The effect of liquidity on stock returns on the JSE

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Abstract

This thesis examines the effect of liquidity on excess stock returns on the Johannesburg Stock Exchange (JSE) over the period 2003 to 2011. It builds on the findings of previous studies that found size, value and momentum effects to be significant in explaining market anomalies by adding a further explanatory factor, namely liquidity. A standard CAPM, as well as a momentum-augmented Fama-French (1993: 3) model are employed to perform regression analyses to examine the effect of the four variables on excess stock returns. Results suggested that the log of the stock's market value best captured the size effect, the earnings yield best captured the value effect and the previous three month's returns best captured the momentum effect. Five liquidity proxies are used: the bid-ask spread first proposed by Amihud (1986: 223), turnover, the price impact measure of Amihud (2002: 31) and two zero return measures proposed by Lesmond *et al.* (1999: 1113). Despite prior studies having found liquidity to be an influential factor, this thesis found the opposite to be true. This finding remains robust, irrespective of the type of liquidity measure used. While size, value and momentum are found to be significant to a certain extent in explaining excess stock returns over the period, liquidity is not found to be significant. This is a surprising result, given that the JSE is seen as an emerging market, which is generally regarded as illiquid. This fact is exacerbated by the fact that the JSE is a highly concentrated and therefore skewed market that is dominated by only a handful of shares. Hence liquidity is expected to be of utmost importance. The result that liquidity is however not a priced factor on this market is therefore an important finding that requires further analysis to determine why this is the case. In addition, significant non-zero intercepts remained, indicating continued missing risk factors.

Key words:

Liquidity; size effect; value effect; momentum effect; excess stock returns; Johannesburg Stock Exchange JSE

Opsomming

In hierdie tesis word die effek van likiditeit op oormaat aandeel-opbrengste op die Johannesburg Effektebeurs (JEB) ondersoek gedurende die periode 2003 tot 2011. Dit bou voort op die bevindinge van vorige studies wat toon dat grootte, waarde en momentum beduidend is in die verklaring van mark onreëlmatighede deur ‘n addisionele verklarende faktor, likiditeit, toe te voeg. ‘n Standaard kapitaalbateprysingsmodel (KBPM) sowel as ‘n momentum-aangepaste Fama-French (1993: 3) model word gebruik om deur middel van regressie analise die effek van die vier veranderlikes op oormaat aandeel-opbrengste te ondersoek. Die resultate toon dat die grootte effek die beste verteenwoordig word deur die logaritme van die aandeel se mark kapitalisasie, die verdienste-opbrengs verteenwoordig die waarde effek en die vorige drie-maande opbrengskoerse verteenwoordig die momentum effek die beste. Vyf likiditeitsveranderlikes is gebruik: bod-en-aanbod spreiding voorgestel deur Amihud (1986: 223), omset, die prys-impak maatstaf van Amihud (2002: 31) en twee nul-opbrengskoers maatstawwe voorgestel deur Lesmond *et al.* (1999: 1113). Afgesien van die feit dat vorige studies die effek van likiditeit beduidend vind, word die teenoorgestelde in hierdie tesis gevind. Hierdie bevinding bly robuus, ongeag van die likiditeitsveranderlike wat gebruik word. Terwyl bevind is dat grootte, waarde en momentum beduidend is tot ‘n sekere mate in die verklaring van oormaat aandeel-opbrengste tydens die periode, is geen aanduiding dat likiditeit ‘n addisionele beduidende verklarende faktor is gevind nie. Hierdie bevinding is onverwags, aangesien die JEB beskou word as ‘n ontluikende mark, wat normaalweg illikied is. Hierdie feit word vererger deur dat die JEB hoogs gekonsentreerd is en dus ‘n skewe mark is wat oorheers word deur slegs ‘n hand vol aandele. Dus word verwag dat likiditeit ‘n baie belangrike faktor behoort te wees. Die bevinding dat likiditeit nie ‘n prysingsfaktor op hierdie mark is nie, is dus ‘n belangrike bevinding en vereis verdere analise om vas te stel waarom dit die geval is. Addisioneel word beduidende nie-nul afsnitte verkry, wat aandui dat daar steeds risiko faktore is wat nog nie geïdentifiseer is nie.

Sleutelwoorde:

Likiditeit; grootte; waarde effek; momentum effek; oormaat aandeel-opbrengste; Johsannesburg Effektebeurs (JEB)

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List of Abbreviations

- ALSI — FTSE/JSE All Share Index
- AMEX — American Stock Exchange
- APT — Arbitrage Pricing Theory
- B/M — Book-to-Market ratio
- BE/ME — Book-to-Market Equity ratio
- BVTMLOG — Natural Log of Book Value To Market
- C/P — Cash flow-to-Price ratio
- CAPM — Capital Asset Pricing Model
- DY — Dividend Yield
- E/P — Earnings-to-Price ratio
- EMH — Efficient Market Hypothesis
- EPS — Earnings Per Share
- EY — Earnings Yield
- JSE — Johannesburg Stock Exchange
- MOM12 — Previous 12-month's return
- MOM3 — Previous 3-month's return
- MPT — Modern Portfolio Theory
- MVLOG — Log of Market Value
- NASDAQ — National Association of Securities Dealers Automated Quotations
- NYSE — New York Stock Exchange
- OLS — Ordinary Least Squares regression
- P/B — Price-to-Book ratio
- P/E — Price-to-Earnings ratio
- TSCS — Time-series cross-sectional data

CHAPTER 1
INTRODUCTION

1.1 INTRODUCTION

The ultimate goal of any active equity manager is to outperform not only the market but also his peers. This has led to a substantial amount of research in this area, with the aim of identifying methods or processes that can be used to achieve excess portfolio returns. However, there has been much debate as to the usefulness of such research due to the claim that markets are in fact efficient and that, as a consequence, share prices fully reflect all available information in the market. This would mean that it is impossible to achieve excess returns above the market. However, this did not discourage market participants and researchers. As a result, it was found that certain market anomalies do exist, suggesting that markets are in fact not efficient and hence that there are opportunities to earn excess returns.

In particular, there is a substantial amount of evidence that there are three main market factors that influence returns: namely the size, value and momentum of listed firms. It has been shown that the combination of these factors better help explain stock returns, rather than simply assuming that there is one single market factor that does this. These findings reach as far back as the seventies and eighties, with the size factor first being documented by Banz (1981: 3), Reinganum (1981: 19) and Fama and French (1992: 427). The value effect was first proposed by Basu (1977: 663) and Reinganum (1981: 19), with the momentum effect being a more recent finding (Jegadeesh and Titman (1993: 65) and Brennan, Chordia and Subrahmanyam (1998: 345)). Subsequent research on these factors has been plentiful. The seminal studies on these anomalies were published by Fama and French over several years (1992, 1993 and 1998), who found that a firm's size and its book-to-market (B/M) ratio are better able to explain stock market returns than its market beta alone. Their three-factor model has received much praise since, with many subsequent studies assuming its accuracy. However, some practitioners questioned whether these two factors alone could indeed explain market returns. This led to further studies being published that expanded the Fama-French model by other factors, which included, amongst others a momentum factor.

Although the majority of studies now agreed that the presence of size, value and momentum factors could explain excess stock returns, the seminal paper published in the mid-eighties by Amihud and Mendelsohn (1986: 223) suggested that liquidity may in fact be another highly influential factor in explaining returns. This was an interesting proposal since Fama and French (1992: 427) identified that although liquidity is an important market-wide aspect, it does not need to be taken into account implicitly in a model since the size and B/M factors subsume its effect. Brennan, Chordia and Subrahmanyam (1998: 345) were the first to extend the Fama-French (1993: 3) model by a liquidity factor, thereby testing whether the earlier statement by Fama and French had any validity. Their work led to renewed interest in determining a stock returns' most influencing factors, since it was shown that after controlling for size, B/M and other variables, liquidity remained an important factor in explaining returns.

So far, the majority of studies published that examine the influence of the above-mentioned factors focus on the more developed markets, in particular the US market. However, as investments in emerging markets, and in particular the South African market, have become increasingly more popular, especially since the financial crisis of 2008, the effect of risk factors on asset pricing has become more of a priority. Several studies have been published that investigate the effect of size, value and momentum factors on stock returns on the Johannesburg Stock Exchange (JSE). These include, amongst others, Plaistowe and Knight (1986: 35), Robins, Sandler and Durand (1999: 53), Fraser and Page (2000: 25), van Rensburg (2001: 45) and van Rensburg and Robertson (2003a: 7 and 2003b: 7). The effect of liquidity on returns on the JSE, however, has not received much attention. The studies by Bailey and Gilbert (2007: 19) and Basiewicz and Auret (2009: 23) are the most notable exceptions, having clearly allowed for the effects of liquidity through the use of a liquidity filter or an adjustment for trading costs. What no study on the JSE has done to date, though, is allow for liquidity explicitly in a model in the form of a liquidity factor, proxied by a number of different liquidity measures. Taking account of liquidity in this way would help better determine if it is indeed a priced factor on the JSE and if it should therefore be taken into account when making stock investment decisions. This research aims to bridge that gap.

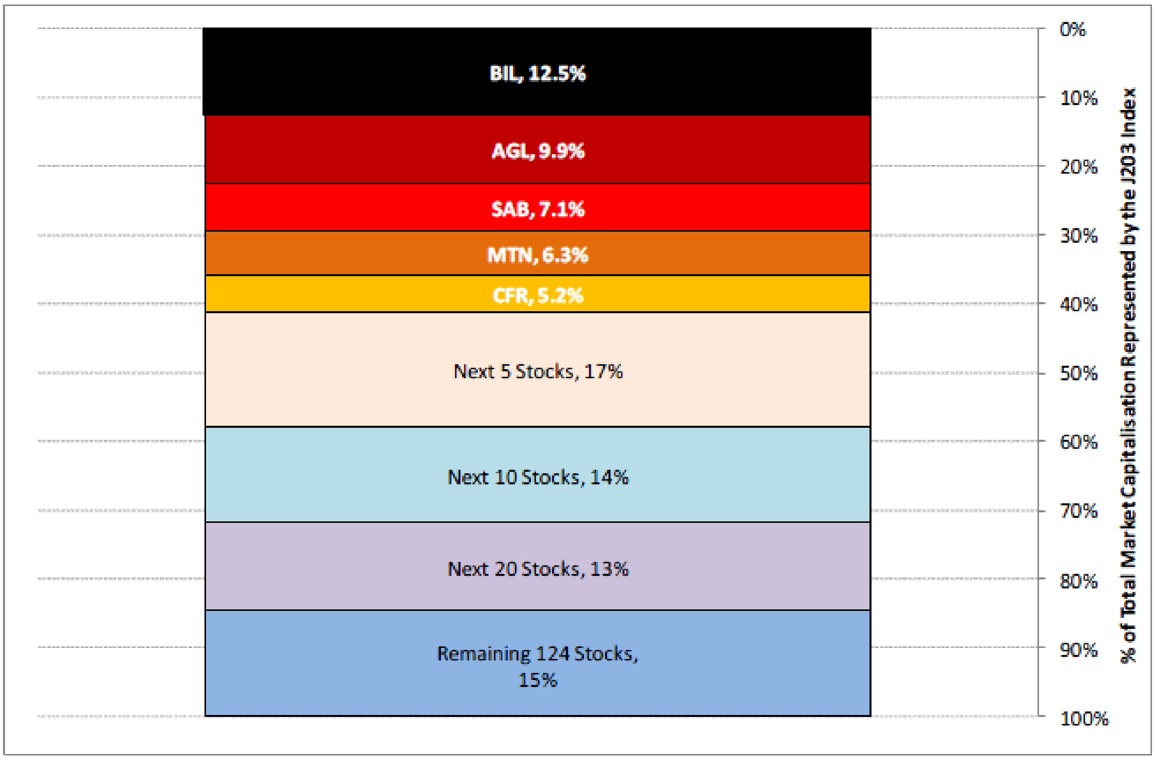
1.2 PROBLEM STATEMENT

Liquidity is generally acknowledged to be an important factor in asset pricing. An asset's expected return is related to its sensitivity to certain state variables that help explain its price shifts. "Liquidity appears to be a good candidate for a priced state variable. It is often viewed as an important feature of the investment environment and macroeconomy, and recent studies find that fluctuations in various measures of liquidity are correlated across assets" (Pástor and Stambaugh, 2003: 643). Hence liquidity and its effect on pricing in terms of a liquidity premium are an important aspect of the market that need to be taken into account. Its impact is especially important for the South African market in the current economic climate for two reasons: firstly because the South African market is seen as an emerging market and secondly because of the financial crisis.

The vast majority of research of the impact of liquidity on stock returns has focused on the United States which is generally accepted to be the most developed and most liquid market in the world. The South African market, in contrast, is seen as an emerging, small and illiquid (albeit well-developed) market in which the effects of il/liquidity would be far more pronounced. But this is not the only difference of this particular market to the US market. The JSE is a highly concentrated market, dominated by only a couple of mining shares. The FTSE/JSE All Share Index (ALSI) is an index consisting of around 164 stocks representing around 99% of the total market capitalisation of all tradable ordinary stocks in South Africa for companies listed on the main board of the JSE. As at July 2011 (and hence the end of the sample period used in this research), in excess of 20% of the FTSE JSE All Share Index was represented by only two mining companies. Additionally, the next 30% was represented by only another five companies, meaning that half of the index was represented by only seven companies. This is represented by Figure 1.1. Hence, the remaining 50% of the index consists of 157 shares, of which a significant number are very small firms (by market capitalisation), which are difficult to invest in and therefore seen as illiquid. As a result, the effect of liquidity on stock returns should be analysed in detail for this market, to determine if it is as influential a factor as it appears to be.

Figure 1.1 Distribution of (market capitalisation) weights on the ALSI (July 2011)

The figure illustrates the concentration of the ALSI by depicting the contribution of various stocks and groups of stocks to the total value of the index as at July 2011.



Source: Raubenheimer, 2012: 58.

The second reason why the effects of liquidity on the JSE are particularly important at this point in time is due to the effects of the financial crisis on markets worldwide. The 'Sub-Prime' crisis was one of the first pointers towards the global Financial Crisis in 2008, where the world suffered its first loss in the global GDP since World War Two. Emerging markets contributed greatly to the growth in global markets indicating a sure road to recovery from the recession. The sovereign debt crisis in Europe followed shortly afterwards sending the global economy into a downward spiral once again. Despite the fact that Greece was bailed out twice, and Ireland and Portugal were also helped by the European Central Bank, the European economy still suffered financial and political turmoil. The global impact of both the US and European Sovereign Debt crises was dampened by the strong growth of the emerging markets. South Africa, an emerging market, showed better than expected growth backed by the new National Credit Act that came into effect in 2007. This forced better credit discipline onto South Africa, allowing it to survive a credit-induced recession. As at mid-2011, they were however still experiencing uncertainty in the recovery of their business cycle as well as the sporadic attitude of businesses and households. This economic turmoil led to a severe decline in financial activity, which in turn led to an exacting dip in market-wide liquidity. As a result, the effects of liquidity on asset pricing have become a rather prominent topic for practitioners and researchers alike, with the aim of determining how pertinent an issue it is and whether investment strategies need to be updated to take account of it explicitly.

This leads to the research question of this thesis. In particular, four questions are asked:

- What is the effect of liquidity on stock returns on the JSE?
- Is it a priced factor?
- Can it help explain the cause of excess stock returns?
- Does it influence and help explain stock returns or is it subsumed by other factors?

The answers to these questions will hopefully assist investors in the South African market in setting up their investment approaches and, in turn, outperform the market by maximising their alpha-generation strategies.

1.4 CLARIFICATION OF KEY CONCEPTS

1.4.1 Liquidity

Liquidity is an elusive concept that is notoriously difficult to define. It is often described as the ease with which an asset can be bought or sold without affecting the underlying price. Therefore, the bigger the price movement due to a sale, the less liquid the underlying asset. Illiquidity has also been defined as the cost of immediate execution (Amihud and

Mendelsohn, 1986: 223). However, these are both overly simplistic definitions since over the years it has emerged that there are numerous dimensions that affect a stocks' liquidity. One cannot only take account of the time and price shifts of the asset, but one also needs to take volume into account. Therefore, for this thesis, several measures are proposed and tested in an attempt to take account of all possible dimensions of liquidity.

1.4.2 Market anomalies

A market anomaly, also known as market inefficiency, is a price or return irregularity that seemingly contradicts the Efficient Market Hypothesis (EMH). The EMH assumes that markets are efficient and therefore prices fully reflect all available information. This would make it impossible for investors to outperform the market. However, the presence of market participants who manage to consistently outperform the market suggest the existence of market anomalies.

1.4.3 Investment strategies

Investors who allocate assets according to different investment strategies believe that the market is not efficient and subsequently that they can outperform it to achieve excess returns by exploiting market anomalies. In terms of equity investing, there are a certain number of investment styles that are generally followed: value, growth, size and momentum strategies. Value strategies focus on investing in shares with a low price relative to their earnings or assets per share, while growth strategies focus on investing in high-earnings-growth companies. Other investors focus on the size of the company, usually represented by the firm's market capitalisation. Finally, momentum investors take the share's former performance into account when investing. It is based on the premise that if investor overreaction is present in the market, then buying past winners may generate excess returns from the temporary over-valuation of the share price.

1.5 CONTRIBUTIONS

This thesis contributes to literature in numerous ways. Firstly, and most importantly, it investigates the effect of liquidity on stock returns on the South African market. In particular, it provides evidence on whether liquidity is a priced factor on the JSE. To the knowledge of the author no such analysis has ever been performed on the South African stock market. In addition, the existence of size, value and momentum factors is also investigated. The aim is to determine which risk factor(s) best explain stock returns.

Secondly, a number of different liquidity measures are tested in order to determine the variation in results that are obtained due to the various measures. This assists in capturing the multiple dimensions of liquidity, which provide an added control for risk. It also helps identify which aspects of liquidity are most prominent for asset pricing on the South African market. Since none of these measures have ever been examined on the JSE, the results will hopefully shed some light as to the behaviour of liquidity in this market.

Therefore, findings will provide additional information as to the extent and significance of the size, value and momentum effects on the South African market and also present evidence of the influence and behaviour of liquidity on an important emerging market.

1.6 RESEARCH DESIGN AND METHODOLOGY

1.6.1 Modelling

Asset pricing models have received much attention in economic literature. Their robustness and efficacy in correctly pricing assets is of utmost importance since an error could lead to severe losses for investors. Despite the substantial amount of literature that has emerged, no single model has been accepted by practitioners and academics alike. While certain models have received more praise than others, drawbacks have been identified for all models to date. This is because it is especially difficult to properly capture the actual behaviour of asset prices, since they seem to behave in patterns that contradict the rational market behaviour that these models are based on. Two rather well known 'irrational' anomalous behavioural patterns are the 'size effect' and the 'value effect', both of which have been mentioned above.

One of the first, and probably most commonly used, asset pricing models is the Capital Asset Pricing Model (CAPM), developed by Sharpe(1964: 425), Lintner (1965: 47) and Mossin (1966: 768). It is a univariate model that assumes that asset prices can be explained by its market beta alone. It states that an asset's systematic risk can be measured by the ratio of its covariance with the market portfolio:

$$E(R_i) = R_f + \sigma_{i,M} \times \frac{(E(R_M) - R_f)}{\sigma_M^2}$$

… (1.1)

Where	$E(R_i)$	is the expected return of asset i;
	R_f	is the return on the risk-free asset;
	$E(R_M)$	is the expected return of the market portfolio M;
	$\sigma_{i,M}$	is the covariance of risky asset i with the market portfolio M;
	σ_M^2	is the variance of the market portfolio M.

