta_{i,B}HML + e_t,$$
where r_i is the return on different portfolio strategies.

**   Significant at the 1% level

*   Significant at the 5% level

In line with the CAPM Jensen alphas, positive monthly alphas are achieved within the market capitalisation-based strategies only. Once again only the market capitalisation strategy is enhanced by including a liquidity bias and none of the monthly alphas are significant at the one, five or ten per cent levels of significance based on the *t*-statistics and *p*-values. Based on this model, earnings-based strategies rank even lower than the volume weighted strategy.

Table 4.15 indicates the Van Rensburg and Slaney two-factor APT model results and rankings. For this model the FTSE/JSE ALSI was replaced by the Financial-Industrial (J250) and Resources (J000) indices as proxies for the market portfolio.

Table 4.15: The Van Rensburg and Slaney two-factor APT model results and rankings

Portfolio Strategy	Van Rensburg and Slaney						
	Intercept (α_i)	*t*-Statistic (α_i)	*p*-Value (α_i)	Coef ($\beta_{i,F}$)	Coef ($\beta_{i,R}$)	Adj R^2	Rank
Market capitalisation strategy	-0.052%	-0.433	0.667	0.803	0.252	0.92	2
Market capitalisation-based liquidity strategy	0.029%	0.276	0.783	0.807	0.237	0.93	1
Earnings weighted strategy	-0.108%	-0.876	0.382	0.801	0.215	0.91	3
Earnings-based liquidity strategy	-0.109%	-0.857	0.392	0.814	0.172	0.90	4
Volume weighted strategy	-0.164%	-1.064	0.289	0.802	0.267	0.87	5

Notes: The following regression equation was conducted: $r_i - r_f = \alpha_i + \beta_{i,F}(R_F - r_f) + \beta_{i,R}(R_R - r_f) + e_i$, where r_i is the return on different portfolio strategies.

** Significant at the 1% level

* Significant at the 5% level

In line with both the CAPM Jensen and Fama-French models, only the market capitalisation-based strategy is enhanced by including a liquidity bias in the portfolio strategy. In this model the market capitalisation-based liquidity strategy is the only strategy that yields a positive monthly alpha. However, once again none of the monthly alphas are significant at the one, five or ten per cent levels of significance based on the *t*-statistics and *p*-values.

Based on both the market independent and market dependent risk-adjusted performance measures, it becomes evident that the earnings-based portfolio strategies underperform their market capitalisation-based counterparts. These results are in contrast to the findings of Chen *et al.* (2010) in the US stock market. This study therefore suggests, in contrast to Arnott *et al.* (2005), that these fundamentals weighted, non-capitalisation-based strategies cannot consistently provide higher returns and lower risks than their traditional capitalisation weighted counterparts. Further research is, however, required to investigate this assumption.

The results of the market independent and market dependent risk-adjusted performance measures indicate that only the market capitalisation-based portfolio strategy is enhanced by including a liquidity bias. In fact, the earnings-based liquidity strategy performs worse than its liquidity-neutral counterpart. These results should be interpreted with caution. As stated in Section 4.2, the data processing step of the research process revealed that the earnings-based liquidity strategy is based on a significantly lower number of shares than the earnings weighted strategy. The relative performance of the earnings-based liquidity strategy can therefore not only be attributed to the liquidity factor included, but also to the composition of shares under review.

In contrast, the market capitalisation-based liquidity strategy included more than 80 per cent of the market capitalisation strategy shares throughout the period under review. Furthermore it included in excess of 90 per cent of the market capitalisation strategy shares in 11 out of the 17 years. The enhanced risk-adjusted performance of the market capitalisation-based liquidity strategy relative to the market capitalisation strategy can therefore primarily be attributed to the liquidity bias in this strategy. However, even though it seems possible to enhance the market capitalisation strategy by including a liquidity bias, the alpha obtained by the market capitalisation-based liquidity strategy is not significant over any of the models employed. Therefore, due to the high p-values obtained, the risk-adjusted performance of this strategy could be attributed to chance.

Lastly, based on the market independent and market dependent risk-adjusted performance measures the volume weighted strategy ranked the lowest in all, but the Fama-French APT model. Therefore, investing in a strategy favouring highly-traded stocks does not pay in the South African equity market.

4.7   CONCLUSION

This chapter addressed the research objectives of the study. The study found a statistically significant effect of liquidity on portfolio return after controlling for the market premium, size and book-to-market factors in small stock and low liquidity portfolios. It was also found that liquidity improves the ability of the Fama-French three-factor asset pricing model in capturing the shared variation in stock returns.

Based on the market independent and market dependent risk-adjusted performance measures, it was found that the fundamentals weighted, non-capitalisation-based

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strategies underperformed their traditional capitalization weighted counterparts. Furthermore, only the market capitalization-based portfolio strategy was enhanced when including a liquidity bias.

The next chapter provides a summary of the study. The results obtained in Chapter 4 are reported and finally, recommendations for further areas of future research are offered.

CHAPTER 5

CONCLUSIONS AND RECOMMENDATIONS

Endings to be useful must be inconclusive.

Delany, 1967: 129.