By defining $\frac{\sigma_{i,M}}{\sigma_M^2}$ as the beta of asset i (β_i), then equation 1.1 can be rewritten as

$$E(R_i) = R_f + \beta_i \left(E(R_M) - R_f\right)$$

… (1.2)

However, an integral assumption of the CAPM is that markets are in equilibrium and that market participants pursue a mean-variance optimising objective. In addition, it requires the identification of the market portfolio, which in reality is unobservable. As a result, this led to several inconsistencies between the theoretical expected returns obtained from the model and those observed in the market. Most notable in this finding was that there are other factors, beside market beta, that explain expected returns beyond that predicted by this model. This led to the emergence of multi-factor models as substitutes for the CAPM in predicting expected asset returns. The Arbitrage Pricing Theory (APT model) proposed by Ross (1976: 341) is one such model, allowing the use of several factors to explain expected returns. It also does not require an assumption as to the market portfolio and therefore allows investors to price assets in inefficient capital markets:

$$E(R_i) = R_f + \beta_{i1}\left(E(RF_1) - R_f\right) + \dots + \beta_{ik}\left(E(RF_k) - R_f\right)$$

… (1.3)

Where	F_k	is the kth systematic risk factor that is common to all assets;
	$E(RF_k)$	is the expected return on an asset with an average sensitivity to movements in F_k;
	$E(RF_k) - R_f$	is the expected risk premium on F_k; and
	β_{ik}	is the sensitivity of asset i's expected return to movements in the risk premium on risk factor k.

In particular, Fama and French (1993: 3) developed a three-factor model that regresses the realised excess returns of an asset on the market factor and two factor-mimicking portfolios (the two factors being a size factor and a value factor). It has received much attention since due to its improved ability to incorporate more factors into adequately explaining asset returns.

This thesis makes use of both the CAPM and a momentum-augmented Fama-French model to determine the effect of size, value, momentum and liquidity in explaining excess stock returns on the JSE.

1.6.2 Data analysis

Data is collected for the FTSE/JSE ALSI, a dataset that represents around 99% of stocks listed on the JSE and is therefore representative of the entire market. Several data checks were applied, thereby ensuring the data is free from outliers, selection and survivorship bias. A time-series cross-sectional (TSCS) estimation with Newey-West standard errors is made use of. Both a single-factor CAPM and a momentum-augmented Fama-French (1993) model are tested, both with and without an added liquidity factor.

The methodology used in this thesis is divided into two sections. First, the size, value and momentum effects are examined on the returns of stocks listed on the JSE. Different measures will be employed to take account of the various effects in the hope of determining the three most appropriate measures for each of the size, value and momentum effects. Next, the effects of liquidity will be added to the analysis, using a number of liquidity proxies. This will assist in analysing the effect of liquidity on stock returns, and will enable one to determine whether liquidity is in fact a priced factor. The tests will be performed through the use of regression analyses. This is done in four steps:

- A measure of size, value, momentum and liquidity are estimated in each month of the sample for each individual stock.
- Portfolios are set up according to the intersection of size, value, momentum and liquidity, the inclusion of the factors being dependent on the type of regression analysis to be performed. This is performed on a yearly basis due to annual rebalancing.
- For each portfolio the monthly excess portfolio return is calculated, in addition to the size, value, momentum and liquidity factors.
- Using the excess returns and factors, the portfolio alphas and betas are estimated and analyzed.

1.7 CHAPTER OUTLINE

The structure of the study is as follows. Chapter 2 provides a review of all relevant literature on risk factors affecting stock returns both internationally and also specifically in South Africa. This includes the effects of size, value, momentum and liquidity factors. Chapter 3 describes the data used and methodology employed in performing the analysis. It illustrates the construction of the portfolios as well as the measurement of their excess returns and evaluation of the size, value, momentum and liquidity factors. Chapter 4 provides a discussion of the empirical findings. Finally, Chapter 5 offers a summary of the findings and any conclusions drawn from them. It also provides some recommendations for future research.

1.8 NATURE AND FORM OF RESULTS

The findings from this papers' analysis indicate that market, size, value and momentum affect and partly explain excess stock returns on the JSE. The magnitude and importance of each of the factors depends on the type of share being analysed. The strongest effect was by far the momentum effect, which showed that the higher the momentum measure, the higher the returns. This is in accordance with the overreaction hypothesis and therefore also indicates that momentum investment strategies generate positive excess returns. These findings were consistent over both models used. Overall, it was found that the size effect was best captured by the firm's market capitalisation, the value effect was best captured by the firm's earnings yield and the momentum effect was best captured by the share's previous 3-month's returns.

However, contrary to the author's expectations and to findings by earlier studies on emerging markets, liquidity was not found to be a significant factor. This result remained robust, irrespective of the type of liquidity measure used. The most insignificant effect was shown by both of the zeros measures, while the bid-ask spread and turnover measures showed some changes to the excess returns, indicating that liquidity does in fact affect returns and should be taken into account in investment decisions. This effect was very weak though, leading to the final conclusion that it is not a priced factor.

1.9 CONCLUSION

Ever since the financial crisis hit markets worldwide, investors have been trying to gauge its ramifications on market-wide principles that had previously been thought of as acceptable. The effect of liquidity is one such principle. Investors have always known of the existence of liquidity and have, up to a certain extent, taken account of it. However, the financial crisis exacerbated its effect on the stock market, therefore reinforcing its importance. Researchers and practitioners have since devoted a considerable amount of time to further analyse the effects of liquidity. However, most of this (and previous) research has focused on the United States market, which is a very different market to that of South Africa. This thesis aims to determine whether liquidity is a priced factor on the JSE and therefore helps in explaining excess stock returns. Previous literature has examined the effect of other important asset pricing variables (such as size, value and momentum) on the JSE but none of them have allowed explicitly for the effects of liquidity. The research presented here aims to fill that gap. In particular, in addition to performing tests on the effects of size, value and momentum factors on excess stock returns, a liquidity factor is added to see its effect on stock return, both on its own as well as in conjunction with the previous three factors. Two types of regression models are used: the standard CAPM and a model similar to that suggested by Fama and French (1993). The results are presented in the following chapters, preceded by an extensive description of the previous analyses that led to this particular research.

CHAPTER 2
LITERATURE REVIEW

2.1 INTRODUCTION

The Efficient Market Hypothesis (EMH) assumes that investors behave rationally and that prices fully reflect all available public information. Hence, the market is assumed to be efficient. However, for many years market participants have argued that this is not the case. In fact, they believe that investors behave irrationally and therefore violate the assumptions of the EMH. Since Modern Portfolio Theory (MPT), as established by Markowitz (1952: 77), is dependent on the assumptions of the EMH, this has led to a great deal of research relating to the validity and extensions of MPT. One such extension is the Capital Asset Pricing Model (CAPM) developed by Sharpe (1964: 425), Lintner (1965: 13) and Mossin (1966: 768), which has become one of the most commonly used models to price risky assets in an efficient market. This model assumes that assets are only exposed to one significant risk, namely market risk. This is a type of risk which cannot be reduced or eliminated through diversification (systematic risk), unlike firm-specific (or unsystematic) risk. However, many critiques of this model have been set forward and as a result multi-factor approaches to asset pricing have been proposed as alternatives. The Arbitrage Pricing Theory (APT) developed by Ross (1976: 341) is one such multi-factor model, addressing some problems of the CAPM. It divides market risk into numerous constituents, each of which represents a systematic risk factor that partially explains and determines asset returns.

However, the APT does not have one specific set of factors. Instead, correct identification of its factors is a very important role in the success of the model. Empirical work devoted to their identification has had important implications for investors on the allocation of their assets. Three stock characteristics have been recognized as the main risk factors: a size factor, a value factor (usually either P/E or B/M) and an overreaction factor. These effects invalidate the assumption of efficiency since they can be exploited to outperform the market, something that in theory should be impossible in an efficient market.

One may ask, though, why these well-documented anomalies continue to be as prevalent as they are. With the amount of literature that is available on them, one might expect investors to seize this opportunity to achieve abnormal profits relative to the market and so assist in restoring market efficiency.

A possible explanation for the persistent continuation of the anomalies is the impact of liquidity on the investment strategies that have been set up to take account of the observed inefficiencies. The abnormal returns one can achieve by exploiting the anomalies are based on results that have been obtained from portfolios that were evaluated using observed, quoted prices. These returns may however not be achievable in reality due to the constraints of liquidity in actual markets. It may not be possible for investors to achieve the desired profits if markets are not only too small but also not particularly liquid. This may just be the case in a fairly small market such as that of South Africa.

2.2 MARKET ANOMALIES

Due to the presence of market anomalies that seem to be indicators of inefficiency and hence potential abnormal profits, much research has been devoted to determining how exactly one can exploit them. It has generally been found that there are three types of effects one can exploit: the size effect, the value effect and the overreaction hypothesis as determined by De Bondt and Thaler (1985: 793). All three exhibit the same kind of behaviour, namely that they can be split into two opposing investment styles: the size effect can be split into large cap versus small cap, the value effect can be split into value versus growth and the overreaction hypothesis can be split into momentum versus contrarian.

2.2.1 Size, value and overreaction anomalies

The seminal study that launched investors and researchers alike to investigate the cross-sectional variation in average stock returns was undertaken by Basu (1977: 663). His study was to lead to research in this area over several decades. Indeed, research is still being published today. Basu (1977: 663) explored the relationship between the performance of stocks on the New York Stock Exchange (NYSE) over the period 1956 and 1971 and their respective price-to-earnings (P/E) ratios. It was found that the portfolios with the two lowest P/E quintiles earned 16.3% and 13.5%, while the portfolios with the two highest P/E quintiles earned between 9.3% and 9.5% per annum, respectively, over the 14-year period. However, the higher returns of the low P/E portfolios were not due to higher risk, as indicated by Jensen's alpha[1]. Similarly, the beta coefficients[2] of the two lower quintile P/E portfolios were

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[1] Jensen's alpha, also referred to as the ex-post alpha, is obtained from a rearranged version of the CAPM model, in the form of the following simple linear regression:

$$R_{At} - r_{ft} = \alpha_A + \beta_A\left(R_{Mt} - r_{ft}\right) + \varepsilon_t$$

where for period t, R_{At} is the return on stock A, r_{ft} is the risk-free rate and R_{Mt} is the market return. The term α_A is the intercept of the regression, β_A is the beta of the stock relative to the market and ε_t is the random error term of the regression. The estimate of the intercept of the regression α_A is Jensen's alpha. It can be interpreted as the differential return of the stock compared to the return required to compensate for the systematic risk assumed by the stock during the evaluation period.

[2] The beta coefficient for a stock (given by β_A in the equation above) measures the sensitivity of a stocks return to market movements. It is a linear measure of systematic risk and is equal to

$$\beta_A = \frac{Cov(R_A, R_M)}{Var(R_M)}$$

Stocks with higher values of beta must offer investors with higher returns to compensate them for bearing higher systematic risk.

less than those of the two upper quintile P/E portfolios. This suggested that investors could have benefited from investing in lower P/E stocks by possibly achieving higher risk-adjusted returns compared to the higher P/E stocks. In turn, this implied that investors did not act rationally since the growth stocks were priced higher than the less risky value stocks, which seemed to offer higher returns. As a result, Basu (1977: 663) concluded that stock prices do not instantaneously reflect all publicly available information, which allows investors to use P/E ratios to outperform the market.

The earnings effect found by Basu (1977: 663) is but one effect. The value effect is another such effect, established from different accounting ratios. The fundamental value of a firm can be compared to its market value by examining sales, cash flows, dividends and book value. Lakonishok, Shleifer and Vishny (1994: 1541) considered the value effect on stocks on the NYSE and American Stock Exchange (AMEX) over the period 1963 to 1990 in order to determine why they achieve higher returns. They did so by considering the book-to-market ratio (B/M), cash flow-to-price ratio (C/P), earnings yield (EY) and growth in sales over the previous five years, used as a proxy for growth of the firm. The results revealed that all of the above mentioned factors affected, to varying degrees, the cross-section of returns for the value strategies. Additionally, tests also indicated that the riskiness of value strategies appeared to be no higher than those for growth strategies. It could therefore be concluded that it was only the factors listed above that determined the abnormal returns.

Banz (1981: 3) examined the relationship between the risk-adjusted return and total market capitalisation of common stocks on the NYSE over the period 1936 to 1975. He ran a regression analysis and found that, on average, small cap firms had higher risk-adjusted returns than large cap firms, a phenomenon he referred to as the ‘size effect’. However, the linearity in the market proportions of the model was misspecified since this effect was found to be significant only in the smallest size quintile and less pronounced in the other four quintiles. This non-linear distribution of abnormal returns remained true even when the log of the market proportions was applied, which should in theory have eliminated the skewness. Banz (1981: 3) attributed these results to a misspecification of the CAPM. He did point out, though, that size itself was not necessarily the actual factor affecting returns, but rather that it was simply a proxy for the true underlying factor. Further research would be required to determine the actual factors, yet Banz (1981: 3) did point out that the P/E ratio could be eliminated from that list. This statement was based on the results of Reinganum (1981: 19), who investigated the earnings yield effect on stock returns. He found that while the earnings yield and value anomalies existed on their own, these two anomalies were seemingly related to the same factors. Indeed, the earnings yield effect disappeared for both NYSE and AMEX stocks over the period 1967 to 1975 when controlled for size, but there was still a significant size effect when the stocks were controlled for earnings. Hence the value anomaly seemed to subsume the earnings yield anomaly. This would suggest that Basu's (1977: 663) P/E effect was not an indication of market inefficiency but rather just a proxy for the size effect. Reinganum (1981: 19) interpreted this as yet another misspecification of the CAPM.

Since then much research was performed on the size effect established by Banz (1981: 3), starting with Roll (1981: 879). He put forth the notion that the difference in risk-adjusted returns between small and large firms may actually be due to improper measurement of the risk. The infrequent trading and therefore low liquidity of small firms' stock may be resulting in downward biased measures of risk (as measured by their beta) and subsequent overestimated risk-adjusted returns, when based on the market model. Shortly after publication of that research, Reinganum (1983: 89) returned with another paper, attempting to give another possible explanation for the size effect, namely January tax-loss selling. Firms, and in particular small firms, experience large returns in January. To determine whether the January effect was related to tax-loss selling, tests were conducted on NYSE and AMEX stocks from 1962 to 1979. It was found that the firms in the lower quartile (largest price declines in early January) experienced greater returns than those firms in the upper quartile (smallest price declines in early January). These results were consistent with the tax-loss selling effect. However, this effect could not entirely explain the January effect. This is because even small firms who were unlikely to be sold for tax reasons (for example prior year's winners) exhibited large returns in January.

So far the research relating to the identification of market anomalies influencing stock returns had focused on fundamental factors relating to the efficiency of stocks and the market. De Bondt and Thaler (1985: 793) took a different approach. They examined the psychological behaviour of individuals in decision making processes, therefore exploring Behavioural Finance for an explanation. Empirical research on monthly stock returns data from the NYSE over the period 1933 to 1982 revealed that investors tended to overreact to the arrival of unanticipated news. This suggested that investors are poor Bayesian decision-makers, overreacting to recent information, be it good or bad. This phenomenon is known as the overreaction hypothesis – individuals overweigh recent information and underweigh long-term fundamental information. They obtained their results by computing the average cumulative abnormal returns (ACAR) over 36-month periods for two portfolios: the winner portfolio (contained stocks of prior winners) and the loser portfolio (contained stocks of the prior losers). It was found that the loser portfolio outperformed the market by, on average, 19.6% per annum and the winner portfolio by, on average, 24.6% per annum. The winner portfolio performed relatively worse than the market though, earning around 5.0% less per annum. Hence abnormal positive returns earned in the loser portfolios accumulated over time, while in the winner portfolio abnormal negative returns were accumulated over time. Using shorter time periods diminished the effect of the positive abnormal returns for the loser portfolio. It was noted too, though, that the January effect seemed to have had an influence on these results too – most of the excessive positive abnormal returns for the loser portfolio were earned in January, even up to five years after formation. Therefore the tax-loss selling effect as well as the overreaction hypothesis may be influencing the abnormal returns.

In their subsequent paper, De Bondt and Thaler (1987: 557) re-evaluated the overreaction hypothesis by taking account of additional factors such as firm size, seasonality and changes in risk as measured by CAPM-betas. Excess returns in January for past winners were found to be negatively related to excess returns in the prior December, which may be indicative of a capital gains tax 'lock-in' effect. CAPM-betas did not explain the winner-loser effect when used as a measure of risk, nor could this effect be mainly attributed to the size effect. All in all, the results supported the overreaction hypothesis found earlier.

Zarowin (1990: 113) re-examined the phenomenon of prior losers outperforming winners, only to conclude that it was not due to investor overreaction but rather due to the size effect. By replicating De Bondt and Thaler's (1985: 793) study, but adding minor adjustments such as investigating the top and bottom quintiles (rather than the 35 or 50 most extreme firms), they concluded that losers significantly outperformed winners and that neither the January effect nor the differences in risk between the stocks could account for this return discrepancy. However, Zarowin (1990: 113) did find that the poorest earners (lowest quintile) were considerably smaller than the best earners (top quintile). When losers were matched with winners of equal size, virtually no difference in returns was observed (except in January). When losers were smaller than winners, they outperformed them; when losers were greater than winners, they underperformed them. Hence the overreaction hypothesis may actually be due to the tendency for losers to be smaller than winners and nothing else. This suggests that the size effect may actually be the driving force behind differences in return after all and that, along with the January effect, it subsumes the overreaction hypothesis.

Jegadeesh and Titman (1993: 65) examined momentum investment strategies based on buying winners and selling losers on the NYSE and AMEX over the period 1965 to 1989, only to find that they achieved positive returns over 3- to 12-month horizons. The profitability of the strategies was not due to systematic risk differences. They found that this strategy realized positive abnormal returns in the short-term, up to 12 months after formation, which slowly dissipated over the following two years. This finding implied that earlier interpretations of the mean reversal of returns documented by De Bondt and Thaler (1985: 793) were most likely overly simplistic and just indications of short-term momentum that was observed around the same time as portfolio formation, ignoring longer-term effects.

Fama and French (1992: 427) recognized the presence of two anomaly effects, the size and value effects, and subsequently attempted to combine them. They investigated the combined roles of market beta, size (as measured by market capitalisation), earnings-to-price (E/P), leverage and book-to-market equity (BE/ME) in the cross-section of stock returns on the NYSE, AMEX and the NASDAQ over the period 1963 to 1990. Empirical studies had recognized each of these factors as possible determinants of abnormal returns, from Banz's (1981: 3) identification of the size effect, to Chan, Hamao and Lakonishok's (1991: 1739) identification of BE/ME as an explanatory variable in the cross-section of returns on Japanese stocks. Beta, used alone or jointly with other variables, had little predictive power for stock returns. On the other hand, size, E/P, leverage and BE/ME did have explanatory power, with size and BE/ME seemingly subsuming the effects of E/P and leverage. This provided further evidence of a misspecification of the CAPM.