5.1 INTRODUCTION AND THEORETICAL DEVELOPMENTS

A substantial amount of research is available aiming to identify portfolio strategies or styles that can be used to achieve excess portfolio returns. Numerous empirical studies indicate that investment styles, such as size, value and momentum, can yield consistent superior returns on a risk-adjusted basis. Certain market anomalies therefore do exist creating opportunities to earn excess returns, suggesting that markets are not as efficient as the efficient market hypothesis assumes.

In the mid-eighties Amihud and Mendelson (1986) were the first to suggest that liquidity might be a missing factor influencing stock returns. Based on this suggestion, Brennan *et al.* (1998) therefore extended the Fama-French (1993) three-factor model to include a liquidity factor. They found liquidity to remain as an explanatory factor of stock returns even in the presence of the size, book-to-market and momentum factors. This finding sparked renewed interest in the topic. Numerous studies on the effect of liquidity on stock returns followed, concentrated mainly on the US stock market. In an emerging market space and more specifically in the South African context, however, studies on the effect of liquidity on stock returns are only starting to become popular. The primary objective of this study was therefore to determine whether liquidity is a risk factor affecting stock returns in the South African equity market in an attempt to contribute to the limited body of knowledge available in this regard.

This chapter consists of three sections. The first section is dedicated to a summary of the results reported in Chapter 4 as well as the implications of these results. The next section evaluates the research contribution and lastly the limitations and areas for future research are provided.

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5.2   CONCLUSIONS

The results of the primary and secondary objectives were reported in Chapter 4. This section provides the conclusions in the context of each identified research objective under separate headings.

5.2.1   Liquidity as a risk factor

The regression coefficients found from regressing liquidity as a residual effect on the excess return of the nine intersection group portfolios indicated a significant effect at the five per cent level in the small-cap and low turnover terciles. As indicated in Table 5.1, the null hypotheses ($H_{0,1-9}$) stating that liquidity has no significant effect on stock return after controlling for the market premium, size and book-to-market factors, could therefore not be rejected for all intersection group portfolios.

Table 5.1: Hypotheses testing $H_{0,1-9}$

Size tercile	Turnover tercile	Null Hypothesis	Decision
Small-cap	Low	$H_{0,1}$	Reject
	Medium	$H_{0,2}$	Reject
	High	$H_{0,3}$	Reject
Mid-cap	Low	$H_{0,4}$	Reject
	Medium	$H_{0,5}$	Fail to Reject
	High	$H_{0,6}$	Fail to Reject
Large-cap	Low	$H_{0,7}$	Reject
	Medium	$H_{0,8}$	Fail to Reject
	High	$H_{0,9}$	Fail to Reject

Notes: See Section 3.3.6 for a discussion on nine hypotheses employed.

The testing of $H_{0,1}$ to $H_{0,9}$ thus indicates that liquidity is not a statistically significant risk factor affecting broad market return in the South African equity market. Instead the effect of liquidity is limited to small and low liquidity portfolios. This finding is beneficial to smaller investors in the market with the capacity to invest in smaller stocks. Institutional investors, however, are limited to the investment in larger sized stocks given the sizeable investment capacity required.

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Next, the researcher analysed the effect of including a liquidity factor in a regression model measuring the effect of the market premium, size and book-to-market factors on intersection group portfolio excess returns. This analysis was done with two different proxies for the market portfolio. First the FTSE/JSE ALSI was employed, where after the analysis was repeated with the FTSE/JSE Financial Industrial and FTSE/JSE Resource 10 indices as proxies for the market portfolio.

As indicated in Table 5.2, for both of the market portfolio proxy regressions, across almost all intersection group portfolios, the inclusion of a liquidity factor led to statistically significant increases in the coefficient of determination (R^2) values. Testing the research hypotheses ($H_{0,10}$) based on the FTSE/JSE ALSI as the market portfolio it could thus be concluded that liquidity as a risk factor significantly improves the Fama-French three-factor model in capturing shared variation in stock returns in the South African equity market.

Table 5.2: Improvement in coefficient of determination (R^2)

Size tercile	Turnover tercile	FTSE/JSE ALSI as market portfolio			FTSE/JSE Financial Industrial and FTSE/JSE Resource 10 as market portfolio		
		R^2 (LIQ excl)	R^2 (LIQ incl)	*p*-value (change)	R^2 (LIQ excl)	R^2 (LIQ incl)	*p*-value (change)
Small-cap	Low	0.660	0.756	0.000**	0.762	0.805	0.000**
	Medium	0.641	0.668	0.000**	0.724	0.728	0.115
	High	0.685	0.732	0.000**	0.710	0.804	0.000**
Mid-cap	Low	0.515	0.610	0.000**	0.665	0.694	0.000**
	Medium	0.641	0.655	0.005**	0.733	0.734	0.484
	High	0.618	0.636	0.002**	0.652	0.700	0.000**
Large-cap	Low	0.638	0.703	0.000**	0.776	0.797	0.000**
	Medium	0.807	0.815	0.005**	0.882	0.883	0.246
	High	0.780	0.818	0.000**	0.821	0.860	0.000**

Notes:

**   Significant at the 1% level

*   Significant at the 5% level

Lastly, to explicitly indicate the directed dependencies among the set of independent variables (liquidity, the market premium, size and book-to-market), a mediation path model

was employed. It was found that liquidity has a significant direct effect and significant mediation effect through the market premium on all intersection group portfolios. The book-to-market factor had no mediating effect, whereas size had some degree of mediation in the smaller sized terciles. It could thus be concluded that liquidity does not only have a significant direct effect on stock return, but also a significant indirect effect through the market premium factor and to a certain extent the size factor. This suggests that directed dependencies are present between liquidity, the market premium and size.

5.2.2   Risk-adjusted performance analysis

Based on all market dependent and market independent risk-adjusted performance measures employed in this study, it became evident that the market capitalisation-based strategy is enhanced by including a liquidity bias, whereas the earnings-based strategy is not. The results of the earnings-based strategies should, however, be interpreted with caution. A large number of shares were excluded from the earnings-based liquidity strategy after including the liquidity bias. The performance relative to the liquidity-neutral earnings weighted strategy can therefore not exclusively be attributed to the liquidity factor included in this portfolio, but also to the different composition of shares under review.

In contrast, the market capitalisation-based liquidity strategy included more than 80 per cent of the market capitalisation strategy shares throughout the period under review. However, even though it seems possible to enhance the market capitalisation strategy by including a liquidity bias, the alpha obtained by the market capitalisation-based liquidity strategy is not significant in any of the models employed.

Lastly, the relative performance of the pure-liquidity volume weighted strategy was analysed. This strategy, favouring highly-traded or 'popular' stocks, is biased towards stocks that attract investor attention. It is therefore, in line with Chen *et al.* (2010: 8), a "liquidity strategy", and serves to fit investors who like to chase popular "hot" stocks. The volume weighted strategy ranked the lowest in all but the Fama-French APT model. Therefore, investing in a strategy favouring highly-traded stocks does not pay.

This chapter now concludes with the contribution, limitations and areas of future research.

5.3   CONTRIBUTIONS OF THE RESEARCH

A number of contributions are evident in the purpose and nature of the research objectives. For the primary objective, this study is the first to determine the effect of liquidity as a risk factor, as a residual on excess portfolio return. It therefore expands on research such as that of Hearn *et al.* (2010) and Reisinger (2012) who analysed the effect of liquidity in its original form in the South African equity market. Next, focusing on liquidity in its original form, it expands on the available research in that it covers a much larger time frame. Whereas Hearn *et al.* (2010) and Reisinger (2012) respectively analysed 12 years (1996 to 2007) and 8.5 years (2003 to mid-2011) this study has a time frame of 17 years (1996 to 2012), more adequately capturing the effects of the Russian debt crisis of 1998, the developed market recession during the early 2000s and the global financial crisis of 2008.

For the secondary objective, this research further contributes to the body of knowledge by presenting empirical findings on the risk-adjusted performance of liquidity-biased portfolio strategies. Although statistically significant priced liquidity premiums were not evident in the primary objective of this study, slight outperformance of biasing portfolio weights to less liquid stocks was observed. These findings were, however, not robust and would not be recommended as a viable investment strategy.

This research provides a better understanding of the return generating processes of the South African equity market. It analyses previously omitted variables in the return generating process and gives an indication of how these factors could influence returns. It could thus be of value to students, academics and researchers in the field of finance and investments. Furthermore, the analysis of risk-adjusted performance of liquidity-biased, pure-liquidity and liquidity-neutral 'style index' strategies could be of value to individual and more specifically to institutional investors who are continuously searching for investment strategies that can yield consistent and superior returns. These findings could shed some light on how a liquidity bias could influence portfolio returns.

5.4   LIMITATIONS AND FURTHER AREAS OF RESEARCH

For the primary objective, liquidity was examined both in its original form and as a residual effect, independent of other known time series determinants of stock returns, namely, the market premium, size and book-to-market. It may be of importance to analyse whether the

measures employed in this analysis were indeed suitable as proxies for these respective determinants. Although the researcher attempted to determine the most appropriate measures to capture the effects of the market premium, size and book-to-market, further research may be required. Similarly, the different liquidity measures employed were in no way complete. The most effective measures, as indicated by previous literature as well as those measures for which data were easily obtainable, were included in this analysis. However, it could be of value to extend the analysis to include other proxies for liquidity.

The use of OLS regressions has often been criticised as too simplistic to analyse time-series data. In particular, the effects of autocorrelation may lead to inefficient results. In the event of serially correlated error terms, autoregressive (AR) modelling techniques were employed to account for the presence of serial correlation; however, a more sophisticated modelling technique may be required. The non-zero intercepts obtained in regression analysis indicate that there are other factors influencing returns that have not yet been taken into account in the models employed. Further research is therefore required to discover what these factors may be.

Lastly, the mediation path model employed indicated various statistically significant mediation effects of liquidity through the market premium and size factors. Liquidity therefore had a significant direct and indirect effect on stock return. More research on this effect is encouraged.

REFERENCES

Acharya, V.V. & Pedersen, L.H. 2005. Asset pricing with liquidity risk. *Journal of Financial Economics*, 77: 375-410.

Achour, D., Harvey, C.R., Hopkins, G. & Lang, C. 1999. Firm Characteristics and Investment Strategies in Africa: The Case of South Africa. *African Finance Journal*, 1(1): 1-67.

Adrian, T. & Shin, H.S. 2009. Money, liquidity, and monetary policy. *The American Economic Review*, 99(2): 600-605.