Based on the results of their previous paper, Fama and French (1993: 3) proposed a three-factor asset-pricing model that incorporated size and value risk premiums in addition to the market risk premium of the CAPM (namely the beta). This model is shown in equation 2.1:

$$R_{i,t} - R_{f,t} = \alpha_i + \beta_i\left(R_{M,t} - R_{f,t}\right) + s_i SMB_t + h_i HML_t + \varepsilon_{i,t} \tag{2.1}$$

where:

$R_{i,t}$	is the return on asset i in month t;
$R_{f,t}$	is the return on the risk-free asset in month t;
α_i	is the regression intercept;
β_i	is the beta coefficient of asset i;
$R_{M,t} - R_{f,t}$	is the market risk premium in month t;
s_i	is the sensitivity of asset i's return to movements in the size risk premium SMB;
h_i	is the sensitivity of asset i's return to movements in the value risk premium HML; and
$\varepsilon_{i,t}$	is the residual (random error) of the regression for asset i in month t.

The factor SMB (Small Minus Big) is the size factor and is calculated as the return on a zero-cost portfolio that goes long stocks of small firms and shorts stock of large firms. Likewise, the value factor, HML (High Minus Low), is calculated as the return on a zero-cost portfolio that has long positions on high B/M firms and short positions on low B/M firms. The model is set up so as to treat both the size and value effects independently.

Fama and French (1996: 55) applied their three-factor model to test the effect of anomalies such as reversals in long-term returns, as found by De Bondt and Thaler (1985: 793), continuation of short-term returns, as found by Jegadeesh and Titman (1993: 65), size, BE/ME, E/P, C/P and past sales growth, factors suggested by Lakonishok *et al.* (1994: 1541), on the returns of common stock. Results showed that the three-factor model explained all of these factors, save for the continuation of short-term returns effect of Jegadeesh and Titman (1993: 65). Since all factors are in one way or another linked to the firm's value, Fama and French (1996: 55) argued that one should expect the effect of some variables to be subsumed by other more influential variables. As a result, this three-factor model can be viewed as a three-factor version of Merton's (1973: 867) intertemporal CAMP (ICAPM) or Ross's (1976: 341) APT, indicating that the alternative variables tested did not reveal additional aspects of risk beyond those explained by the size and B/M factors.

However, Vassalou and Xing (2004: 831) re-examined this finding and concluded that Fama and French's (1996: 55) factors SMB and HML, which they found to be the main factors affecting stock returns, are actually only proxies for another, more prevalent factor, namely default risk. Both the size and B/M effects existed only in those segments of the market that exhibited the highest default risk. This would indicate that default is a variable worth considering, in addition to size and B/M. They did however state that SMB and HML also appear to incorporate other price information not linked to default risk, therefore further research is required to determine what exactly this information content may be.

Fama and French (2006: 491) reviewed the effects of B/M, profitability and asset growth. By running cross-section regressions, using lagged profitability, asset growth and accruals as proxies for expected profitability and investment, they found that they did have predictive power for abnormal stock returns. Instead of considering return effects one variable at a time, they tested and examined incremental cross-sectional effects of all variables based on the fitted values. However, the variables tested did not exclusively account for the forecasts; many variables contributed to the forecasts. Better proxies are needed to account for the entire effect. However, overall, they found that their results corresponded with existing literature, although no indication was obtained whether the relations obtained were due to rational or irrational pricing.

Lewellen and Nagel (2006: 289) considered the conditional CAPM to evaluate whether it may explain the abnormal returns earned by stocks, when the CAPM fails to do so. In theory, this model should explain the abnormal returns by taking account of the covariances between betas, the market risk premium and market volatility. The authors formed value-weighted portfolios consisting only of NYSE and AMEX common stock over the period 1964 to 2001 and used short-window regressions to estimate time series of conditional alphas and betas for portfolios set up using size, B/M and momentum strategies. They found that the conditional and unconditional alphas of all portfolios were very similar, both being large and significant, a direct breach of the conditional CAPM. Although the conditional betas did vary considerably from year to year, the variation was not extreme enough to account for the anomalous pricing errors. Indeed, the betas did not covary with the market risk premium so as to explain the magnitudes of the alphas. They concluded that the conditional CAPM does not explain asset-pricing anomalies either.

Up to this point any research conducted and results obtained had been based on portfolios. Avramov and Chordia (2006: 1001) decided to analyse whether asset pricing models can also account for the size, value and momentum effects for single stocks. They tested seven different models, including the CAPM and the Fama and French (1993: 3) three-factor model, both as it was originally published as well as augmented by liquidity and momentum factors. 7875 stocks from the NYSE, AMEX and NASDAQ over the period 1964 to 2001 were used in the analysis. Betas of individual stocks were varied with firm size and B/M, as well as several macroeconomic variables such as turnover and past returns. Regression analysis based on the variables mentioned was performed to obtain risk-adjusted returns which were, in turn, regressed on size, B/M, turnover and past returns. It was found that time-varying beta multifactor asset pricing models could explain the size and B/M effects, while models with constant beta could not. However, none of the models could capture the effect of liquidity or momentum on the cross-section of returns, even when returns were adjusted by the corresponding factors.

Boynton and Oppenheimer (2006: 2617) recognised that biases may be distorting the return measures. They tested two biases for their influences on market size, contrarian, momentum and B/M anomalies for stocks on the NYSE, AMEX and NASDAQ over the period 1926 to 2001. First, they controlled for delisting effects, next for measurement error bias (with reference to the bid-ask spread bounce). While corrections for the biases did decrease the market size, contrarian and B/M anomalies, they did not entirely eliminate them. However, correcting for bias increased the momentum anomaly.

2.2.2 Stock market anomalies on the JSE: South African evidence

Over the years, all of the anomalies discussed above have also been examined on the Johannesburg Stock Exchange (JSE). Plaistowe and Knight (1986: 35) compared the cumulative weekly returns obtained from winner and loser portfolios up to a year after being formed. 35 shares from the industrial sector over the period 1973 to 1980 were used in the analysis. Shares were ranked according to the B/M ratios, with shares that were classified as trading at a premium being placed in the winner portfolio, and those that were classified as trading at a discount being placed in the loser portfolio. They found that the loser portfolio did not exhibit abnormal returns relative to the RDM 100 Index of industrial shares, whereas the winner portfolio did.

In response to De Bondt and Thaler's (1985: 793) observation of the overreaction hypothesis on the NYSE, Page and Way (1992: 34) tested its existence on the JSE. Winner and loser portfolios were constructed based on 36-month prior cumulative excess returns for shares trading on the JSE over the period 1974 to 1989. It was found that portfolios of prior losers significantly outperformed portfolios of prior winners which was consistent with the overreaction hypothesis. The loser portfolios achieved an average outperformance of the market of between 9% and 12%, while their winner counterparts underperformed between 3% and 7%. All in all, the loser portfolios outperformed the winner portfolios by a total of almost 15% 36 months after formation. Consistent with US evidence, the majority of abnormal returns were only realised in the second and third years after formation. Additionally, the asymmetry of returns observed by De Bondt and Thaler (1985: 793) was also found in their analysis, although to a somewhat smaller degree. The results indicated long-term weak-form inefficiency on the JSE over the period investigated.

Several years after publication of this study Cubbin, Eidne, Firer and Gilbert (2006: 39) re-examined the overreaction hypothesis on the JSE to determine whether there was still evidence of it. They used shares listed on the JSE between October 1983 and December 2005, adjusted for survivorship bias, to construct winner and loser portfolios according to their P/E ratios. It was found that the loser portfolios outperformed the winner portfolios, on an average compounded return basis, by 11.15% per annum, relative to the Equally Weighted Index (EWI) and by 11.5% per annum relative to the All Share Index (ALSI). This finding was consistent with the overreaction hypothesis. However, they did find one significant difference between their results and those of De Bondt and Thaler (1985: 793) and Page and Way (1992: 34). In their studies the loser portfolios immediately outperformed the winner portfolios in cumulative terms. Cubbin *et al.* (2006: 39) found that in cumulative terms the winner portfolio actually first outperformed the loser portfolio for the first eight months, after which the loser portfolio started outperforming the winner portfolio.

Robins, Sandler and Durand (1999: 53) examined whether the size, value and January effects observed in international markets also existed on the JSE. Data on industrial shares listed on the JSE over the period 1986 to 1995 was analysed. Results indicated evidence of the January effect, but no size or value effect was found to be significant. The lack of evidence of the value effect was inconsistent with prior South African studies (Plaistowe and Knight, 1986: 35 and Page and Way, 1992: 34). Auret and Cline (2011: 29) expanded the study of Robins *et al.* (1999: 53) by considering the original period used by the earlier authors (1988 to 1995) as well as a second period (1996 to 2006) to determine whether they would obtain the same results for both periods. They did not find any significant value, size or January effects in either period.

Fraser and Page (2000: 14) assessed value and momentum strategies on the JSE from 1973 to 1997 using cross-sectional regression. They found that both strategies could explain the cross-sectional returns on the JSE when tested independently. There was no indication of a correlation between the two strategies. Van Rensburg (2001: 45) took a closer look at style anomalies on the JSE. He used monthly stock return data for industrial shares listed on the JSE between 1983 and 1999 to test for the presence of style-based return anomalies from a set of 23 factors. Tests identified eleven factors that remained significant after portfolios were risk adjusted. Three types of 'groupings' were identified: value (earnings yield and dividend yield), quality (market capitalisation, turnover, leverage and cash flow-to-debt) and momentum (past three, six and twelve month's returns). Cluster analysis suggested that three style factors could be regarded as an economical representation of style-based risk on the JSE. These were E/P (representing the value effect), market capitalisation (representing the quality effect) and twelve months past positive returns (representing the momentum effect). This suggested that any asset pricing model needs to be adjusted to take account of these three sources of style-based risk.

Van Rensburg and Robertson (2003a: 7) re-examined the style anomaly debate on the JSE, building on the work of Van Rensburg (2001: 45). He adopted the portfolio-based approach to examine the effects of style anomalies. Van Rensburg and Robertson (2003a: 7) on the other hand implemented a characteristic-based approach, examining the returns of each individual share on the JSE over the period 1990 to 2000. The share returns were cross-sectionally regressed on several style-based factors in order to determine a time series of factor payoffs. Those factors identified as having high payoffs were subsequently used in a stepwise permutation multivariate analysis. The multifactor model continually added factors that improved its explanatory power, while deleting those factors that did not. The univariate test identified six factors as being most significant: price-to-book ratio (P/B), dividend yield (DY), P/E, C/P, price-to-profit ratio and size (as measured by market capitalisation). The subsequent multivariate analysis identified P/E and size as the most influential style-based factors, subsuming all other factors. Unlike the findings of Fraser and Page (2000) and Van Rensburg (2001), Van Rensburg and Robertson (2003a: 7) did not find any of the momentum-based factors to be significant. Van Rensburg and Robertson (2003b) extended their earlier study by applying the Fama and French (1992: 427) methodology for a more detailed examination on the size and P/E factors identified above. Applying the methodology to the same data set as in Van Rensburg and Robertson (2003a: 7), they found results both consistent and inconsistent with international evidence. They found that, consistent with international evidence, value firms (i.e. firms with low P/E ratios) earned higher returns and had lower betas. However, they also found that small size firms earned higher returns but had lower betas, which was inconsistent with international evidence which generally found them to have high betas (indicating higher risk). This finding would indicate, for the first time, that on the JSE returns are inversely related to beta. Furthermore, the findings of Fraser and Page (2000: 14) and Van Rensburg and Robertson (2003a: 7) in that size and value effects, as measured by market capitalisation and P/E respectively, operate independently of each other was confirmed in Van Rensburg and Robertson's (2003b: 7) study.

Strugnell, Gilbert and Kruger (2011: 1) extended the work of Van Rensburg and Robertson (2003b: 7) based on stock returns from the JSE for the period 1994 to 2007. Their results confirmed earlier findings, with the size and value effect also being significant in their analysis. More surprising though was their discovery of a negative relationship between stock returns and beta, a result that was consistent with that of Van Rensburg and Robertson (2003b: 7). They concluded that this result was not due to the specific sample that was used in the 2003 paper since Strugnell *et al.* (2011: 1) covered a later, longer period. When the effects of thin trading[3] were taken into account, however, the significance of the estimated betas reduced considerably. At best, one may conclude that beta is irrelevant in return-generating asset pricing models (such as the CAPM) on the JSE, in any case when based on the ALSI as market proxy. They also found that analysis of intermediate quintile portfolios revealed that the size effect appeared to be concentrated in the smallest quintile of stocks on the JSE, with no significant difference in returns having

[3] Thin trading occurs when there are very few buy or sell orders in the market, resulting in low volume days. This leads to more volatile prices and lower liquidity, making it more difficult to trade. The low number of bids and asks will typically also lead to a higher bid-ask spread.

been observed in the other four, larger quintiles. However, this was not the case with the value effect, which appeared to have been observed across all stocks, although not uniformly. Consistent with Van Rensburg and Robertson (2003b: 7), they found that the size and value effect operated independently.

Bailey and Gilbert (2007: 19) examined the effect of liquidity on P/E return anomalies on the JSE. They proposed that liquidity actually affects trading strategies to such an extent so as to, at least partially, explain the return anomalies. The profits suggested by investing in the strategies designed to take advantage of pricing anomalies “may not be either real, or achievable, due to the lack of liquidity in the market necessary to trade shares at these observed prices” (Bailey & Gilbert, 2007: 19). This suggested that it may only be possible to achieve those profits in very large and highly liquid markets such as the NYSE. The JSE, on the other hand, is a relatively small and illiquid market, possibly preventing or reducing the realisation of anomalous profits. The authors analysed the effects of liquidity on the profits of stocks on the ALSI for the JSE for the period 1982 to 2005, taking account of survivorship bias. They introduced a liquidity cap, where shares were not included in the portfolio if the average trading volume of that share was too low relative to the potential size of that share’s position in the portfolio. Specifically, the liquidity cap was set as 50% of the expected trading volume in a month. Seven differently sized portfolios were established and the effect of the liquidity cap was analysed on each one. It was found that liquidity did affect the abnormal profits, although in an asymmetrical way. The liquidity cap affected large investors more than small investors, restricting the type and hence amount of shares they could have potentially invested in. The shares that were being restricted were low P/E shares which were found in the bottom end of the market. This is because those shares were too illiquid to invest in. Once excluded from the analysis, the abnormal returns were virtually eliminated. Hence, those investors hoping to benefit from abnormal returns from low P/E stocks should do so only if they are prepared to accept liquidity risk. The opposite result was found for high P/E stocks. It was found that the liquidity constraint only affected larger portfolios, increasing excess losses. Therefore, the simplest way to profit from abnormal returns is to short most of the liquid stocks.

A follow-up paper by Gilbert and Strugnell (2010: 31) examined the effects of survivorship bias on the mean reversion of returns, in particular with reference to the papers by Cubbin *et al.* (2006: 39) and Bailey and Gilbert (2007: 19). Both of the papers included delisted shares in their data set in order to avoid the effects of survivorship bias. Gilbert and Strugnell’s (2010: 31) paper extended their studies by expanding the period by another 21 months and then comparing the results to another study based on the same period but comprising only currently listed shares. The aim was to determine if it really is necessary to add delisted shares to a data set needed for the analysis of mean reversion, since collecting data on delisted companies is a time-consuming and expensive process. Data was collected for shares listed on the ALSI for the JSE for the period 1984 to 2007. It was found that survivorship bias does affect results. However, this is not necessarily true for every type of research. In particular, it appears that the results of Cubbin *et al.* (2006: 39) and Bailey and Gilbert (2007: 19) on mean reversion of returns would not have been affected had their database not been adjusted for survivorship bias.

Basiewicz and Auret (2009: 23) decided to analyse the cross-sections of returns on the JSE yet again due to the disagreement on the pricing anomalies and more importantly the factors driving those anomalies. They expanded the sample and based it on a different data set, namely an unrestricted sample of all firms listed on the JSE between 1989 and 2005. In addition, they also adjusted the data for trading costs and liquidity. Both the size and value effects were found to be significant, with both effects persisting after adjustments for trading costs and liquidity were made. It was also found that price constraints had a far more significant effect than liquidity constraints. B/M was observed to have the strongest predictability for abnormal returns, while E/P had the weakest. However, the return estimates all turned out to be a lot lower than previous studies suggested, indicating the possibility that excluding adjustments for trading costs and liquidity may in fact be partially responsible for the excessively high returns documented earlier. Lastly, the size effect and value effect were found to be independent of each other.

Basiewicz and Auret (2010: 13) tested the Fama and French (1993: 3) three-factor model of asset pricing on the JSE. The data they used was based on stocks listed on the JSE over the period 1992 to 2005. In addition, they compared the performance of this model to the CAPM and APT models, in particular in explaining size and value effects. Tests were performed on both grouped and ungrouped data. The time-series tests on grouped data revealed that the three-factor model accounted for the value effect, while tests on ungrouped data revealed that the BE/ME ratio lost its predictive power once size was included in the model. Overall, the size effect lost some of its predictive power, but it had not disappeared entirely. The authors proposed that the Fama and French (1993: 3) three-factor model provided an adequate means to predict expected returns for stocks on the JSE.

2.3 LIQUIDITY MEASURES

The number of studies examining the existence of market anomalies resulting in abnormally high stock returns is extensive. Many propositions have been put forth to identify and explain the sources of these anomalies. The most common of these are factors such as the size of the firm, the value of the firm and past performance of the stock. However, in the more recent studies many researchers have now alluded to another potentially highly influential factor that could in part subsume the factors found to date: namely, the effect of (il)liquidity on stock returns.

It has been hypothesized that liquidity may in fact be able to explain why abnormal returns continue to exist, especially when so much research has been devoted to determining their driving factors. One would expect market participants to set up investment strategies designed to take advantage of these factors, resulting in the disappearance of abnormal returns. However, this has not been the case, indicating that there are other, possibly more important factors driving returns that have not yet been exposed.

Most of the research to date has not considered the effects of liquidity on returns. The most notable exceptions are the papers by Bailey and Gilbert (2007: 19) and Basiewicz and Auret (2009:23), who explicitly allowed for the effects of liquidity. It is important to take account of it, since ignoring liquidity implicitly assumes that investors are able to trade at closing prices, which may not always be the case in reality. This is especially true in smaller, less liquid markets such as the JSE. Therefore, this assumption is not valid.

It is therefore important to determine what the market understands under the term ‘liquidity’, as well as what measures have been proposed to measure it. Literature on this topic has increased in the recent past, indicating the importance that market participants, as well as researchers, are placing on recognizing and taking account of liquidity.

2.3.1 Bid-ask spread

Liquidity has been an elusive topic for many years now since it is not only difficult to define, but it is also difficult to quantify. It was first introduced into literature by Keynes (1930: 67), who proposed that ‘an asset is more liquid than another if it is more certainly realisable at short notice without loss’ (Keynes, 1930: 67). Demsetz (1968: 33) attempted to quantify liquidity as defined by Keynes (1930: 67), suggesting that the bid-ask spread of a stock gives an indication of that stocks’ level of liquidity. He stipulated that the bid-ask spread provides an indication of the immediacy of a transaction. Traders who require the asset need to be willing to accept a higher price in order to fulfil the immediacy of the trade, while sellers can benefit from selling at higher prices to indulge the trader’s needs. Numerous authors have supported Demsetz's (1968: 33) measure of liquidity, amongst them Tinic (1972: 79) and Amihud and Mendelson (1986: 223). In particular, Amihud and Mendelson (1986: 223) argued that the quoted ask price reflects a premium for immediate buying, while the quoted bid price reflects a discount for immediate sale. Therefore, the bid-ask spread gives an indication of “the cost of immediate execution” (Amihud & Mendelson, 1986: 223), which is the definition of illiquidity according to the authors. They tested the spread-return relationship using stock returns from the NYSE over the period 1961 to 1980. Their results suggested that the liquidity of a stock is an increasing function of its price. Similarly, returns were also an increasing function of the spread. These results remained robust even after adding the size of the firm as an explanatory variable to the regression equations. However, this definition and its subsequent measure of liquidity have been criticised as overly simplistic. It has been suggested that liquidity has numerous dimensions (time, price and volume) and that Keynes' definition takes account of only one of those dimensions, namely time.

Several years after Demsetz (1968: 33) proposed the bid-ask spread as a proxy for liquidity, Benston and Hagerman (1974: 353) put forth that even though the bid-ask spread can be used as a proxy for liquidity, there are certain stock and market characteristics of the spread that ultimately influence the magnitude of the measure. The characteristics analysed by the authors are stock price, number of stockholders (a proxy for trading scale), number of dealers (a proxy for competition) and unsystematic risk. Data was obtained for 314 over-the-counter (OTC) firms over a five year period (1 January 1963 to 31 December 1967). They found that all four characteristics had statistically significant, non-linear relationships with the respective bid-ask spreads. Stock price was found to be the most significant explanatory variable, with more expensive shares exhibiting higher spreads. However, this relationship was not proportional, with a doubling of stock price resulting only in a 59% increase in price. Trading scales as well as competition were both negatively related to spreads, with a doubling in the number of stockholders and the number of dealers resulting in a 16.5% and 26.8% decrease in spread, respectively. This indicated the existence of economies of scale in trading. Lastly, both systematic and unsystematic risks were tested to determine their relations to bid-ask spreads. It was found that only unsystematic risk was related to spreads.

Stoll and Whaley (1983: 57) were the first to incorporate the effect of transaction costs on the size effect. Previous studies had provided evidence that risk-adjusted returns for small firms were substantially larger than those for large firms. However, the authors hypothesised that this result may have been due to portfolios consisting mainly of small stocks incurring higher transaction costs compared to portfolios with larger stocks. They therefore re-evaluated the risk-adjusted returns, taking account of transaction costs to determine whether this 'missing factor' could explain, at least partially, the small firm effect. The data used was obtained from the Center for Research in Security Prices (CRSP), and consisted of NYSE stocks traded on the exchange between 1955 and 1979. It was found that the small firm effect did indeed exist; however, its emergence and magnitude depended on the investment horizon of the particular investment. For an investment horizon of one month, returns on small firms were shown to be consistently negative. For horizons between three and twelve months, the returns were not significantly different from zero. Therefore, abnormally large positive risk-adjusted returns were only shown to appear for portfolios with investment horizons of more than a year when taking account of transaction costs.

Eleswarapu and Reinganum (1993: 373) re-examined the liquidity occurrence by considering the same measures on the NYSE as Amihud and Mendelson (1986: 223), but with an updated period (1961 to 1990). Their results indicated a seasonality component, with the only statistically significant return-spread relationship being evident in January, and no other months. In addition, they also found a significant size effect, even after adjusting for spreads and risk (in terms of beta). Hence it could be concluded that the premium associated with the bid-ask spread is primarily a seasonal phenomenon.

The bid-ask spread does have some limitations though. As Grossman and Miller (1988: 617) pointed out, the bid-ask spread measures the market maker’s return if both sides of the trade were to be completed simultaneously. However, in most actual markets the orders do not arrive simultaneously. Therefore, the price may change between the time one buys or sells, and the market maker may end up making more or less than the quoted spread. Therefore, the bid-ask spread gives no indication of the immediacy the market makers provide, which is what the definition of liquidity had been based on.

2.3.2 Turnover and volume traded

Although it was widely accepted that transaction costs affect the demand for assets, Constantinides (1986: 842) showed that they were actually only a second-order effect when measuring returns according to equilibrium asset return models. However, this was not the case when applying two-asset intertemporal models, in which case the transaction costs exhibited first-order effects. By constructing endogenous equilibrium asset returns models that take account of an investors’ expected utility, Constantinides (1986: 842) was able to show that investors take on large transaction costs by significantly reducing the volume and frequency of trade, resulting in lower turnover. As a result, turnover (which is of course linked to volume of trade) allows one to take account of transaction costs for different trade sizes. He also found that the liquidity premium due to transaction costs was small. Lastly, the effect of volatility on returns was also examined. It was found that the more volatile an asset’s return, the higher the trading cost due to the need to rebalance more frequently.

Using the turnover rate as a proxy for liquidity, Datar, Naik and Radcliffe (1998: 203) re-examined Amihud and Mendelson's (1986: 223) model using all non-financial stocks listed on the NYSE over the period 1962 to 1991. They defined the turnover rate as the number of stocks traded divided by the number of stocks outstanding. They believed this to be a superior measure of illiquidity to the bid-ask spread since it not only makes more intuitive sense, but it is also more readily available on a monthly basis. Their results were consistent with those of Amihud and Mendelson (1986: 223). Stock returns were negatively related to the turnover rate, even after controlling for the size, B/M and beta risk factors. This supported the belief that less liquid stocks provide higher returns. Using a trimmed dataset to remove the potential effect of outliers, similar results were obtained. This suggested that the results were not driven by a small number of dominant outliers. On the contrary to Eleswarapu and Reinganum (1993: 373), no January seasonality effect was found, with returns being significantly related to turnover rates throughout the year.

Brennan, Chordia and Subrahmanyam (1998: 345) tested whether there is a relationship between returns and several risk and non-risk firm characteristics. They first used an APT type model to determine the risk factors that are most prevalent in estimating returns by following a principal components approach. They then repeated the analysis using the Fama and French (1993: 3) model. The risk factors used were firm size, B/M, dividend yield, lagged returns, as well as measures of liquidity such as share price and trading volume. Therefore, a proxy for liquidity was included in the models, thereby estimating for the first time the effect of this factor on asset returns. They opted for trading volume as this proxy since it is directly linked to liquidity and it is also available monthly which is not the case with the bid-ask spread. Data was obtained for both NYSE and NASDAQ stocks over the period 1966 to 1995. The size and B/M effects were found to be significant in the first model (using principal components analysis), while in the Fama and French (1993: 3) model the effects were attenuated both in magnitude and significance. Both models found a robust negative cross-sectional relationship between returns and trading volume. This effect was evident for risk-adjusted as well as risk-unadjusted returns, implying that trading volume was in fact acting as a proxy for liquidity, and not simply as a loading on some factor that was not included in the analysis. Lastly, since trading volume is measured differently on the NYSE and NASDAQ, separate variables were included for the two exchanges. It was found that the NASDAQ stocks exhibited much lower returns even after adjusting for the different risk factors.

2.3.3 Time to optimum disposal

Lippman and McCall (1986: 43) referred to two dimensions in their measure of liquidity – time and price. This lesser-used measure takes account of the trade-off of the price impact if a trade were to go through and the price an investor could possibly obtain if he were to wait a while in order to acquire a better price. The authors assumed that the investors decide upon their own optimal policy in terms of how long they would be willing to wait and what price they would ultimately be prepared to buy at. The time it would take the investors to complete a trade was then used as the measure of liquidity. If the optimum time to disposal was small, then the asset would be classified as liquid, and vice versa. However, even though this measure is theoretically tractable and intuitive, it has been disregarded by many researchers and hence there is hardly any existing empirical evidence on it. This may be due to the difficulty of obtaining the data needed for the measure.

2.3.4 Price impact

Certain practitioners used the liquidity ratio as a proxy for liquidity. In particular, they used a liquidity ratio known as the Amivest measure, which was the ratio of the sum of daily volume to the sum of daily return. However, there was some debate as to the validity of the liquidity ratio as a proxy for liquidity. Grossman and Miller (1988: 617) criticised its use, drawing attention to the fact that it is based solely on average price changes and average trading volumes from the past. Hence, it cannot take account of what will happen to the price of an asset if a larger-than-normal order was to be executed in the market. In addition, it cannot differentiate whether any price variations are due to the lack of liquidity or the arrival of new information. To overcome this problem, Brennan and Subrahmanyam (1996: 441) and more importantly Amihud (2002: 31) introduced measures of (il)liquidity that took account of the average daily association between a unit of trading volume and the resulting price change. Even though their measures were still linked to the liquidity ratio, they were able to look at the price variation over time to take account of the effect of different sized trades on the price.

Brennan and Subrahmanyam (1996: 441) noted that one of the main causes of illiquidity was adverse selection which occurred due to the presence of informed traders. They stated that most of the previous literature on the relationship between an asset's liquidity and return had focused on the bid-ask spread as a measure of the level of liquidity. However, the authors were not convinced of its usefulness due to its noisy nature (many large trades occur outside the spread, as well as many small trades within it). Another measure of liquidity was therefore proposed, namely price impact. The reasoning behind this measure was that, since liquidity was defined as the ease with which you can trade large quantities of an asset over a short period of time without affecting the price too much, this measure would be directly linked to that definition. Price impact was measured as the slope of the relationship between trading volume and price changes, denoted by λ. In effect, λ represented the slope coefficient in a regression of price changes on signed order size, based on transactions data. This allowed them to estimate both the variable and fixed costs of transacting, which in turn would provide information on the influence of adverse selection on asset returns.

Results, based on NYSE-listed stocks between 1984 and 1987 and taking account of the Fama and French (1993: 3) risk factors of size and B/M, indicated that there was a significant concave relationship between the premium and the variable cost component. However they also found that there was a convex relationship between the premium and the fixed cost component, which was inconsistent with the Amihud and Mendelson (1986: 223) model. In contrast to Eleswarapu and Reinganum (1993: 373), no evidence of a seasonality effect was found in the liquidity premium.

Amihud (2002: 31) followed several years later with his study which was to become one of the cornerstones for measuring liquidity. He showed a statistically significant time-varying relationship between stock liquidity and expected returns. Amihud (2002: 31) postulated that the measures of liquidity used up to the point of publication of his research required microstructure data for their calculation, a type of data that was not available in most markets for long periods of time. The measure he proposed overcame this setback by being based on returns and volume data on a daily basis, both of which are readily available in most markets. He defined stock illiquidity as the average ratio of the absolute value of the daily return over the dollar trading volume on that day, a measure that is closely related to the concept of price impact. Testing data for stocks listed on the NYSE over a 34-year period from 1963 to 1997, he found that liquidity positively and significantly affected ex ante stock returns, whereas unexpected liquidity negatively and significantly affected contemporaneous stock returns. These results persisted even in the presence of size, momentum and beta, indicating that excess returns due to the effects mentioned above may have been partially due to changes in market liquidity. Hence, according to Amihud's (2002: 31) results, if liquidity is priced correctly, then liquidity should predict future returns.

Pástor and Stambaugh (2003: 642) formulated another type of measure that is in line with the notion of the price impact of liquidity. It is called the return reversal measure and relies on the theory that order flow brings about greater return reversals when liquidity is lower. An ordinary least squares (OLS) regression was run to determine the coefficient λ that represented the expected return reversal for a given trading volume. The thought behind this measure was that order flow in one direction on a particular day was to be followed by a price change in the opposite direction on the following day. Hence for less liquid assets, order flow would bring about more significant price reversals (that is, they expected λ to be negative and greater in absolute value the less liquid the stock). This measure was therefore related to the volume dimension of liquidity. Pástor and Stambaugh (2003: 642) investigated whether liquidity was a state variable important for asset pricing, since it was generally seen to be a variable affecting the investment environment and macroeconomy, as well as being a variable had been found to be correlated across assets. Data was obtained for stocks listed on the NYSE and AMEX between 1966 and 1999. Results indicated that stocks with high sensitivities to liquidity had on average a 7.5% higher return p.a. than stocks with low sensitivities to liquidity. These results persisted even after adjusting for size, value and momentum factors. The measure also exhibited significant commonality across stocks. Thus liquidity seemed to be a priced state variable.

Acharya and Pedersen (2005: 375) used an augmented version of the Amihud (2002: 31) measure of illiquidity in a model where investors were assumed to behave like one-period agents. They defined a normalised measure of illiquidity that capped the maximum return per dollar volume at 30%. This was because the authors believed that a per-trade cost higher than 30% was excessive and would only have been due to low volume days. Their measure was incorporated in a liquidity-adjusted CAPM developed by the authors, where the expected return on a stock depended on its expected level of liquidity and the covariances of both the asset's return and the market return with liquidity. The model provided a good fit for portfolios set up according to the level of liquidity, liquidity variation and size, but a poor fit for portfolios set up according to B/M factors. In particular, they investigated three different risk premiums and found that the risk premium due to liquidity sensitivity to market returns displayed the most important source of liquidity risk (a premium of 0.82%), while the return premium due to commonality in liquidity (0.08%) and the risk premium due to return sensitivity to market liquidity (0.16%) were less important, though still significant. Therefore liquidity explained around 1.1% of cross-sectional returns. Lastly, the model also illustrated that liquidity was not only persistent, but also that it could predict future returns (while in the case of contemporaneous returns it seemed to co-move with them).

The Amihud (2002: 31) measure was introduced by Gonzáles and Rubio (2011: 53) into the mean-variance framework in order to determine the optimal portfolio choice for stocks listed on the Spanish Stock Market between 1991 and 2004. Two methods were used to determine the effect of liquidity on optimal portfolio construction. First, another constraint was added to the traditional mean-variance optimization to obtain the liquidity constrained frontier. Second, the traditional objective function was adjusted by the use of a risk aversion parameter which also took account of the level of liquidity which would be accepted by individual investors. Results showed that the optimal portfolio choice was strongly affected by the effects of liquidity. The association between liquidity and portfolio choice was found to be heavily dependent on the level of market liquidity. It was also found that those investors that had no particular preference for the level of liquidity they would accept ended up with optimal portfolios that had much lower levels of liquidity than those investors that did specify some level of liquidity preference.

2.3.5 Zeroreturn

Lesmond, Ogden and Trzcinka (1999: 1113) argued that trading costs are important in estimating the effect of liquidity on returns. However, estimates of these costs are often very difficult to obtain, or even in certain cases impossible to obtain. They therefore developed a new measure to estimate transaction costs which only required the time-series of daily stock returns. It was called the zeroreturn measure. The argument behind this measure was that informed investors only trade if the return they obtain would be profitable even after taking account of transaction costs. Therefore, if the value of the information did not compensate for the costs of trading, then the informed marginal trader would not trade. This would result in a zero return since there would be no price movement from the previous day. A stock with high transaction costs would have less price movements than a stock with low transaction costs. Hence, for traders searching for liquidity, they would not trade those stocks with high transaction costs if liquidity is low. The authors proposed two versions of zero returns as proxies for liquidity. The first measure was based simply on the daily proportion of zero returns in a particular month. The second measure allowed only for stocks with positive-volume days that exhibited high transaction costs, since even on those days they were likely to exhibit zero returns due to the costs possibly not having any information-revelation. Using daily returns data for firms listed on the NYSE between 1963 and 1990, Lesmond *et al.* (1999: 1113) found that for some of the smallest firms, as much as 80% of daily returns are zero in any one year. Even some of the largest firms exhibited up to 40% of daily returns to be zero in a year. The analysis revealed transaction costs of up to 1.2% for the largest decile firms, and up to 10.3% for the smallest decile firms. In addition, the estimates had an 85% correlation coefficient with the spread-plus-commissions measure, which at that point in time had become the most commonly used measure of transaction costs. Their estimates of trading costs were also substantially lower than those obtained from the spread-plus-commissions measure, pointing towards the possibility that the previous measure had actually overstated transaction costs (by as much as 50%).

2.3.6 Weighted order value

Marshall (2006: 21) proposed a different measure of liquidity that also takes account of all three dimensions. The NYSE, AMEX and NASDAQ are all examples of hybrid quote-driven markets. However, Marshall argued that since most international markets are actually order-driven markets, the majority of the research that had been performed up to that point in time may not be applicable since it was performed on data obtained from the three markets listed above. He therefore examined a new measure of liquidity on stocks listed on an order-driven market, the Australian Stock Exchange (ASX), over the period 1991 to 2002. Previously used trade-based measures were ex post rather than ex ante measures (such as trading volume and turnover), providing no indication of what would happen in the future. Even though the bid-ask spread does provide a good indication of liquidity available to small investors in order-driven markets, it does not provide the true cost of trading for larger investors since they may not be able to fill their orders at the best bid or ask price. The liquidity proxy developed in this paper is the Weighted Order Value (WOV), which is better suited to order-driven markets since it takes account of not only the bid-ask spread but also the depth of the market. It is defined as the positive square root of the weighted bid value multiplied by the weighted ask value. Orders in the order book are weighted according to the probability that they will be executed. Beta, size, B/M and ROE are used as control variables to take account of their well documented effect on risk-adjusted excess returns. The analysis illustrated a negative relationship between returns and the WOV, implying that investors require higher returns for holding less liquid stocks. This finding was consistent with previous literature. In addition, the results were found to be evenly spread over the year, with no seasonality effects being evident. This was in contrast to the results found by Eleswarapu and Reinganum (1993: 373). Hence liquidity proxies in pure order-driven markets provided the same results as those found in earlier studies.

2.3.7 The volatility of liquidity

Pereira and Zhang (2010: 1077) analysed the relationship between stock returns and the volatility of liquidity. Most of the previous literature assumed that liquidity was constant over the data period, an assumption the authors disagreed with. They measured liquidity according to a stochastic price impact model, using the Amihud (2002: 31) measure as a proxy for liquidity. Earlier papers that had considered the volatility of liquidity found that stocks with more volatile liquidity exhibited lower returns. This finding contradicted the usual risk-return trade-off documented by other authors. By implementing a utility-maximising strategy in the form of a constant relative risk aversion (CRRA) model on NYSE and AMEX stocks listed on the respective exchanges between 1963 and 2005, the puzzling findings from earlier studies were confirmed. According to this model, a rational risk-averse investor would adapt his trading to the particular state of liquidity in the market, trading large quantities when liquidity was high and low quantities when it was low. Consequently, a high liquidity state would provide an investor with enough time to properly time his trades. Therefore a lower liquidity premium (which was defined as the additional return that an investor would require on an illiquid stock in order to obtain the same amount of utility as a perfectly liquid stock would provide) would be needed for this case. This was consistent with the negative relation between stock returns and the volatility of liquidity – stocks with higher volatility of liquidity would require a lower return premium. Pereira and Zhang (2010: 1077) also found that price impact Granger caused[4] trading volume in the time series: a greater price impact brought about a lower trading volume. This supported their earlier result that the return premium was a decreasing function of the volatility of liquidity due to investors adapting their investment strategies according to the state of liquidity in the market.