Ahmed, H.J.A. 2009. Trading activities and cross-sectional variation in stock expected return: Evidence from the Kuala Lumpur Stock Exchange. *International Business Research*, 2(2): 29-33.

Aitken, M. & Comerton-Forde, C. 2003. How should liquidity be measured? *Pacific-Basin Finance Journal*, 11: 45-59.

Akinjolire, A. & Smit, E.vdM. 2003. South Africa unit trust performance and strategy in a changing economic climate. *Investment Analyst Journal*, 58: 41-50.

Amihud, Y. 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5: 31-56.

Amihud, Y. & Mendelson, H. 1986. Asset pricing and the bid-ask spread. *Journal of Financial Economics*, 17: 223-249.

Amihud, Y. & Mendelson, H. 1989. The effects of beta, bid-ask spread, residual risk, and size on stock returns. *The Journal of Finance*, 44(2): 479-486.

Amihud, Y. & Mendelson, H. 2006. Stock and bond liquidity and its effect on prices and financial policies. *Financial Markets and Portfolio Management*, 20: 19-32.

Amihud, Y., Mendelson, H. & Pedersen, L.J. 2005. Liquidity and asset prices. *Foundations and Trends in Finance*, 1(4): 269-364.

Arnott, R.D., Hsu, J. & Moore, P. 2005. Fundamental indexation. *Financial Analyst Journal*, 61(2): 83-99.

Bank, M., Larch, M. & Peter, G. 2010. *Investors' compensation for illiquidity – evidence from the German stock market*. Working Paper, University of Innsbruck.

Bannon, W. 2008. Indirect effects. *Research Pathways*, 1(2). Online]. Available: http://www.williambannonassociates.org/files/Research_Pathways_Winter_2008_1_2_.pdf. [20 November 2013].

Banz, R. 1981. The relationship between return and market value of common stocks. *Journal of Financial Economics*, 9: 3-18.

Baron, R.M. & Kenny, D.A. 1986. The Moderator-Mediator Variable Distinction in Social Psychological Research: Conceptual, Strategic, and Statistical Considerations. *Journal of Personality and Social Psychology*, 51(6): 1173-1182.

Basu, S. 1977. Investment performance of common stocks in relation to their price-earnings ratios: a test of the efficient market hypothesis. *Journal of Finance*, 32: 663-682.

Bekaert, G., Harvey, C.R. & Lundblad, C. 2003. *Liquidity and expected returns: Lessons from emerging markets.* EFA 2003 Annual Conference Paper No. 690. [Online]. Available: http://www.kelley.iu.edu/clundbla/liquidity_Sept_8_2003.pdf [18 January 2011].

Bernstein, P.L. 1987. Liquidity, stock markets, and market makers. *Financial Management*, 16(2): 54-62.

Bervas, A. 2006. *Market liquidity and its incorporation into risk management*. Banque de France, Financial Stability Review No.8. [Online]. Available: http://www.banque-france.fr/fileadmin/user_upload/banque_de_france/publications/Revue_de_la_stabilite_financiere/etud2_0506.pdf. [18 January 2011].

Black, F. & Scholes, M. 1973. The pricing of options and corporate liabilities. *The Journal of Political Economy*, 81(3): 637-654.

Bodie, Z., Kane, A. & Marcus, A.J. 2003. *Essentials of investments.* 8th edition. New York: McGraw Hill.

Bowie, D. & Bradfield, D. 1993. A review of systematic risk estimation on the JSE. *De Ratione*, 7(1): 6-22.

Boyce, J. 2002. *Market research in practice.* Roseville: McGraw-Hill Australia Pty Limited.

Brennan, M.J. & Subrahmanyam, A. 1996. Market microstructure and asset pricing: On the compensation for illiquidity in stock returns. *Journal of Financial Economics*, 41: 441-464.

Brennan, M.J., Chordia, T. & Subrahmanyam, A. 1998. Alternative factor specifications, security characteristics, and the cross-section of expected stock returns. *Journal of Financial Economics*, 49: 345-373.

Brown, S.J., Goetzmann, W., Ibbotson, R.G. & Ross, S.A. 1992. Survivorship bias in performance studies. *The Review of Financial Studies*, 5(4): 553-580.

Bureau for Economic Research (BER). 2010. Stellenbosch University.

Campbell, G. 1979. *Risk and return on the Johannesburg Stock Exchange*. Unpublished MBA thesis, Johannesburg: University of the Witwatersrand.

Cant, M.C., Gerber-Nel, C., Nel, N. & Kotzé, T. 2005. *Marketing research.* Claremont: New Africa Education.

Carhart, M.M. 1997. On persistence in mutual fund performance. *The Journal of Finance*, 52(1): 57-82.

Chai, D., Faff, R. & Gharghori, P. 2010. New evidence on the relationship between stock liquidity and measures of trading activity. *International Review of Financial Analysis*, 19: 181-192.

Chan, H. & Faff, R. 2003. An investigation into the role of liquidity in asset pricing: Australian Evidence. *Pacific-Basin Finance Journal*, 11: 555-572.

Chatterjee, S. & Hadi, A.S. 2013. *Regression Analysis by Example.* Hoboken, New Jersey: John Wiley & Sons.

Chauhan, S. 2012. *The effects of financial liberalisation in emerging market economies*. Unpublished master's thesis, University of South Africa, Pretoria.

Chen, N-F., Roll, R. & Ross, S.A. 1986. Economic forces and the stock market. *The Journal of Business*, 59(3): 383-403.

Chen, Z., Ibbotson, R.G. & Hu, W. 2010. Liquidity as an investment style. Yale SOM Working Paper. [Online]. Available: http://www.zebracapm.com/files/Chen_Ibbotson_Liquidity_paper.pdf [10 November 2010].

Chen, Z., Ibbotson, R.G. & Hu, W. 2013. Liquidity as an investment style. *Financial Analyst Journal*, 69(3): 30-44.

Chordia, T., Roll, R. & Subrahmanyam, A. 2001. Market liquidity and trading activity. *The Journal of Finance*, 56(2): 501-530.

Chordia, T., Sarkar, A., Subrahmanyam, A. 2005. An empirical analysis of stock and bond market liquidity. *Review of Financial Studies*, 18: 85–129.

Chuhan, P. 1994. *Are institutional investors an important source of portfolio investment in emerging markets?* Working Paper, World Bank, International Economics Department, Washington D.C. [Online]. Available: http://econ.worldbank.org/external/default/main?pagePK=64165259&theSitePK=469382&piPK=64165421&menuPK=64166093&entityID=000009265_3961005200859 [18 January 2011].

Chung, M. C., Han, K. C. & Tse, M. K. 1996. Interrelationship among the Price Indexes of the NYSE, AMEX, and OTC. *International Review of Economics and Finance*, 5(1): 63-75.

Clayton, L., Dempsey, M. & Veeraraghavan, M. 2008. Are beta, firm size, liquidity and idiosyncratic volatility related to stock returns? Australian Evidence. *Investment Management and Financial Innovations*, 5(4): 145-158.

Coldwell, D. & Herbst, F. 2004. *Business research*. Lansdowne: Juta.

Collis, J. & Hussey, R. 2003. *Business research – a practical guide for undergraduate and postgraduate students*. 2nd Edition. Palgrave Macmillan: Great Britain.

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

Cornell, B., Hirshleifer, J. & James, E. 1997. Estimating the cost of equity. *Contemporary Finance Digest*, 1(1): 5-26.

Correia, C. & Uliana, E. 2004. Market segmentation and the cost of equity on the Johannesburg Stock Exchange. *South African Journal of Accounting Review*, 18(1): 65-86.

Correia, C., Flynn, D., Ulliana, E. & Wormald, M. 2010. *Financial Management.* 6th edition. Cape Town: Juta.

Damodaran, A. 2010. *Comatose markets: What if liquidity is not the norm?* [Online]. Available: http://papers.ssrn.com/sol3/papers.cfm?abstract_id=1729408&download=yes [18 January 2011].

Datar, V.T., Naik, N.Y. & Radcliffe, R. 1998. Liquidity and stock returns: An alternative test. *Journal of Financial Markets*, 1: 205–219.

De Beer, J. & Keyser, N. 2007. *JSE returns, political developments and economic forces: a historical perspective*. Unpublished paper delivered at the biannual conference of the Economic History Society of South Africa. 10-12 September, Fourways.

DeFusco, R.A., McLeavey, D.W., Pinto, J.E. & Runkle, D.E. 2004. Statistical concepts and market returns, in CFA Institute (eds.). *Ethical and Professional Standards and Quantitative Methods.* OH: Pearson Custom Publishing.

DeFusco, R.A., McLeavey, D.W., Pinto, J.E. & Runkle, D.E. 2011. *Quantitative Investment Analysis.* Hoboken, New Jersey: John Wiley & Sons.

Delany, S.R. 1967. *The Einstein Intersection.* Middletown: Wesleyan University Press.

Doane, D.P & Seward, L.E. 2011. Measuring skewness: a forgotten statistic? *Journal of Statistics Education*, 2: 1-18.

Durbin-Watsin Significance Tables. 2012. [Online]. Available: http://www.imm.bwl.uni-muenchen.de/dateien/3_lehre/market_analysis/durbin_watson_tables.pdf. [20 May 2013].

Eisfeldt, A. 2002. *Endogenous liquidity in asset markets*. Working paper, Northwestern University.

Eleswarapu, V.R. 1997. Cost of transacting and expected returns in the Nasdaq market. *The Journal of Finance*, 52(5): 2113-2127.

Eleswarapu, V.R & Reinganum, M.R. 1993. The seasonal behavior of the liquidity premium in asset pricing. *Journal of Financial Economics*, 34: 281-305.

Fama, E.F. & French, K.R. 1992. The cross-section of expected stock returns. *Journal of Finance*, 47(2): 427-465.

Fama, E.F. & French, K.R. 1993. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33: 3-56.

Fama, E.F. 1970. Efficient capital markets: A review of theory and empirical work. *The Journal of Finance*, 25(2): 383-417.

French, C.W. 2003. The Treynor capital asset pricing model. *Journal of Investment Management*, 1(2): 60-72.

FTSE/JSE. 2010. *FTSE/JSE infoMax User EOD Manual V 1.8.* [Online]. Available: http://www.jse.co.za/Libraries/JSE_-_Products_Services_-_Information_Products_-_Subscription_Documentation_-_Indices/01_FTSE-JSE_Africa_Index_Series_InfoMax_End_of_Day_Specifications_1_8.sflb.ashx [18 January 2010].