Longstaff (2001: 407) analysed the optimal portfolio allocation when taking account of the volatility of liquidity. Most intertemporal portfolio choice models assume that investors can trade unlimited amount of stocks continuously. However, in reality investors face liquidity constraints since it may sometimes be impossible to initiate or unwind positions for certain stocks. This is directly linked to the thin trading found in many markets. Longstaff (2001: 407) defined liquidity as the amount of shares that can be traded per period. This strategy appeared to endogenously imply that investors faced borrowing and short-selling constraints, even though no such constraints were imposed in reality. A continuous-time partial-equilibrium model was applied to determine the optimal weights which in turn were used to establish the investor's derived utility of wealth. By comparing the constrained and unconstrained utilities of wealth, the shadow price of liquidity was calculated. This was repeated for various parameter values. It was found that the liquidity discount was of considerable size and significance. Hence the effect of liquidity constraints should not be ignored in asset pricing and portfolio construction since it can severely alter the outcome.

2.3.8 Multiple measures

Most of the papers on liquidity measures mentioned so far considered only one single measure as a proxy for liquidity and used that to test whether the level of an assets' liquidity was priced in the cross-section of returns. Since so many measures were put forth, practitioners and researchers alike were left with an extensive list of possible proxies that each had their own merits. However, as with any type of real-world problem, the abundance of choice led many to wonder which of these measures was in fact 'the best' for different types of analyses. That is when studies were performed to compare different measures in

[4] The Granger causality test is a statistical hypothesis test used to determine whether one time series can assist in forecasting another. According to Granger causality, if X "Granger-causes" (or "G-causes") Y, then past values of X should contain information that helps predict Y above and beyond the information contained in past values of Y alone. Through the use of a series of t-tests and F-tests on lagged values of X, this test analyses whether those X values provide statistically significant information about future values of Y. Next, lagged values of Y are also included in the regression analysis to determine whether they also have statistically significant forecasting power.

the hope of narrowing the choice down to a few measures that could be described superior to others.

Chordia, Roll and Subrahmanyam's (2000: 3) paper considered numerous liquidity proxies to determine whether or not liquidity exhibits commonality. In other words, they examined whether liquidity co-varied over time for individual stocks and the market as a whole. The authors pointed out that no prior studies had ever focused on anything other than the market microstructure effects of liquidity on single assets. They however wanted to explore the common underlying determinants of liquidity and determine whether they possibly co-vary over time. Using transactions data for the NYSE for the most recently available year, namely 1992, the authors found significant evidence of commonality. Liquidity measures such as the quoted spreads, quoted depth and effective spreads of individual stocks all provided indications of co-movement with market-wide liquidity. The results remained robust even after taking account of certain individual causes of liquidity such as trading volume, volatility and price. Hence liquidity risk could be described as a type of systematic risk that is priced in equity markets. Linked to this research, Hasbrouck and Seppi (2001: 383) also examined common underlying factors driving liquidity. Trade and quote data for the 30 stocks in the Dow Jones Industrial Average (DJIA) in 1994 were obtained over 15-minute intervals. Through the use of principal components analysis (PCA), cross-firm common factors were found to be significant in both signed and absolute order flows. The first principal component explained around 7.8% of total flow variance. When considering the common co-variation in several liquidity proxies (such as the bid-ask spread as well as the quoted number of shares traded), the results were less significant. Although the proxies did assist in explaining part of the variation over time, the common factors obtained by PCA were relatively small.

Jones (2002) documented the existence of a time-series relationship between both the bid-ask spread and turnover (used as measures for market liquidity) and expected market returns. Hence, he was more interested in the relation over time rather than in the cross-section of returns. Using spread data from stocks on the Dow Jones over the period 1900 to 2000, as well as turnover data for stocks listed on the NYSE between 1900 and 2000, the analysis illustrated that the measures could both predict excess stock returns up to three years ahead. High liquidity (high turnover or low spreads) predicted high stock returns. Hence, the time-series variation of liquidity is an important indicator of future expected returns.

Keene and Peterson (2007: 91) analysed the interaction between liquidity and other variables that had been determined to be important factors in forecasting stock returns, such as size, B/M and momentum. The Fama and French (1993: 3) model was adjusted and implemented, including an added factor for liquidity. Six liquidity proxies were used: dollar volume of shares traded, share turnover, as well as the standard deviation and coefficient of variation of both measures. 54 portfolios were constructed from monthly data obtained from the CRSP data file over the period 1963 to 2002, leading to 54 time-series regressions. The results implied that liquidity was indeed a priced factor explaining part of the variation in returns even after taking account of size, B/M and momentum. However, the significance of non-zero intercepts suggested that there were still missing risk factors affecting returns.

Ghysels and Pereira (2008: 679) tested the effect of three liquidity measures on the optimal portfolio choice using a nonparametric approach to estimate the optimal asset allocations. Using daily data from the NYSE over the period 1963 to 2000, the authors constructed two portfolios (one including small shares and one large shares) taking account of three different liquidity measures: price impact (Amihud, 2002: 31)), dollar volume traded (Brennan *et al.*, 1998: 345) and turnover (Datar *et al.*, 1998: 203). Since none of the measures took account of the time dimension of liquidity, a CRRA utility function was used to describe investors with three different investment horizons: 1 day, 1 week and 1 month. The analysis showed that the optimal asset allocation depended on both the asset and the investment horizon. For small stocks, the optimal allocation was a strongly increasing function of liquidity at short daily and weekly horizons. The results remained robust for all three measures of liquidity. For large stocks, however, liquidity had no effect on the optimal allocation. For longer investment horizons (one month) liquidity did not influence the allocations for small or large stocks. The authors also used the findings of the nonparametric approach to identify a parametric estimator. The results remained robust.

Goyenko, Holden and Trzcinka (2009: 153) tested the effectiveness of several liquidity proxies on both high-frequency and low-frequency data to determine if they really do measure liquidity and also to verify which measures are superior to others. They tested all widely used measures of liquidity, such as the LOT, zeroreturns, Amihud (2002: 31) and Amivest measures, amongst others. Three new proxies for effective and realized spread, as well as nine new proxies for price impact were also tested. The effective and realized spreads as well as several price impact measures were computed on two high-frequency data sets. The same calculations were subsequently performed on a low-frequency data set and compared to the results from the high-frequency data sets. Using a random sample of 400 stocks from the NYSE, AMEX and NASDAQ over the period 1993 to 2005, their results demonstrated that the proxies were equivalent for both sets of data. In fact, the low-frequency data measures captured the high-frequency data results so well that the authors concluded that the cost and effort of using high-frequency data is not worth it. In particular, the Amihud (2002: 31) measure was found to be a superior proxy for price impact. Hence, it was concluded that the liquidity proxies that had been used in past literature did in fact measure liquidity.

In a more recent paper, Chai, Faff and Gharghori (2010: 181) examined the relationships between liquidity proxies and certain trading characteristics to determine whether there are common sources of liquidity. In particular, they wanted to analyse how certain proxies are related to each other and also how they are related to the trading characteristics of equities. As Marshall and Young (2003: 173) pointed out, the U.S. market is a quote-driven market. However, since most international markets are actually order-driven markets, Chai *et al.* (2010: 181) focused their study on data obtained from the Australian stock exchange, which is an order-driven market. These markets tend to be more transparent and so exhibit a higher level of liquidity. Six different liquidity proxies were examined: the proportional bid-ask spread, turnover, Amihud's (2002: 31) illiquidity measure, Pástor and Stambaugh's (2003: 642) return reversal measure, the zeroreturn measure and turnover-adjusted number of zero daily volumes. Results showed that in the cross-section of returns, the correlations amongst the liquidity proxies analysed were low. This indicated that different proxies corresponded to different dimensions of liquidity. When analysing the relation between the proxies and stock’s trading characteristics, it was found that they were strongly related, indicating that trading characteristics represented an important source of liquidity. However, this was not the case with the return reversal measure, which was found not to depend on trading characteristics at all.

2.3.9 Liquidity measures in emerging markets

Most of the studies mentioned so far have based their results on the US market, arguably one of the most liquid markets in the world. The liquidity of emerging markets may present a completely different picture. In these types of environments, liquidity may exhibit extreme features. This is due to investment and therefore growth in emerging markets having reached record highs over the last twenty years. Returns in these markets can be as high as 90%, far exceeding returns in the US market. This points to high volatility, and therefore risk, inherent in emerging states. In addition, often investors may encounter barriers to investing, leading to emerging markets being highly illiquid. Even though papers have been published that measure the effect of liquidity within certain emerging markets, none of them have compared different proxies for liquidity to determine which are most applicable and efficient in these types of markets. Lesmond (2005: 411) analysed the effectiveness of five of the most common liquidity measures. These were Roll’s measure (1984) (this proxy measured the bid-ask bounce-induced negative serial auto-correlation in returns in order to estimate the effective spread), the Amivest measure, the Amihud (2002: 31) price impact measure, turnover and a version of the zeroreturns measure based on likelihood estimation (also referred to as the Lesmond, Ogden and Trzcinka (LOT) measure). The measures were tested against the quoted bid-ask spread. Results indicated that liquidity costs varied greatly over emerging markets, ranging from Taiwan's liquidity costs of 1% to Russia's costs of 47%. South Africa had liquidity costs of just over 6%, which was quite low in comparison to other emerging markets. This indicated that the South African market is relatively liquid. Lesmond (2005: 411) analysed the measures both on a cross-country and within-country basis. Each measure showed weaknesses and strengths. However, overall the LOT measure and Roll's measure represented cross-country liquidity effects better than the other measures. Within-country liquidity was best measured by the LOT measure and Amihud (2002: 31) measure. This was also the case in the South African market. Three types of tests were performed to determine the efficacy of the measures for within-country liquidity, namely regression analysis, factor analysis and a likelihood ratio test. In the case of South Africa, all three tests identified the LOT measure followed by the Amihud (2002: 31) measure as the most effective measures of liquidity. In addition, according to the factor analysis performed, a single factor was sufficient to represent the majority of variation in liquidity of all measures. Turnover performed worst in terms of measuring liquidity. Lastly, the political climate in each emerging market was also examined to determine the extent to which that may affect liquidity. It was found that markets with high incremental political risk exhibited higher transaction costs by 10 basis points according to the LOT measure or a 1.9% increase according to the Amihud (2002: 31) measure. Therefore the political stability of a particular country also has an effect on transaction costs and hence the level of liquidity.

Bekaert, Harvey and Lundblad (2007: 1783) also examined the efficacy of liquidity measures in emerging markets. However, they only considered two measures: firstly, the zeroreturn measure and secondly a measure that takes account of the length of the non-trading (or zero-return) interval. These measures were used due to their simplicity to both obtain data for and to compute. The analysis revealed that, as the authors expected, the measures were positively correlated with bid-ask spread and negatively correlated with turnover within the emerging stock markets. In addition, the zeroreturns measure also predicted future stock returns, whereas other measures such as turnover did not. Lastly, since certain emerging markets are now integrated, Bekaert *et al.* (2007: 1783) also examined the possible effect of the liberalization process on the relation between stock returns and liquidity. They suggested that post liberalization, those countries that became integrated should exhibit higher liquidity due to the process giving foreign investor the ability to also invest in that particular market. A model was developed that differentiated between integrated and segmented markets and time periods. Results suggested that liquidity was a main factor driving returns. However, the liberalization process did not fully remove the effects of liquidity.

In the most recent paper included in this literature review, Lischewski and Voronkova (2012: 8) analysed the effects of market, size, B/M and liquidity factors on the stock returns of the biggest Central Eastern European (CEE) market, the Polish market. They argued that some research had been done on emerging markets before, but that most of those studies omitted the CEE markets. Several liquidity measures were employed in the analysis in order to ensure the robustness of the results. These included the zeroreturn measure, the LOT measure, the Amihud (2002: 31) measure, as well as Roll’s (1984) measure of effective spread. Results supported evidence of previous studies, in that market, size and B/M factors have significant explanatory power for Polish stock returns. They did not manage to capture the entire equity premium though, so the effect of liquidity was analysed. It was found that, even though liquidity managed to reduce part of the excess abnormal returns, it did not manage to explain them fully. The authors therefore concluded that liquidity was not a priced factor for stocks on the Polish market.

However, comparatively little research has been performed for the South African stock market, the JSE. De Villiers (1996: 76) discussed the appropriateness of six liquidity measures. These were the bid-ask spread, volatility ratio, volume of trade, liquidity ratio, price elasticity and time to optimum disposal. In 1992 the Katz Committee defined liquidity as the annual turnover expressed as a percentage of market capitalisation. De Villiers (1996: 76) in turn examined the six measures to determine their importance and possible effectiveness on the JSE. However, no empirical analysis was performed. He concluded that no single measure could be seen as the most effective on the JSE since they all capture different dimensions. Further research on measures that capture more dimensions would be needed.

While Bailey and Gilbert (2007: 19) did attempt to incorporate the impact of liquidity on the mean reversion of stock returns on the JSE, they did not apply any of the liquidity measures mentioned above. This was due to the lack of data necessary for the calculation of the measures. Basiewicz and Auret (2009: 23) modified their data to take account of transaction costs and therefore liquidity. Although the authors recognized that the JSE is quite illiquid, they also did not employ any of the above mentioned liquidity measures in to their model. Therefore neither of these papers really analysed the effect of the most common liquidity proxies that have been used so widely internationally on the returns of shares listed on the JSE. This study will attempt to bridge that gap in literature.

2.4 SUMMARY

The existence of the size, value and momentum effects has been well documented. These risk factors seem to be able to explain most of the abnormal returns earned by common stock. Ample research has also been performed on the existence of these anomalies on the South African stock exchange, the JSE. It has been found that they affect returns on the JSE in the same manner as elsewhere in the world and therefore can be used to construct investment strategies that take these anomalies into account in order to try and outperform the market. However, little-to-no research has been performed within the South African environment to also incorporate the effects of liquidity on the performance of common stock. This is still the case as at writing of this thesis, despite international evidence clearly pointing out not only the existence, but also the importance, of liquidity as a determinant of stock returns.

Many measures of liquidity have been proposed, each of them warranting its advantages but also disadvantages. However, no one measure has been put forth as being superior to others. The aim of this paper is to take account of several of the liquidity measures, together with the size, value and momentum effects, to determine the effect of liquidity on returns on the JSE. If liquidity does indeed play as big a role as expected, then the inclusion of it in the construction of investment strategies based on size, value and momentum should enable us to fully explain and capture the effects of abnormal excess risk-adjusted stock returns.

CHAPTER 3
RESEARCH METHODOLOGY

3.1 INTRODUCTION

An empirical method is applied to analyse the effect of four different factors on asset pricing: size, value, momentum and liquidity. Data is obtained for all stocks that were listed on the Johannesburg Stock Exchange (JSE) All Share Index (ALSI) over an 8.5 year period (2003 to 2011). Different databases are used to obtain two types of data: daily data for the estimation of stock liquidity and monthly data for the asset pricing analysis.

An Ordinary Least Squares (OLS) methodology is applied to examine whether the observed cross-sectional variation in stock returns can be explained by several liquidity measures. This is done while controlling for well-established determinants of returns such as size, value and momentum, all of which are easily observable stock characteristics. In order to achieve this, stocks are sorted into different portfolios according to the four factors, after which an OLS regression analysis will be performed on each portfolio. The results will illustrate whether the four factors (and in particular liquidity) are indeed priced factors on the JSE. This method, which has become standard practice in asset pricing tests, is similar to that used by Lischewski and Voronkova (2012: 8), with the main adjustment being the additional momentum effect that will be taken into account in this research.

3.2 LIQUIDITY PROXIES

Five measures of liquidity are used in this analysis, all of which have precedence in the literature. The measures are bid-ask spread, turnover, price impact and two measures of zeroreturn. They are each outlined below. The bid-ask spread was first suggested as a liquidity measure by Amihud and Mendelson (1986: 223). Since it has had such an influential effect on subsequent research in this area, this measure was included in this thesis to examine its strength compared to some of the newer measures. The choice of which of the more recent liquidity measures to include was based on the results of the study done by Lesmond (2005: 411). He found the zeroreturns and the Amihud (2002: 31) price impact measures to be the most effective measures of liquidity on the South African market, according to the *t*-statistics of regression tests based on the measure, while turnover performed the worst in terms of the level of significance of the *t*-statistic. In order to examine whether the same results apply to the data set used in this thesis, all three measures were included.

3.2.1 Bid-ask spread

The proportional spread, based on the bid-ask spread measure first introduced by Amihud and Mendelson (1986: 223), is used as a measure of transaction costs. The proportional bid-ask spread for stock i in month t is calculated as

$$pspread_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{p^A_{i,d,t} - p^B_{i,d,t}}{0.5p^A_{i,d,t} + 0.5p^B_{i,d,t}}$$

... (3.1)

where $p^A_{i,d,t}$ is the daily closing ask price for stock i on day d in month t and $p^B_{i,d,t}$ is the daily closing bid price for stock i on day d in month t. $D_{i,t}$ is the number of trading days for which data observations for stock i in month t were available.

The proportional spread is based on the quoted spread, which is the original measure suggested by Amihud and Mendelson (1986: 223). It provides a direct measure of transaction costs. According to results from previous studies, we would expect the spread to be negatively related to liquidity – stocks with higher spreads tend to have lower liquidity. The sign of the measure was flipped in order to make it a measure of liquidity and not illiquidity. This ensures consistency with the other measures.

However, as pointed out by several authors, the bid-ask spread measure does have certain shortcomings. In particular, it takes no account of transactions that occur outside of the spread. Many trades do occur at prices other than the bid or ask prices since certain market participants may be willing to buy or sell at higher or lower prices in order to fill their trades. The spread takes no account of this.

3.2.2 Turnover

Turnover for stock i in month t is defined as the ratio of the number of shares traded to the number of shares outstanding in that particular month. More precisely, it can be defined as

$$turnover_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{VOL_{i,d,t}}{shares_{i,d,t}}$$

... (3.2)

where $VOL_{i,d,t}$ is the total trading volume for stock i on day d in month t and $shares_{i,t}$ is the total number of shares outstanding for stock i on day d in month t. $D_{i,t}$ is the number of trading days for which data observations for stock i in month t were available.

The turnover ratio is expected to be positively related to stock liquidity. In other words, the higher the turnover of a particular firm, the more liquid its stock. This measure provides an indication of liquidity by capturing trading frequency. It is therefore a rather intuitive measure with the added benefit that it is easy to construct. However, as with the spread measure, critiques have been set forward for it. In particular, the turnover ratio fails to capture the cost per trade, which can vary considerably across assets. In addition, since trading volume receives considerable attention during liquidity crunches such as occurred during the 2008 financial crisis, turnover tends to increase during these periods, rather than decrease. This would indicate an increase in liquidity when in fact these periods are indicative of low market liquidity.

3.2.3 Price impact

The price impact measure of Amihud (2002: 31), or illiquidity ratio, is defined as the “daily price response associated with one dollar of trading volume” (Amihud, 2002: 32):

$$Illiquidity_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{|r_{i,d,t}|}{v_{i,d,t}}$$

... (3.3)

where $r_{i,d,t}$ is the return for stock i on day d in month t and $v_{i,d,t}$ is the Rand trading volume in millions for stock i on day d in month t. $D_{i,t}$ is the number of trading days for which data observations for stock i in month t were available.