FTSE/JSE. 2013. *Ground rules for the management of the FTSE/JSE Africa index series*. [Online]. Available: http://www.jse.co.za/Products/FTSE-JSE/Documents.aspx [18 April 2013].

FWN Group. 1996. 18 Trading champions share their keys to top trading profits. [Online]. Available: http://www.sterlingvenueventures.com/books/18%20Trading%20Champions%20Share%20Their%20Keys%20To%20Top%20Trading%20Profits.pdf [18 January 2010].

Gabrielsen, A., Marzo, M. & Zagaglia, P. 2011. Measuring market liquidity: An introductory survey. Quaderni DSE Working Paper No. 802.

Gilbertson, B. & Goldberg, M.N. 1981. The market model and the Johannesburg Stock Exchange. *Investment Analyst Journal*, 17:40-42.

Goodwin, T.H. 1998. The Information ratio. *Financial Analysts Journal*, 54(4):34-43.

Hair, J.F., Babin, B., Money, A.H. & Samouel, P. 2003. *Essentials of business research methods.* New Jersey: John Wiley and Sons Inc.

Hair, J.F., Wolfinbarger Celsi, M., Money, A.H., Samoual, P. & Page, M. 2011. *Essentials of business research methods.* New York: M.E. Sharp.

Hamon, J. & Jacquillat, B. 1999. Is there value-added information in liquidity and risk premiums? *European Financial Management*, 5: 369-393.

Hasbrouck, J. & Schwartz, R.A. 1988. Liquidity and Execution Costs in Equity Markets. *Journal of Portfolio Management*, 14(3): 10-16.

Hasbrouck, J. 2002. Stalking the 'efficient price' in market microstructure specifications: An overview. *Journal of Financial Markets*, 5(3): 329-339.

Hearn, B., Piesse, J. & Strange, R. 2010. *An augmented capital asset pricing model: liquidity and stock size in African emerging financial markets.* [Online]. Available: http://www.africametrics.org/documents/conference08/day2/session4/hearn_piesse_strang e.pdf [18 January 2011].

Hearn, B.A. & Piesse, J. 2009. Liquidity in developed, emerging and frontier equity markets: is simplicity the best approach? Working paper, University of Sussex.

Hibbert, J., Kirchner, A., Kretzschmar, G., Li, R. & McNeil, A. 2009. *Liquidity premium literature review of theoretical and empirical evidence*. [Online]. Available: http://www.barrhibb.com/documents/downloads/Liquidity_Premium_Literature_Review.PD F [18 January 2013].

Hicks, J. 1967. *Critical essays in monetary theory*. Oxford University Press, Oxford.

Hirt, G.A. & Block, S.B. 2003. *Fundamentals of investment management*. McGraw-Hill Irwin: Boston.

Hu, S. 1997. Trading turnover and expected stock returns: The trading frequency hypothesis and evidence from the Tokyo Stock Exchange. Working Paper, National Taiwan University.

Huberman, G. & Halka, D. 2001. Systematic liquidity. *The Journal of Financial Research*, 24(2): 161-178.

Hui, B. & Heubel, B. 1984. *Comparative liquidity advantages among major U.S. stock markets*. Lexington: Data Resources Inc.

Hurston, Z.N. 1942. *Dust tracks on a road: An autobiography.* Pennsylvania: J.B. Lippincott Company.

Idzorek, T.M., Xiong, J.X. & Ibbotson, R.G. 2010. *The liquidity Style of Mutual Funds. Zebra Capital Management.* [Online]. Available: http://www.zebracapm.com/files/The_Liquidity_Investment_Style_in_Mutual_Funds_v7_O ctober_10_2010.pdf [18 January 2011].

Jang, B-G., Koo, H.K., Liu, H. & Loewenstein, M. 2007. Liquidity premia and transaction costs. *The Journal of Finance*, 62(5): 2329-2366.

Jegadeesh, N. & Titman, S. 1993. Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48: 65-91.

Jensen, M.C. 1968. The performance of mutual funds in the period 1945-1964. *Journal of Finance,* 23: 389-416.

Johannesburg Stock Exchange. [S.a.]. *FTSE/JSE Africa index series: A comprehensive guide.* [Online]. Available: http://www.jse.co.za/Libraries/FTSE-JSE_-_Education_-_Comprehensive_Guide/FTSEGuide.sflb.ashx [18 January 2011].

Johannesburg Stock Exchange. 2012. FTSE/JSE Index Series, Quarterly Review, December 2012. [Online]. Available: http://www.jse.co.za/Products/FTSE-JSE/Indexreviews.aspx [20 January 2012].

Jones, C. 2002. A century of stock market liquidity and trading costs. Working paper, Columbia University.

Jun, S-G., Marathe, A. & Shawky, H.A. 2003 Liquidity and stock returns in emerging markets. *Emerging Markets Review*, 4(1): 1-24.

Kang, X. 2012. Evaluating alternative beta strategies. *Journal of Indexes Europe*, March/April: 8-19.

Kaplan, P.D. & Knowles, J.A. 2004. Kappa: A generalized downside risk-adjusted performance measure. *Journal of Performance Measurement*, 8(3): 42–54.