An advantage of this measure is that it can be used even for days where there is no price change, as is the case in many emerging markets. In fact, Lesmond (2005: 411) showed that the Amihud measure was one of the best measures of price impact in South Africa. An advantage of this ratio over turnover is that it takes account of the price movement of a particular stock, therefore incorporating two dimensions of liquidity (price and volume). However, it must be noted that since this ratio is undefined for zero-volume days, the average can be determined only over positive-volume days.

This ratio provides an indication of the price impact of order flows. If a small trade causes a large price impact (the price changes), then the stock is regarded as illiquid. Similarly, if a large trade causes only a small price impact, the stock is seen as liquid. Hence this measure is negatively related to liquidity. Its sign was flipped in order to make it a measure of liquidity and not illiquidity. This ensures consistency with the other measures.

As with the other measures mentioned so far, the illiquidity ratio also has some drawbacks. Since the measure is based on the average turnover and the average volume, both obtained from past data, it gives no indication as to the effect of large trades on the stock price. In addition, the ratio cannot distinguish between price fluctuations due to the arrival of new information and lack of liquidity.

3.2.4 Zeroreturn

Two measures of zeroreturn were developed by Lesmond, Ogden and Trzcinka (1999: 1113). The first measure includes all days on which a zero return was observed for a particular stock. The second measure however, only includes those days for which positive-volume days with zero returns were observed. The first zeroreturn measure can be defined as

$$zeros_{i,t} = \frac{zeroreturn_{i,t}}{tradingdays_{i,t}} \qquad \text{... (3.4)}$$

where $zeroreturn_{i,t}$ is the number of zero daily return days for stock i in month t and $tradingdays_{i,t}$ is the number of trading days for stock i in month t.

The second definition of zeroreturns takes account of the number of positive volume zero returns days:

$$zeros2_{i,t} = \frac{posVOLzeroreturn_{i,t}}{tradingdays_{i,t}} \qquad \text{... (3.5)}$$

where $posVOLzeroreturn_{i,t}$ is the number of positive volume zero daily return days for stock i in month t and $tradingdays_{i,t}$ is the number of trading days for stock i in month t.

The argument behind this measure is that informed investors only trade if the return they obtain will be profitable even after taking account of transaction costs. Therefore, if the value of the information does not compensate for the costs of trading, then the informed marginal trader will not trade. This would result in a zero return since there would be no price movement from the previous day.

The sign of the measure was flipped in order to make it a measure of liquidity and not illiquidity. In order to convert the zeroreturn measures above into measures of liquidity, the adjusted proxies of $(1 - zeros_{i,t})$ and $(1 - zeros2_{i,t})$ for the first and second measures defined above were used, respectively. This ensures consistency with the other measures.

An advantage of this measure is that it requires only information on daily stock returns. Hence it is easily measurable. This is especially important in emerging markets (such as the

JSE) where data may be hard to come by. Bekaert *et al*. (2007: 1783) used this measure as a proxy for liquidity in emerging markets and found that it significantly predicts returns in these markets. Therefore, it should be an appropriate proxy for liquidity on the JSE.

This measure has some drawbacks too. Firstly, lack of information flow may cause zero return days. Secondly, smaller firms tend to have lower levels of trading than larger firms, causing more zero return days. However, the measure takes no account of either of these occurrences. Lastly, zeroreturn takes no account of price fluctuations that occur during the day. It therefore cannot properly capture the complete behaviour of a stock.

3.3 VARIABLE SELECTION

Previous literature has documented the influence of size, value and momentum factors on stock returns on the JSE. In particular, van Rensburg (2001: 45) identified market capitalisation, earnings yield and three- and twelve-months past returns to be significant factors on the JSE. Auret and Sinclaire (2006: 31) and Basiewicz and Auret (2009: 23) found that the B/M ratio had strong predictive power for stock returns. Accordingly, six variables are included in this research, each of which represents a particular factor within the model (two size variables, two value variables and two momentum variables).

3.3.1 Size variables

Size has been identified as a significant influencing factor explaining abnormal returns. In particular, market capitalisation has proved to be the most accurate measure of size. The South African market, however, is unique in terms of the distribution of shares according to market capitalisation. This market is dominated by a small number of companies and is therefore significantly positively skewed. A transformation in the form of the natural logarithm of market capitalisation is therefore applied to this variable in an attempt to eliminate its non-normality.

For comparative reasons, the earnings per share (EPS) were included as a second size variable.

3.3.2 Value variables

Value indicators represent the relationship between the price of a firm and its value, thereby providing appropriate measures of value. Typical measures that have been proposed by previous literature (refer to Chapter 2) are price-to-earnings and price-to-book. However, the P/E multiple has presented researchers with certain drawbacks during times of negative earnings since this would lead to negative P/E ratios. To avoid this, the inverse of the P/E ratio (i.e. earnings yield) is used instead in this study.

Lastly, the book-to-market (B/M) ratio has been one of the most commonly used measures of value by researchers and practitioners alike. For consistency with the earnings yield measure above, the inverse of the market-to-book multiple is also used. To ensure that the base value of the measure does not take on unnecessarily small values, the natural logarithm of B/M was used as a value variable.

3.3.3 Momentum variables

Past studies, as well as market participants, argue that investment strategies based on momentum and/or price-reversal can outperform the market. However, the research on variables that can capture the momentum effect is not as extensive as that for the size and value effects. Therefore many different variables could potentially be tested. In order to limit the selection of variables, one particular South African study will be used as the basis for the choice of momentum variables used in this thesis, namely that of van Rensburg (2001: 45). He found three variables to be the most significant indicators for momentum strategies on the JSE. These are the 3-, 6- and 12-months past stock returns. This study will therefore limit its choice of momentum variables to the previous 3- and 12-months stock returns.

Table 3.1 summarizes the size, value and momentum variables used in this thesis.

Table 3.1: Size, value and momentum and variables

The table lists the variables selected for inclusion in this thesis. Variables are listed per category (column 1). The codes associated with each indicator, as used throughout the thesis, are provided in column 2. Column 3 provides a description of the variable while the formula used for derived variables and ratios are shown in the last column.

Category	Code	Description	Formula
Size	• MVLOG • EPS	• Log of market value • Earnings per share	• ln[market value] • earnings / # shares in issue
Value	• BVTMLOG • EY	• Natural log of book value to market • Earnings yield	• ln[book value to market] • earnings / price
Momentum	• MOM3 • MOM12	• Previous 3-month's return • Previous 12-month's return	• ([Total return$_t$ – Total return$_{t-3}$])/[Total return$_{t-3}$] • ([Total return$_t$ – Total return$_{t-12}$])/[Total return$_{t-12}$]

3.4 DATA COLLECTION AND ANALYSIS

3.4.1 Data collection

Daily as well as monthly data was obtained for securities listed on the Johannesburg Stock Exchange ALSI over the period 1 January 2003 to 30 April 2011. Daily data, needed for the measurement of liquidity proxies, was obtained from I-Net Bridge and Bloomberg. The monthly data necessary for the size, value and momentum variables was obtained from I-Net Bridge, Bloomberg and Datastream. In order to remove the effects of survivorship bias, all companies that were listed on the ALSI during the period are included in the dataset, irrespective of whether or not they were delisted before end of the period under consideration. For a list of shares that were delisted or that have incomplete data during the period under review, refer to Appendix A.1. In total, 203 companies are included in the analysis.

The period being used for this analysis covers an entire investment cycle (bull market, bear market, as well as extreme market conditions). The sample starts in January 2003 and covers the following five years of exceptionally strong bull-run market behaviour. The year 2008 was signified by the financial crisis which led to market crashes around the world. In 2009 the markets picked up again, indicating another bull run. However, this was short-lived, with the market entering another downward spiral in 2010 due to the European debt crisis. This allows us to properly investigate the performance of portfolios constructed according to different risk factors in all types of market conditions. As a result, one is better able to draw conclusions as to the effectiveness of investment strategies based on the risk factors, as well as the effect of liquidity on the outcomes.

3.4.2 Data analysis

The data was analysed to test for any abnormalities or biases and hence corrections that would need to be done on it. The data was first analysed for any potential biases, after which descriptive statistics were performed on the treated data.

3.4.2.1 Data-snooping

According to White (2000: 1097), data-snooping occurs when previously used data is reused for model selection or inference. As a result, data-snooping "may yield misleading inferences when properties of the data are used to construct the test statistics" (Lo & MacKinlay, 1990: 431). The danger inherent in ignoring its effect has been well documented. This thesis therefore takes data-snooping into account, thereby eliminating any potential misleading results.

In effect, data-snooping results from the misuse of statistics, in particular statistical inference. Misleading results are obtained, be it due to deliberate data-snooping or due to ignorance of the researcher in terms of statistical knowledge. It most commonly occurs as a result of two 'errors'. Firstly, when no hypothesis is specified before the analysis, then it is possible for the researcher to specify an inappropriate hypothesis based on the results obtained (which he will have examined *prior* to specifying the hypothesis). In other words, the results obtained influence the hypothesis, which can lead to data-snooping bias. Secondly, narrowing the data used for the analysis to a specific period over which a particular result is expected to occur can also lead to data-snooping bias. In other words, if a researcher wants to obtain a specific outcome and he is aware that the use of a longer period may not result in the desired outcome, then he may be tempted to use a subsample of the period which he believes would provide it.

Therefore, in order to avoid data-snooping bias, the data was examined to determine whether or not it would result in biased outcomes. First, the ‘hypotheses’ used in this analysis are based on the findings of previous studies, both internationally and locally. In addition, the majority of previous analyses are based on US data, with little South African evidence. As a result, the *expected* outcomes are not affected by this data but rather by previous findings. Secondly, the data period used is unique to this study in terms of length and recentness. As mentioned above, the period used covers an entire market cycle, thereby eliminating any potentially misleading results due to the period only covering a particular part of the cycle. Lastly, in terms of the liquidity effects, no research of this magnitude has been performed on South African data. Therefore, the points just mentioned are also applicable to the data obtained for analysing liquidity.

3.4.2.2 Infrequent trading

Infrequent trading (also called thin trading) occurs when there are very few buy or sell orders in the market, resulting in low volume days. Therefore, if thin trading exists for a particular stock, then there may be zero-volume days, resulting in inconsistency of trade for consecutive trading periods. One possible way to avoid the effects of infrequent trading would be to introduce liquidity filters into the construction of portfolios. This would omit many small capitalisation stocks, which tend to exhibit the highest proportion of thin trading. Additionally, setting up value-weighted, as opposed to equally-weighted, portfolios can also potentially eliminate the effects of thin trading. In this thesis six liquidity filters were used on value-weighted portfolios.

3.4.2.3 Survivorship bias

Ignoring companies in your data set that were delisted over the period under consideration can lead to survivorship bias in results. This is because the data consists only of the survivors, not the entire set of companies that were actually listed at some point in time during the period. Since the characteristics of the survivor-companies tend to be systematically different from the delisted companies, the results obtained from such an analysis would be biased.

Gilbert and Strugnell (2010: 31) examined the effects of survivorship bias on the mean reversion of stock returns on the JSE. They found that it did not affect their results. However, they did point out even though survivorship bias did not affect the mean-reversion of returns, it remained a relevant effect that cannot simply be ignored, especially for different types of tests.

Failure to take account of survivorship bias can lead to overly optimistic conclusions since those companies that were delisted over the period being analysed will not be included in the sample. Therefore, in order to avoid this from occurring, those companies that were delisted over the sample period have been included in the analysis for the period of time for which data is available.

3.4.2.4 Look-ahead bias

Look-ahead bias occurs when the data being used for an analysis is reported for a particular point in time, even though it may not have been available to the public at that point. It is therefore important to be aware of what data would have been publicly available at particular points in the past and only base the analysis on that specific data. If this type of bias is ignored, the results tend to be significantly different from the results obtained from bias-free data. This, in turn, could lead to incorrect conclusions.

The data employed in this analysis was obtained from databases that are only updated once data becomes publicly available. This should eliminate any potential look-ahead bias.

3.4.2.5 Outliers

In order to normalise the distribution of the variables used in this analysis, the effect of outliers needs to be removed. This is because the Normal distribution does not produce outliers. A procedure known as Winsorisation is used to remove outliers. In the first step, any variables that exhibited significant positive skewness were transformed using the natural logarithm. These variables are listed in Appendix A.2. Next, any values further than five standard deviations from the median are removed. Note the use of the median instead of the mean, since the mean is much closer to the outliers than the median in an asymmetrical distribution. The mean and standard deviation are subsequently recalculated for the updated data set. These are used, in turn, to winsorise any remaining outliers, defined as observations that are further than three standard deviations from the mean. In effect, what winsorisation does is replace extreme values by certain outer boundary values (in this case the mean plus/minus three standard deviations).

Note, however, that transformation and winsorisation are only employed on the size, value and momentum variables, and not on the liquidity proxies. This is due to the fact that this research aims to determine the effect of the original liquidity proxies on excess returns and therefore aims to take account of extreme values. Future research which takes account of outliers may indeed be necessary (see Section 3.4.2.6).

3.4.2.6 Descriptive Statistics

Several measures of central location, variation and linear relationship were obtained for the data. These included the mean, standard deviation, skewness, kurtosis and coefficient of correlation. Graphical techniques were employed to provide an indication of the distribution of the data. These methods were employed separately on the two types of data (first on the monthly liquidity proxy data and secondly on the monthly size, value and momentum variable data). Please refer to Appendices A.3 and A.4 for details.

The statistics and histograms of the monthly liquidity proxy data indicate mostly low correlations and skewed distributions. The exceptions are the bid—ask spread, which displays the most normalised distribution, although some outliers do seem to possibly be present, and the two zeros measures, which are highly correlated (which is not a surprising result since these measures are directly linked by definition). This would indicate that, although the different proxies do not capture similar effects, a transformation may indeed be required to normalise the distributions. However, as mentioned earlier, this research aims to determine the effects of the original variables (without transformations) on excess share returns in order to enable direct comparison with the majority of previous literature. Nonetheless, as will be illustrated in Section 3.6, the regression model will take account of non-normality of variables through the use of Newey-West estimators. Even so, future research is advised in this area, in particular in determining the effects of these liquidity proxies on excess returns if transformations are performed on the skewed measures (turnover, price impact and both zeros measures) and outliers are taken into account. Refer to papers by Hasbrouk (2009: 1445) and Cooper, Groth and Avera (1985: 203), who applied transformation to numerous liquidity proxies.

The statistics and histograms of the size, value and momentum variables indicate low correlations and mostly normalised distributions. Hence different variables do not capture similar effects, which could lead to incorrect conclusions. In addition, the transformations applied (where applicable) were successful in eliminating skewness.

3.5 CLASSIFICATION OF PORTFOLIOS

To investigate the effect of liquidity on the returns obtained from shares listed on the South African stock market, the shares are first sorted into portfolios according to size, value and momentum trading strategies, after which the effect of liquidity is analysed. Four factors are included in the model. The SMB (Small-Minus-Big) size factor and the HML (High-Minus-Low) value factor, both originally introduced by Fama and French (1993: 3), as well as a momentum factor GMP (Good-Minus-Poor) are constructed. In addition, in order to take account of the effect of liquidity, a liquidity factor is also included in the model in the form of IMV (Illiquid-Minus-Very liquid).

For each indicator of size, value and momentum outlined in Section 3.3, two size portfolios, three value portfolios and two momentum portfolios are created. The decision to construct only two size portfolios but three value portfolios is similar to the method used by Fama and French (1992: 427), who found that the value factor played a bigger role in average stock returns. This is supported by the findings of Strugnell *et al.* (2011: 1), who found the same to be true on the JSE. Due to the limited amount of shares available for investing on the JSE, only two momentum portfolios were constructed. This reduces the number of portfolios that need to be constructed, thereby enabling a larger number of shares to be included in each portfolio. It should be noted that many studies split each effect into at least five portfolios, often even more, and then analysed only the most extreme of them (i.e. the upper and lower quintile/decile portfolios). However, the majority of those studies focused on the US market, which consists of around 14 000 listed stocks in any given year. The South African market is comparatively very small, with the ALSI consisting of only approximately 160 listed stocks, which represent around 99% of the entire JSE market capitalisation in any given year. Therefore, splitting each effect into more than three portfolios would result in very few stocks being included in each portfolio which, in turn, might lead to incorrect conclusions.

At the end of June of each year stocks are sorted independently according to size, value and momentum[5]. The size effect is measured by two variables: market capitalisation and earnings per share (EPS). The value effect is measured by B/M and earnings yield, while the momentum effect is measured by the previous 3-month’s and 12-month’s returns.

The size portfolios are split into two sizes: big (B) and small (S) according to the median value of the size variable. Three value portfolios are set up according to the 3rd and 6th deciles of the variables’ ranked values: low (L), medium (M) and high (H). Similar to the size portfolios, the two momentum portfolios are also split according to the variables’ median values: poor (P) and good (G). Therefore 12 portfolios are constructed according to the intersection of the size, value and momentum deciles: L/B/P, L/B/G, L/S/P, L/S/G, M/B/P, M/B/G, M/S/P, M/S/G, H/B/P, H/B/G, H/S/P and H/S/G. Value-weighted monthly returns are calculated for the 12 portfolios for the following year from June of the current year through May of the following year. Each year the portfolios are reformed based on the new values of

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[5] The decision to rebalance the portfolios annually is based on an attempt to imitate the assumed actual experience of an average investor. More frequent rebalancing will incur high trading costs, which most average investors are unwilling to accept. Refer to Basiewicz and Auret (2009: 26) for further details about this assumption.

each of the variables used to measure the three effects. Returns are then calculated again for the following year. Since numerous variables are being used to take account of each of the size, value and momentum effects, different combinations of these variables for each of the portfolios listed above will be tested to see the significance of each variable in predicting stock returns. The monthly returns for the 12 portfolios, less the risk-free rate, are the dependent variables used in the regressions.

The SMB risk factor, which proxies for the size effect, is calculated by subtracting the averages of the monthly returns of the six small (L/S/P, L/S/G, M/S/P, M/S/G, H/S/P, H/S/G) and the six big (L/B/P, L/B/G, M/B/P, M/B/G, H/B/P, H/B/G) size portfolios. The returns for the HML value risk factor are obtained from the differences between the average monthly returns on the four high (H/B/P, H/B/G, H/S/P, H/S/G) and four low (L/B/P, L/B/G, L/S/P, L/S/G) value portfolios. Similarly, the returns for the GMP momentum risk factor are obtained from the differences between the average monthly returns on the six good (L/B/G, L/S/G, M/B/G, M/S/G, H/B/G, H/S/G) and poor (L/B/P, L/S/P, M/B/P, M/S/P, H/B/P, H/S/P) momentum portfolios.

The portfolios set up so far have ignored liquidity. In order to take account of the effect of liquidity, two portfolios are set up according to the median value of the liquidity variable: illiquid (I) and very liquid (V). Low values of the respective illiquidity measure indicate highly liquid stocks, while high values indicate illiquid stocks. In June of each year the liquidity groups are formed based on the previous year's liquidity. An annual average for liquidity is then obtained from monthly measures. The corresponding IMV risk factor is obtained from the difference between the average monthly returns on the 12 illiquid (I/L/B/P, I/L/B/G, I/L/S/P, I/L/S/G, I/M/B/P, I/M/B/G, I/M/S/P, I/M/S/G, I/H/B/P, I/H/B/G, I/H/S/P, I/H/S/G) and 12 very liquid (V/L/B/P, V/L/B/G, V/L/S/P, V/L/S/G, V/M/B/P, V/M/B/G, V/M/S/P, V/M/S/G, V/H/B/P, V/H/B/G, V/H/S/P, V/H/S/G) portfolios.