Keene, M.A. & Peterson, D.R. 2007. The importance of Liquidity as a factor in asset pricing. *The Journal of Financial Research*, 30(1):91-109.

Keller, G. 2005. *Statistics for management and economics.* 7th edition. Belmont, CA: Thomson Higher Education.

Kidd, M. 2013. Director of Centre for Statistical Consultation, Stellenbosch University. Stellenbosch: Personal interview. 20 November.

Kruger, P. & van Rensburg, P. 2008. Evaluating and constructing equity benchmarks in the South African portfolio management context. *Investment Analyst Journal*, 67: 5-18.

Kyle, A.S. 1985. Continuous Auctions and Insider Trading. *Econometrica*, 53(6): 1315-1335.

Lagos, R. & Rocheteau, G. 2008. *Liquidity in asset markets with search frictions.* Federal Reserve Bank of Minneapolis, Research Department Staff Report 408 [Online]. Available:

http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1. 141.6974&rep=rep1&type=pdf. [18 January 2011].

Lamba, A.S. & Otchere, I. 2001. An analysis of the dynamic relationships between the south african equity market and major world equity markets. *Multinational Finance Journal*, 5(3): 201-224.

Levine, D.M. & Stephan, D.F. 2009. Even you can learn statistics: A guide for everyone who has ever been afraid of statistics. New Jersey: Pearson Education.

Lin, C. 2010. *Financial liberalization and liquidity commonality*. Working paper: National University of Singapore.

Lintner, J. 1965a. The valuation of risk assets and the selection of risky investments in stock portfolios and capital budgets. *Review of Economics and Statistics*, 73: 13-37.

Lintner, J. 1965b. Security prices, risk and maximal gains from diversification. *Journal of Finance*, 20: 587-615.

Liu, W. 2006. A liquidity-augmented capital asset pricing model. *Journal of Financial Economics*, 82: 631-671.

Loderer, C. & Roth, L. 2005. The pricing discount for limited liquidity: evidence from SWX Swiss Exchange and the Nasdaq. *Journal of Empirical Finance*, 12(2): 239-268.

Longstaff, F.A. 2001. Optimal portfolio choice and the valuation of illiquid securities. *The Review of Financial Studies*, 14(2): 407-431.

Longstaff, F.A. 2009. Portfolio claustrophobia: Asset pricing in markets with Illiquid Assets. *American Economic Review*, 99(4): 1119-1144.

Mabhunu, M. 2004. The market efficiency hypothesis and the behaviour of stock returns on the JSE securities exchange. *MComm dissertation. Rhodes University.*

Maginn, J.L., Tuttle, D.L., Pinto, J.E. & McLeavey, D.W. 2007. *Managing investment portfolios – A dynamic process.* 3rd edition. New Jersey: John Wiley and Sons Inc.

Maltz, A. 2005. *ICB indices on track for Jan 3.* Fin24. [Online]. Available: http://www.fin24.com/Companies/ICB-indices-on-track-for-Jan-3-20051227 [20 January 2013].

Marshall, B.R. & Young, M. 2003. Liquidity and stock returns in pure order-driven markets: evidence from the Australian stock market. *International Review of Financial Analysis*, 12: 173-188.

Matignon, R. 2005. *Neutral network modeling using sas enterprise miner*. Bloomington: Authorhouse.

McDaniel, C.F. & Gates, R. 2001. *Marketing research essentials.* 3rd edition. Cincinnati, OH: South-Western College.

McGregor BFA (Pty) Ltd. 2012. *Research domain.* Software and database. Johannesburg.

McLeod, W. & Van Vuuren, G. 2004. Interpreting the Sharpe ratio when excess returns are negative. *Investment Analyst Journal*, 59: 15-20.

Meyer, M.C. 1998. The persistence of unit trust performance for the period July 1985 – June 1995. *South African Journal of Business Management*, 29(3): 100-108.

Mkhize, H. & Msweli-Mbanga, P. 2006. A critical review of the restructuring of the South African capital market. *International Review of Business Research Papers*, 2(2): 80-91.

Moore, S., Neville, C., Murphy, M. & Connolly, C. 2010. *The ultimate study skills handbook*. Berkshire: Open University Press.

Mossin, J. 1966. Equilibrium in a capital asset market. *Econometrica*, 34(4): 768-83.

Mouton, J. 1996. *Understanding social research.* Pretoria: Van Schaik.

Muller, C. & Ward, M. 2013. Style-based effects on the Johannesburg Stock Exchange: A graphical time-series approach. *Investment Analyst Journal*, 77: 1-16.

Padgette, R.L. 1995. Performance reporting: the basics and beyond. *Journal of Financial Planning*, 8(4): 172-180.

Pástor, l. & Stambaugh, R.F. 2003. *Liquidity risk and expected stock returns. Journal of Political Economy,* 111(31): 642-685.

Piqueira, N.S. 2008. *Marketwide liquidity and another look at liquidity risk*. Working paper, University of Houston.

Polonsky, M.J. & Waller, D.S. 2005*. Designing and managing a research project: a business student's guide*. Thousand Oaks: Sage Publications.

Puplava, J.J. 2000. *Rogue wave-rogue trader*. [Online]. Available: http://www.financialsense.com/contributors/james-j-puplava/the-perfect-financial-storm/rogue-wave-rogue-trader [18 April 2010].