Lastly, the proxy for the market factor needed in the regression analysis is obtained as the excess market return $r_{mt} = R_{mt} - R_{ft}$ where R_{mt} is the return on the market portfolio and R_{ft} is the risk-free rate of return. The FTSE/JSE All Share Index serves as a proxy for the market portfolio and the rate on the three-month treasury bill is used to proxy as the risk-free rate of return. Data on these were obtained from I-Net Bridge.

3.6 METHODOLOGY

The methodology used in this thesis is divided into two sections. First, the size, value and momentum effects are examined on the returns of stocks listed on the JSE over the entire sample period. Different variables will be employed to take account of the various effects in the hope of determining the three most appropriate variables. Next, the effects of liquidity will be added to the analysis, using, in turn, each of the five liquidity proxies. This will assist in analysing the effect of liquidity on stock returns, and will enable one to determine whether liquidity is in fact a priced factor.

A stepwise approach is used to perform these analyses. The analysis starts with an APT-type approach. The two Fama-French factors SMB and HML, along with the momentum factor GMP are analysed to observe their effect on asset pricing. This is done by first sorting the data according to size, value and momentum values according to each of the variables discussed in Section 3.3, resulting in twelve portfolios that will be analysed at a time. The standard CAPM is then estimated for each portfolio:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + \varepsilon_{jt} \quad \text{... (3.5)}$$

where

where	$r_{jt} = R_{jt} - R_{ft}$	is the excess portfolio return, where R_{jt} is the return on portfolio j in month t and R_{ft} is the risk-free rate of return in month t;
	α_j	is the regression intercept;
	β_{jm}	is the beta coefficient of portfolio j relative to the market;
	$r_{mt} = R_{mt} - R_{ft}$	is the excess market return, where R_{mt} is the market return in month t and R_{ft} is the risk-free rate of return in month t; and
	ε_{jt}	is the residual (random error) term of the regression for portfolio j in month t.

Next, the model is extended by the SMB, HML and GMP factors:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + s_{jSMB} SMB_t + h_{jHML} HML_t + g_{jGMP} GMP_t + \eta_{jt} \quad \text{... (3.6)}$$

where	r_{jt}, α_j, β_{jm} and r_{mt}	are as above
	s_{jSMB}	is the sensitivity of portfolio j's return to movements in the size risk premium SMB;

h_{jHML}	is the sensitivity of portfolio j's return to movements in the value risk premium HML;
g_{jGMP}	is the sensitivity of portfolio j's return to movements in the momentum risk premium GMP;
η_{jt}	is the residual (random error) term of the regression for portfolio j in month t; and
SMB_t, HML_t, GMP_t	are the size, value and momentum factors, respectively, in month t.

Running and comparing both of these regressions will provide evidence on whether size, value and momentum are priced factors on the South African stock market, in addition to the market factor beta (β).

To analyse the effects of liquidity on asset pricing, the stocks are sorted into two liquidity-portfolios in addition to the portfolios for the earlier regressions. Equations (3.5) and (3.6) are then re-estimated for each of the 24 portfolio combinations. Following, both models are extended by the IMV liquidity factor:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + i_{jIMV} IMV_t + u_{jt} \qquad \text{... (3.7)}$$

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + s_{jSMB} SMB_t + h_{jHML} HML_t + g_{jGMP} GMP_t + i_{jIMV} IMV_t + v_{jt} \qquad \text{... (3.8)}$$

where the variables are as defined above, with the additional sensitivity factor i_{jIMV} of portfolio j's return to movements in the illiquidity risk premium IMV and the error terms u_{jt} and v_{jt} for regressions (3.7) and (3.8) respectively.

Time-series cross-section (TSCS) returns data often exhibits both autocorrelation and heteroskedasticity. However, the Ordinary Least Squares (OLS) methodology relies upon the assumption that the regressors are exogenous, with homoskedastic and serially uncorrelated errors. If not taken into account, autocorrelation and heteroskedasticity can lead to OLS estimates that are statistically inefficient and possibly even produce misleading inferences. Therefore, in order to take account of this possible inefficiency in results, the Newey-West (1987: 703) method is applied to the OLS estimation in this research to adjust the standard errors of the estimated coefficients for serial correlation. Hence, the models are estimated using a pooled cross-section time series OLS estimator with Newey-West standard errors with six lags. Refer to Appendix B for further details.

The regression results will consist of a number of regression diagnostics (i.e. statistical measures) such as the coefficients of the independent variables with their respective *t*-

statistics, as well as the R^2, adjusted R^2 and Durbin-Watson statistic of the particular model. The excess portfolio return r_{jt} is the dependent variable in the regressions, while SMB_t, HML_t, GMP_t and IMV_t are the independent variables. The *t*-statistics of the independent variables will give an indication as to whether the respective factors are indeed significant in explaining excess returns. First, the standard CAPM (equation 3.5) and momentum-augmented Fama-French model (equation 3.6) will be analysed to determine which of the size, value and momentum measures best capture excess returns on the JSE. This is done by comparing the R^2 measures for the different portfolio combinations in order to gauge which portfolios indicated the best fit. The coefficients (and their significance levels) of the various dependent variables will also be compared to see which best capture the variation in excess returns. The higher the coefficients and their respective *t*-statistics, the more effective the model is in explaining excess stock returns on the JSE.

Next, the effect of liquidity in explaining excess stock returns is analysed. The portfolios that are set up according to the intersection of size, value and momentum are analysed. This means that first the size, value and momentum factors SMB_t, HML_t and GMP_t will be analysed to see their effectiveness in achieving excess returns by comparing the results of equations (3.5) and (3.6). If they are indeed effective, then the alpha coefficients (i.e. the intercepts α_j) should change significantly when comparing model (3.6) to (3.5). Only if this is the case can it be concluded that the size, value and momentum factors are influencing factors of stock returns on the JSE.

However, these results give no indication of whether liquidity is also an influencing factor. Therefore the next step is to sort portfolios according to four factors: liquidity, size, value and momentum. Equations (3.5) and (3.6) are re-analysed on these newly formed portfolios and the results are compared to those obtained in the previous step. If the addition of liquidity as a sorting factor is an influencing factor, then the R^2 measures for the portfolios are expected to increase, indicating a better fit. The proportion of significant alphas is also compared to the previous results. If the proportion decreases when liquidity is taken into account, then liquidity is an influencing factor and vice versa.

The analysis is then extended by one further step, namely the inclusion of liquidity as a dependent variable. Equations (3.5) and (3.6) are extended by the addition of the liquidity factor IMV_t to form the new models (3.7) and (3.8) respectively. The R^2 measure, as well as the factor coefficients and their significance levels for the new regressions (3.7) and (3.8) are compared with those obtained in the previous step (i.e. those without the IMV_t factor). If a noticeable change is observed, then it can be concluded that liquidity is indeed an influencing factor on excess stock returns on the JSE.

CHAPTER 4
EMPIRICAL FINDINGS

4.1 INTRODUCTION

In this section the regression analyses as specified in Section 3.6 are estimated and tested. This is done in four steps:

- A measure of size, value, momentum and liquidity are estimated in each month *t* of the sample for each individual stock.
- Portfolios are set up according to the intersection of size, value, momentum and liquidity, the inclusion of the factors being dependent on the type of regression analysis to be performed. This is performed on a yearly basis due to annual rebalancing.
- For each portfolio the monthly excess portfolio return is calculated, in addition to the size, value, momentum and liquidity factors SMB, HML, GMP and IMV respectively.
- Using the excess returns and factors, the portfolio alphas and betas are estimated and analyzed.

The analysis was performed in two stages. The first stage was in effect a preliminary test to determine which measures best captured the size, value and momentum effects for the sample under consideration. The second stage then made use of the preliminary findings to test the effect of liquidity in generating excess portfolio returns.

In the first stage, the portfolios were sorted according to size, value and momentum variables only. In other words, in the first stage, liquidity was omitted. The results of the regressions were then analysed to determine which measure best captured the respective effect. These three measures were then used in the second stage to form new portfolios according to liquidity, size, value and momentum effects. Therefore, the five liquidity proxies, together with one measure for each of the size, value and momentum effects, were used, in turn, to set up the portfolios. This approach serves to best determine the effect of liquidity on excess portfolio returns, since each measure of liquidity is separately combined with the size, value and momentum measures known to be most effective for this particular data set. This enables more focus to be placed on the effect of liquidity.

The results of the analyses are presented below and in Appendix 3. The coefficients and *t*-statistics of the intercepts, as well as all explanatory variables are presented, along with each portfolio's R^2, adjusted R^2, and Durbin-Watson statistic. R^2, the coefficient of determination, measures the goodness of fit of a model. It gives an indication of the proportion of variability in a data set that is taken into account by the model, and therefore aids in determining how well the particular model can predict future outcomes. An R^2 of 1.0 indicates that the regression line perfectly fits the data, while measures less than 1.0 provide decreasing approximations of how well the regression line fits the real data points.

The associated measure of R^2, the adjusted R^2, adjusts the coefficient of determination for the number of data observations and the number of explanatory variables included in the model. Hence, unlike the earlier measure, the adjusted R^2 increases only if the new term improves the model more than would be expected by chance.

Lastly, the Durbin-Watson statistic tests for autocorrelation in the residuals of a statistical regression analysis. This statistic always lies between 0 and 4, with a value of 2 indicating that there is no autocorrelation in the sample. Values less than 2 indicate positive autocorrelation, while those closer to 4 indicate negative autocorrelation. Regressions with Durbin-Watson measures far removed from 2 (i.e. less than 1 or greater than 3) can lead to incorrect forecasts since the level of statistical significance can be over- or underestimated. Since the regression models used in this research are based on Newey-West standard errors (which should take autocorrelation into account), Durbin-Watson measures around 2 are to be expected.

4.2 DETERMINATION OF IDEAL MEASURES FOR SIZE, VALUE AND MOMENTUM

The impact of the various size, value and momentum factors is determined in two steps. First, regressions that analyse only the excess market return $r_{mt} = R_{mt} - R_{ft}$ to explain excess stock returns are examined according to equation 3.5. Second, regressions that use the excess market return $r_{mt} = R_{mt} - R_{ft}$, as well as the mimicking returns for size, value and momentum, SMB_t, HML_t and GMP_t respectively, as explanatory variables are examined according to equation 3.6. Both of these regression analyses are performed on portfolios set up according to the intersection of the various measures for size, value and momentum. The results are subsequently compared in order to determine the optimal combination of these measures in capturing excess portfolio returns.

The results of the standard CAPM regression analyses are presented in Appendix C.2. The results indicate that the market only captures part of the variation in stock returns, with values of R^2 generally lying between 0.1 and 0.4, and some portfolios even exhibiting R^2 values as low as 0.02. The higher values of R^2 are found in the big-stock, good-momentum and low- and medium-valued portfolios. For the small-stock, poor-momentum portfolios R^2 values of less than 0.2 are the norm. These portfolios are where the inclusion of the size, value and momentum factors will have their best attempt at exhibiting marginal explanatory power. In addition, as expected, the Durbin-Watson measures of all regressions lie close to 2, indicating that there is no autocorrelation in the sample.

Overall, the portfolio set up using the earnings yield (EY) as a measure of value, the log of the firms' market value (MVLOG) as a measure of size and the previous 3-month's returns (MOM3) as a measure of momentum exhibited the best explanatory power in terms of R^2. In addition, ten of the twelve portfolios showed market betas (β_{jm}) with statistical significance at the 1% level, which is more and higher than most other combinations of measures did. These results are presented in Table 4.1.

Table 4.1 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.249 (-1.651)	0.869 (6.487)*	0.3068	0.2993	2.6838	-0.629 (-0.676)	0.872 (6.918)*	0.3692	0.3624	2.4514
	Small (S)	-4.788 (-3.640)*	0.564 (4.053)*	0.1398	0.1305	1.9599	0.278 (0.319)	1.019 (9.737)*	0.3564	0.3494	2.3355
Medium (M)	Big (B)	-2.585 (-3.015)*	0.679 (5.188)*	0.2723	0.2644	2.4516	-0.262 (-0.218)	0.999 (4.558)*	0.4274	0.4212	2.6033
	Small (S)	11.417 (0.825)	2.010 (1.477)	0.0252	0.0146	2.3212	-1.339 (-1.772)	0.815 (5.115)*	0.3685	0.3616	2.0135
High (H)	Big (B)	-2.536 (-2.653)*	0.705 (4.550)*	0.2724	0.2645	2.1335	-2.047 (-2.421)**	0.786 (7.582)*	0.3855	0.3788	2.1112
	Small (S)	-3.977 (-3.849)*	0.617 (3.661)*	0.2120	0.2034	1.8602	12.577 (1.043)	2.088 (1.768)	0.0340	0.0235	2.3581

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

The results of the standard CAPM indicated that, in the absence of any other explanatory variables, excess market returns fail to capture over 50% of stock portfolio returns. Adding mimicking returns for size, value and momentum should hopefully increase the explanatory power. This is investigated through the use of a momentum-augmented Fama-French model (see equation 3.6). The regression results for all possible combinations of measures are presented in Appendix C.3. The addition of the three factors increased the amount of variation captured by the model (as measured by the R^2) to between 0.4 and 0.6. Hence the explanatory power of the excess returns has doubled. It should also be noted that the Durbin-Watson measures of all regressions tend to lie between 1.7 and 2.5, indicating that, as before, there is no autocorrelation in the sample. The market betas are nearly all more than five standard errors from zero, with a definite improvement from the results of the standard CAPM. The *t*-statistics on the SMB slopes tend to range between 1 and 10. Hence SMB, the mimicking return for the size factor, seems to capture shared variation in stock returns that is missed by the other factors. In addition, this factor appears to be related to size. With the exception of high value, good momentum stocks, the slopes on SMB decrease from lower to higher value stocks.

Similarly, the *t*-statistics on the slopes on the HML factor, the mimicking return for the value factor, tend to lie between 1 and 3. For each size category, the HML slopes increase for an increase from low to high value stocks. Therefore, HML clearly captures some of the shared variation that is missed by the market return, as well as the SMB and GMP factors.

Lastly, the *t*-statistics on the slopes on the GMP factor, the mimicking return for the momentum factor, tend to lie between 1 and 5. For each size as well as each value category the GMP slopes increase from poor momentum to good momentum stocks. This is probably the clearest pattern that can be observed for all portfolio measure combinations. Hence, it can be stated with strong certainty, that GMP captures shared variation that is missed by the other factors.

Given the strength of the slopes, it comes as no surprise that the addition of these three factors into the regressions results in noticeable increases in R^2. As mentioned earlier, R^2 lies between 0.4 and 0.6, therefore having doubled the explanatory power of the excess returns. For example, for the standard CAPM portfolio, which states that the market alone can explain the excess returns, only one (out of twelve) of the portfolios set up according to the EY, MVLOG and MOM3 measures (which produced the most impressive results) demonstrated R^2 values greater than 0.4 (see Table 4.1). In the four-factor regressions, eight of the twelve equivalent portfolios demonstrate R^2 values greater than 0.4, with all R^2 values being greater than 0.35 (see Table 4.2).

Considering the beta coefficients (β_{jm}) of the four-factor regressions, an interesting effect can be noticed. In the standard CAPM regression results presented in Table 4.1, the univariate beta coefficient for the portfolio with the smallest size, value and momentum stocks is 0.869. At the other extreme, the beta for the portfolio with the biggest size, value and momentum stocks is 2.088. The corresponding values of the four-factor regression results for the equivalent portfolios (which are presented in Table 4.2) are 1.014 and 1.032 respectively. Therefore, adding the SMB_t, HML_t and GMP_t factors to the regressions collapses the betas towards 1.0. This behaviour can be attributed to the correlation between the market and SMB_t, HML_t or GMP_t.

As with the standard CAPM, the portfolios set up according to the intersection of the earnings yield (EY) as a measure of value, the log of the firms' market value (MVLOG) as a measure of size and the previous 3-month's returns (MOM3) as a measure of momentum exhibited the best predictive powers. The SMB_t, HML_t and GMP_t factors all illustrate relatively high *t*-statistics, indicating that these factors capture a considerable amount of the variation in stock returns that is missed by the market return. In addition, the R^2 values are all above 0.35 and are, overall, higher than on the similar portfolios set up using different measures. In addition, all market betas (β_{jm}) showed statistical significance at the 1% level. And lastly, for each of the SMB_t, HML_t and GMP_t factors, eight of the twelve respective coefficients are statistically significant, which no other portfolio measure combination can demonstrate. These results are presented in Table 4.2.

Hence, for all analyses going forward, the size, value and momentum measures used as proxies for the respective factors will be held constant as MVLOG, EY and MOM3 respectively. The ideal measure for the value factor comes as a bit of a surprise. Most previous studies (both nationally and internationally) have found the book value to market measure to be the best measure of value stocks. However, although this measure did provide similar results to those of the earnings yield, it was found that the intersection of the above three measures provided the best results. Still, Fraser and Page (2000: 14) found earnings yield and market capitalisation to be the most economical representation of style-based risk on the JSE for value and size factors, respectively. This is in fact in line with the findings in this research. The use of the previous three month's returns as a measure for momentum though, is in contrast to their findings. Since very little research has been conducted as to the most appropriate measure for momentum, this is not a cause for concern.

While the absolute values of the Fama and French (1993: 3) models tend to be higher and therefore more significant, the results obtained here are similar. This is particularly true in terms of the added explanatory power obtained by the inclusion of the SMB_t, HML_t and GMP_t factors.

4.3 THE IMPACT OF LIQUIDITY ON STOCK PRICING

To determine the impact of liquidity on stock pricing, regression results are analysed according to four different models. First, results from the standard CAPM and the momentum-augmented Fama-French model are examined for portfolios sorted only according to size, value and momentum variables. Next, liquidity is added to the sorting of portfolios, and the previous two models are re-run and re-examined on these newly sorted

Table 4.2 **Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum**

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	0.313 (0.268)	1.014 (5.540)*	-0.073 (-0.492)	-0.002 (-0.013)	-0.620 (-2.827)*	0.3768	0.3488	2.6469	-1.342 (-1.733)	0.813 (7.724)*	-0.195 (-1.519)	0.249 (1.470)	0.404 (2.385)**	0.4487	0.4239	2.5136
	Small (S)	-2.510 (-3.090)*	0.761 (6.653)*	0.296 (2.125)**	-0.506 (-2.539)**	-1.035 (-4.950)*	0.4430	0.4180	2.2729	-1.264 (-1.276)	0.857 (5.728)*	0.567 (4.215)*	-0.752 (-4.252)*	0.625 (2.543)**	0.5236	0.5022	2.0503
Medium (M)	Big (B)	-1.007 (-1.600)	0.832 (9.239)*	-0.244 (-3.839)*	0.272 (3.174)*	-0.650 (-4.634)*	0.3919	0.3646	2.5331	-0.978 (-0.849)	0.937 (4.836)*	-0.111 (-1.082)	0.159 (1.118)	0.359 (2.278)**	0.4654	0.4414	2.6849
	Small (S)	0.451 (0.257)	1.009 (3.490)*	2.253 (9.759)*	1.131 (3.776)*	-0.386 (-1.422)	0.9811	0.9802	2.3829	-1.429 (-1.348)	0.806 (4.011)*	0.026 (0.299)	-0.006 (-0.054)	0.002 (0.006)	0.3727	0.3445	2.0225
High (H)	Big (B)	-1.102 (-1.279)	0.849 (6.807)*	-0.352 (-4.137)*	0.435 (3.740)*	-0.580 (-2.848)*	0.4019	0.3750	2.1580	-2.168 (-2.973)*	0.792 (7.692)*	-0.468 (-5.269)*	0.654 (5.280)*	0.123 (0.798)	0.5825	0.5637	2.1786
	Small (S)	-2.430 (-2.930)*	0.772 (5.212)*	-0.323 (-2.697)*	0.437 (2.872)*	-0.693 (-2.640)*	0.3834	0.3557	2.0523	0.897 (0.586)	1.032 (3.984)*	1.738 (8.162)*	1.462 (5.311)*	0.524 (1.446)	0.9779	0.9769	2.5165

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

portfolios. This will provide an indication of whether the addition of liquidity to portfolio sorting has a significant effect. Lastly, a liquidity factor is added to both models, the results of which are then compared to the two previous regression results. This is done in order to determine whether the addition of liquidity as a factor within the model provides more explanatory power and hence ascertain if liquidity is indeed a priced factor on the JSE.