Ramorwa, B.P. 2012. *Corporate payout policy in South Africa: Have share repurchases replaced cash dividends?* MComm dissertation, University of the Witwatersrand.

Reilly, F.K., & Brown, K. 2008. *Investment analysis and portfolio management.* 8th edition. Mason, OH: South-Western College Publishing.

Reinganum, M. R. 1981. Misspecification of capital asset pricing: Empirical anomalies based on earnings' yields and market values. *Journal of Financial Economics,* 9(1): 19-46.

Reisinger, A. 2012. *The effect of liquidity on stock returns on the JSE*. MComm dissertation. University of Stellenbosch.

Roll, R. 1977. A critique of the asset pricing theory's tests. *Journal of Financial Economics*, 4: 129-176.

Roll, R. 1978. Ambiguity when performance is measured by the Securities Market Line. *The Journal of Finance*, 33(4): 1051-1069.

Roll, R. 1980. Performance evaluation and benchmark errors. *The Journal of Portfolio Management*, 6(4):5-12.

Ross, S.A. 1976. The arbitrage theory of capital asset pricing. *Journal of Economic Theory*, 13: 341-360.

Ross, S.A. 1977. Return, risk, and arbitrage, in Friend, I. and Bicksler, J. (eds.), *Risk and return in finance*, Ballinger, Cambridge, MA, 189-218.

Rouwenhorst, K.G. 1999. Local return factors and turnover in emerging stock markets. *The Journal of Finance,* LIV(4): 1439-1464.

Sarr, A. & Lybek, T. 2002. *Measuring liquidity in financial markets*. IMF Working Paper. [Online]. Availble: http://www.imf.org/external/pubs/ft/wp/2002/wp02232.pdf [16 January 2011].

Sharpe, W.F. 1964. Capital asset prices: a theory of market equilibrium under conditions of risk. *The Journal of Finance*, 19(3): 425-442.

Sharpe, W.F. 1966. Mutual fund performance. *Journal of Business*, 39: 119-138.

Sharpe, W.F. 1994. The Sharpe ratio. *The Journal of Portfolio Management*, 21(4): 49-58.

Siconolfi, M., Raghavan, A. & Pacelle, M. 1998. All bets are off: How the salesmanship and brainpower failed at Long-term capital. *The Wall Street Journal*, 16 November: A1.

Sortino, F.A. & Price, L.N. 1994. Performance measurement in a downside risk framework. *The Journal of Investing*, 3(3): 59-64.

Sortino, F.A. & Van der Meer, R. 1991. Downside risk: Capturing what's at stake in investment situations. *The Journal of Portfolio Management*, 17(4): 27-31.

South African Reserve Bank (SARB). 2011. [Online]. Available: http://www.resbank.co.za/pages/default.aspx [18 March 2012].

Stahel, C.W. 2005. *Liquidity across developed and emerging markets*. Working paper: George Mason University.

StatSoft Inc. 2012. Statistica (data analysis software system), Version 11.

Stewart, D.W. & Kamins, M.A. 1993. *Secondary research: Information sources and methods.* Newbury Park, CA: Sage.

Stoll, H.R. & Whaley, R.E. 1983. Transaction costs and the small firm effect. *Journal of Financial Economics*, 12: 57-79.

Stowe, J., Robinson, T., Pinto, J. & McLeavey, D. 2010. Return concepts, in CFA Institute (eds.), *Equity.* OH: Pearson Custom Publishing.

Strong, R.A. 2008. Portfolio construction, management, and protection. Cengage Learning.

Theart, L. 2011. Liquidity as an investment style, email to Z. Chen [Online], 10 November. Available e-mail: lt@sun.ac.za.

TimbukOne (Pty) Ltd. 2012. *Research domain.* Software database. Johannesburg.

Valle e Azevedo. J. 2011. *Econometrics: regression analysis with time series data.* University of Lisbon- Econometrics, Class notes. [Online]. Available: http://docentes.fe.unl.pt/~azevedoj/Web%20Page_files/Teaching_files/9_TS_Basics.pdf. [8 May 2013].

Van Rensburg, P. & Slaney, K. 1997. Market segmentation on the Johannesburg Stock Exchange. *Journal for studies in economics and econometrics*, 21(3): 1-23.

Van Rensburg, P. 2002. Market segmentation on the Johannesburg Stock Exchange II. *Journal for studies in economics and econometrics*, 26(1): 83-99.

Von Wielligh, J.F.C. & Smit, E.vdM. 2000. Persistence in the performance of South African unit trusts. *South African Journal of Business Management*, 31(3): 120-129.

Wooldridge, J.M. 2009. *Introductory econometrics: A modern approach*, 4th ed, South-Western.

World Federation of Exchanges. 2012. *Statistics, annual 1996-2010*. [Online]. Available: http://www.world-exchanges.org/statistics [16 January 2011].

Zikmund, W.G. 2003. *Business research methods.* 7th edition*.* Ohio: Thomson Learning.

Zikmund, W.G., Babin, B.J., Carr, J.C. & Griffin, M. 2010. *Business research methods.* 8th edition*.* Mason, Ohio: South Western Publishing.

Zikmund, W.G., Ward, S., Lowe, B., Winzar, H. & Babin, B.J. 2011. *Marketing Research.* 2nd edition. South-Western: Cengage Learning.