4.3.1 Portfolios sorted according to size, value and momentum

In this section, the standard CAPM and momentum-augmented Fama-French model are analysed for portfolios set up according to the intersection of size, value and momentum factors. The measures used for each are the earnings yield (EY) as a proxy for the value effect, the log of the firms' market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Table 4.3 reports the estimation results across the twelve portfolios and the two alternative risk specifications represented by the standard CAPM and the momentum-augmented Fama-French models.

The results for the standard CAPM indicate that the risk-adjusted average returns, which are represented by the α_j's of the regressions, are not significantly different from zero for the majority of portfolios. In fact, only five out of twelve portfolios showed significant alphas. The majority of intercepts are negative, suggesting a negative risk-premium for the respective portfolios. However, for two of the three portfolios that show positive alphas, the intercept is very large, suggesting large positive risk-premiums. This is the case for portfolios that contain small sized firms. A comparison of the estimated alphas suggests that momentum factors influence the risk-adjusted returns. The coefficients' magnitudes generally increase as momentum increases. Thus, stocks featuring higher momentum are characterised by higher risk-premia. This could be due to either the market regarding these stocks are riskier, or, and this is the more likely option, as a better investment and hence more popular. Since momentum strategies are based on investments in those stocks that performed well over the past period, the results would suggest that these types of approaches do in fact generate excess stock returns. Neither size nor value factors show any definite influences. The estimated market betas (β_{jm}) of the standard CAPM are all positive and predominantly significantly different from zero (except those of the two portfolios that also showed very large, positive alphas).

In order to determine whether size, value and momentum are influencing the risk-premia on the South African stock market, the momentum-augmented Fama-French model is estimated for the same portfolios as above. An increase or a decrease in magnitude across all alphas in comparison to those of the standard CAPM indicates that size, value or momentum are influencing factors. Panel B of Table 4.3 presents the estimation results for

Table 4.3 Comparison of estimation results across size, value and momentum portfolios and different risk specifications

The table reports the regression results for the standard CAPM and the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, with the corresponding levels of significance being reported where applicable. The models are estimated using Newey-West standard errors with six lags.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}
Panel A:Standard CAPM											
Low (L)	Big (B)	-1.249	0.869*				-0.629	0.872*			
	Small (S)	-4.788*	0.564*				0.278	1.019*			
Medium (M)	Big (B)	-2.585*	0.679*				-0.262	0.999*			
	Small (S)	11.417	2.010				-1.339	0.815*			
High (H)	Big (B)	-2.536*	0.705*				-2.047**	0.786*			
	Small (S)	-3.977*	0.617*				12.577	2.088			
Panel B:Momentum-augmented Fama-French model											
Low (L)	Big (B)	0.313	1.014*	-0.073	-0.002	-0.620*	-1.342	0.813*	-0.195	0.249	0.404**
	Small (S)	-2.510*	0.761*	0.296**	-0.506**	-1.035*	-1.264	0.857*	0.567*	-0.752*	0.625**
Medium (M)	Big (B)	-1.007	0.832*	-0.244*	0.272*	-0.650*	-0.978	0.937*	-0.111	0.159	0.359**
	Small (S)	0.451	1.009*	2.253*	1.131*	-0.386	-1.429	0.806*	0.026	-0.006	0.002
High (H)	Big (B)	-1.102	0.849*	-0.352*	0.435*	-0.580*	-2.168*	0.792*	-0.468*	0.654*	0.123
	Small (S)	-2.430*	0.772*	-0.323*	0.437*	-0.693*	0.897	1.032*	1.738*	1.462*	0.524

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

the momentum-augmented Fama-French model with Newey-West standard errors. Those portfolios with low momentum stocks increased their alpha coefficients from the standard CAPM, while those portfolios with high momentum stocks decreased their alpha coefficients.

Hence, including size, value and momentum factors in the model increases the strength of the relation between the intercepts of the low momentum portfolios, while it leads to a reduction in the intercepts' relation for high momentum portfolios. In addition, the number of significant intercepts has decreased even further (in comparison to the standard CAPM), signifying that this model explains even more of the excess returns. This indicates that size, value and momentum factors do influence stock pricing on the South African market. The betas of the momentum-augmented Fama-French model are all positive and significant at the 1% level. Hence, overall, the three factors do seem to influence and explain excess returns on the JSE and since the alphas are not particularly significant, it seems that these factors capture most of the returns. However, since the alphas are still somewhat different form zero, this would suggest that there might be another factor influencing the excess returns on the South African market.

4.3.2 Portfolios sorted according to liquidity, size, value and momentum

As previous literature has illustrated, liquidity has been shown to influence excess stock returns (see Chapter 2). Therefore, in order to test whether liquidity might in fact be an additional factor influencing excess stock returns on the JSE, the portfolios are reformed taking account of liquidity, as well as size, value and momentum. The portfolios are formed according to five different measures of liquidity, namely the bid-ask spread, turnover, the price impact measure and two zeros measures. This enables one to identify distinctions in the regression results according to the different liquidity measures. First, the standard CAPM and the momentum-augmented Fama-French model are tested, the results of which are compared to those obtained earlier (see Section 4.3.1). Next, a liquidity factor is added to both models to determine if it improves the predictive power of the respective models. Hence, it allows the added effect of liquidity to be determined, both with and without the additional effects of size, value and momentum. Table 4.4 provides an overview of the estimated alphas for the different risk specifications and across the five illiquidity measures.

Just over half of the estimated alphas of the standard CAPM are significantly different from zero for the majority of portfolios, in comparison to just under half of the alphas being significant for the case where liquidity is ignored. In the case of the momentum-augmented Fama-French model, just over 40% of the portfolios show significant alphas, as opposed to only 25% in the previous case that disregarded liquidity. Hence, in both cases, the proportion of significant alphas increased, which could possibly indicate that the inclusion of liquidity in portfolio formation may be unnecessary. However, in order to test this theory, further analyses need to be performed. One such test would be to add a liquidity factor to both models to determine its effect. This was done , the results of which are presented in Table 4.4, as well as in Appendix C.6 and Appendix C.7. The first model is a liquidity-augmented CAPM and the second model is a liquidity-and-momentum-augmented Fama-French model.

A comparison of the estimation results in Panels A and B with those of the corresponding liquidity-augmented models in Panels C and D reveals a similar pattern of results. Therefore, the addition of the liquidity factor does not seem to have an influence on estimation results. In fact, the number of significant intercepts increases marginally after adding the liquidity factor. According to the standard CAPM and its liquidity-augmented counterpart, the zeros2 measure is the only of the five measures that showed a slight decrease in significance of alphas, which would indicate that the addition of the particular factor actually improved the models' predictive power in explaining excess stock returns. However, the same cannot be said for the momentum-augmented Fama-French model and its liquidity-augmented counterpart, which showed no improvement whatsoever after adding the liquidity factor. A comparison with the estimation results in Table 4.3 shows that the factor according to which portfolios are sorted significantly influences results. Sorting according to size, value and

Table 4.4 Comparison of alphas across alternative risk specifications and measures of liquidity

The table reports the regression results for the intercepts, i.e. the excess returns, for four asset-pricing models: the standard CAPM (Panel A), the momentum-augmented Fama-French model (Panel B), the liquidity-augmented CAPM (Panel C) and the liquidity-and-momentum-augmented Fama-French model (Panel D). The models are estimated for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect, the previous 3-month's returns (MOM3) as a proxy for the momentum effect and lastly five different liquidity measures as liquidity proxies. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, with the corresponding levels of significance being reported where applicable. The models are estimated using Newey-West standard errors with six lags.

				Liquidity measure				
Liquidity	**Momentum**	**Value**	**Size**	Bid-ask	Turnover	Price impact	Zeros1	Zeros2
Panel A: Standard CAPM								
Illiquid	Poor	Low	Big	-1.311	-1.786**	-1.310	-1.469	-1.435
			Small	-2.521**	-4.012*	-4.495**	-2.853	-3.116
		Medium	Big	-2.522*	-2.800*	-2.469**	-2.518**	-2.508**
			Small	-2.043	-5.778*	-4.812*	-4.493*	-4.342*
		High	Big	-2.554*	-2.444**	-2.546*	-2.497**	-2.516**
			Small	-5.055*	-4.497	-5.503*	-3.071*	-1.719
	Good	Low	Big	-0.534	-1.114	-0.532	-0.564	-0.571
			Small	-2.912*	-3.446*	-4.368*	-1.548	-2.106
		Medium	Big	-0.270	-0.239	-0.253	-0.294	-0.207
			Small	-2.402	-2.793*	-3.499*	-3.743**	-2.510
		High	Big	-2.219**	-3.153*	-2.265**	-2.293**	-3.107**
			Small	-2.427**	-3.585*	-0.724	-0.440	-1.257
Liquid	Poor	Low	Big	-3.760*	-2.102*	-1.025	-2.541*	-2.188*
			Small	-4.356*	-5.093*	-4.386*	-5.346*	-5.069*
		Medium	Big	-3.228*	-2.830*	-2.498*	-2.834*	-3.264*
			Small	-5.612**	-4.485**	-4.541**	-4.529**	-4.314
		High	Big	-4.205*	-3.780*	0.854	-2.741**	-2.586**
			Small	-2.404*	-2.886*	-2.072*	-4.270*	-4.087*
	Good	Low	Big	-1.682	-0.024	-1.382	-0.248	1.796
			Small	0.515	0.148	-0.783	-0.423	-0.674
		Medium	Big	-3.084*	-1.597	-2.625*	-1.128	-0.714
			Small	-1.241	-1.316	-1.243	-2.746*	-1.268
		High	Big	-0.837	1.588	0.211	-3.126	-3.226**
			Small	-2.896	-2.348	-2.555	-2.624	-2.441

Table 4.4 Continued

Panel B: Momentum-augmented Fama-French model								
Illiquid	Poor	Low	Big	-0.334	-1.602	-1.642	-1.288	-1.373
			Small	-1.634	-2.035*	-2.503	-0.303	-0.408
		Medium	Big	-1.288	-1.522**	-1.952**	-1.577**	-2.062**
			Small	-0.185	-2.176**	-2.859*	-1.767	-1.938
		High	Big	-1.454	-1.767	-2.297**	-1.524	-1.869**
			Small	-2.787*	-1.173	-2.591*	-2.330*	-0.724
	Good	Low	Big	-0.774	-2.297*	-1.802**	-1.485	-1.755**
			Small	-3.130*	-4.214*	-4.589*	-2.048	-3.625
		Medium	Big	-0.452	-1.399	-1.337	-0.902	-0.937
			Small	-1.880	-2.040**	-2.650*	-2.995	-2.022
		High	Big	-1.896**	-3.605*	-2.752*	-2.097**	-3.081**
			Small	-2.441**	-2.850*	-2.023	0.321	-0.508
Liquid	Poor	Low	Big	-3.037**	-1.688	-0.621	-2.459*	-2.165*
			Small	-2.939*	-2.450*	-2.736*	-3.888*	-4.246*
		Medium	Big	-1.947*	-1.653**	-1.997*	-1.147	-1.699**
			Small	-2.813**	-1.707	-1.455	-2.037	-2.076
		High	Big	-1.853	-2.933*	-2.087	-1.157	-1.351
			Small	-1.575*	-1.551	-1.418	-2.484*	-2.344*
	Good	Low	Big	-2.944*	-1.290	-2.027	-2.121	-0.356
			Small	-0.560	-0.019	-0.409	-0.977	-1.471
		Medium	Big	-3.461*	-2.271**	-3.019*	-2.649	-1.909
			Small	-0.960	-0.557	-0.390	-1.713	-1.073
		High	Big	-2.406	-0.231	-2.626	-3.556*	-3.699*
			Small	-0.941	-1.486	-0.535	-1.741	-1.822
Panel C:Liquidity-augmented CAPM								
Illiquid	Poor	Low	Big	-1.714**	-1.480	-0.769	-1.892**	-1.596
			Small	-2.927*	-3.597*	-4.483	-3.170	-3.304
		Medium	Big	-2.769*	-2.582*	-2.293**	-2.620*	-2.533*
			Small	-2.630	-4.908*	-4.127*	-4.929*	-4.638*
		High	Big	-2.833*	-2.233**	-2.434*	-2.592**	-2.546**
			Small	-5.065*	-3.552*	-5.465*	-3.287*	-1.819
	Good	Low	Big	-0.913	-0.914	-0.214	-0.779	-0.633
			Small	-3.137*	-2.989**	-3.840*	-1.833	-2.307
		Medium	Big	-0.550	-0.203	-0.018	-0.423	-0.246
			Small	-2.781	-2.673*	-3.363*	-3.877**	-2.577
		High	Big	-2.477*	-3.154*	-2.140**	-2.415**	-3.154**
			Small	-2.772*	-3.542*	0.535	-1.745	-1.594

Table 4.4 Continued

Liquid	Poor	Low	Big	-3.584*	-1.995**	-1.108	-2.470**	-2.121**
			Small	-4.208*	-5.720*	-4.870*	-5.215*	-5.009*
		Medium	Big	-3.127*	-3.204*	-2.715*	-2.749*	-3.307*
			Small	-4.976*	-6.320**	-5.400**	-3.859**	-4.071**
		High	Big	-4.187*	-3.892*	-1.873	-2.666**	-2.528**
			Small	-2.592*	-3.278*	-2.098*	-4.126*	-4.020*
	Good	Low	Big	-1.408	-0.241	-1.615	-0.041	1.835
			Small	0.749	-0.302	-1.193	0.024	-0.586
		Medium	Big	-2.950*	-2.070**	-2.749*	-0.879	-0.590
			Small	-1.178	-1.797	-1.462	-2.667*	-1.194
		High	Big	-0.708	1.186	0.026	-2.956	-3.170
			Small	-2.401	-4.192	-3.552	-1.960	-2.187
Panel D: Liquidity-and-momentum-augmented Fama-French model								
Illiquid	Poor	Low	Big	-0.763	-1.617	-0.941	-1.799**	-1.615**
			Small	-2.123	-1.885**	-2.346	-0.672	-0.596
		Medium	Big	-1.549**	-1.519**	-1.621	-1.696*	-2.109**
			Small	-0.879	-1.714	-2.047**	-2.261**	2.344
		High	Big	-1.772**	-1.611	-2.006**	-1.634**	-1.926**
			Small	-2.827*	-0.308	-2.325**	-2.580*	-0.894
	Good	Low	Big	-1.230	-2.183**	-1.459	-1.751**	-1.876**
			Small	-3.426*	-3.807*	-4.136*	-2.390	-3.852
		Medium	Big	-0.793	-1.411	-1.065	-1.067	-1.014
			Small	-2.351	-1.913	-2.530**	-3.138**	-2.106
		High	Big	-2.213*	-3.516*	-2.488*	-2.230*	-3.216**
			Small	-2.902*	-2.638*	-0.580	-1.114	-1.075
Liquid	Poor	Low	Big	-2.770**	-1.837	-0.577	-2.395*	-2.079**
			Small	-2.705*	-3.293*	-3.061*	-3.740*	-4.122*
		Medium	Big	-1.770*	-2.230*	-2.110*	-1.043	-1.737**
			Small	-2.119**	-3.000	-2.200	-1.178	-1.674
		High	Big	-1.752	-3.264*	-2.973**	1.056	-1.288
			Small	-1.800*	-1.844**	-1.338	-2.277*	-2.241*
	Good	Low	Big	-2.631*	-1.616	-2.408*	-1.935	-0.311
			Small	-0.349	-0.211	-0.942	-0.467	-1.311
		Medium	Big	-3.305*	-2.696*	-3.154*	-2.375	-1.776
			Small	-0.900	-0.864	-0.621	-1.607*	-0.963
		High	Big	-2.282	-0.622	-2.742	-3.350*	-3.677*
			Small	-0.448	-2.646	-1.418	-0.907	-1.444

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

momentum leads to only a quarter of the portfolios showing significant alphas for the momentum-augmented Fama-French model, whereas sorting according to liquidity increases the number of significant intercepts to just over 40%. This is the case for all but two of the liquidity measures (namely zeros1 and zeros2), for which the number of significant alphas either decreased or remained constant. This demonstrates that it is important not to rely on just one single measure of liquidity, but rather to employ various measures in order to avoid biased results that may not be supported by other measures. This is especially true for an elusive concept such as liquidity, the measurement of which is a rather challenging and daunting task.

It is also of interest to consider the coefficients of the market, size, value and momentum factors and to compare them to earlier results. Refer to Appendix C for details. The estimated market betas (β_{jm}) of the standard CAPM have not changed considerably, especially when considering those portfolios that were set up using the bid-ask spread, as well as both zeros measures. When a liquidity factor is added to the momentum-augmented Fama-French model, the results are not as straightforward. The estimated market betas remained relatively stable for the illiquid firms according to most liquidity measures. For liquid firms, portfolios set up according to the bid-ask spread and price impact measures showed an increase in market betas. Hence, depending on the type of measure used, liquidity may strengthen the effect of the market factor for liquid firms. However, the inclusion of liquidity in the model seems to have no effect on illiquid firms, irrespective of the type of measure employed.

For liquid firms, inclusion of the liquidity factor marginally increases the coefficients of the size factor, while for illiquid firms it decreases as well as increases the coefficients, depending on the type of liquidity measure used. However, the changes that do occur are minimal at best and therefore the inclusion of liquidity can be concluded not to be a significant influencing factor on size.

Coefficients for the value factor exhibited the weakest effects after liquidity was added to the model. For the bid-ask spread the coefficients did not change at all, while for both of the zeros measures the coefficients remained relatively stable. The only effect was found for illiquid firms, for which the coefficients increased (by very small amounts) for several measures. Therefore, one could conclude that the inclusion of liquidity strengthens the effect of the liquidity factor for illiquid firms, although this is minimal and highly dependent on the type of measure used.

Lastly, the inclusion of liquidity into the model had no effect on the momentum factor coefficients for the zeros measures. According to the turnover and price impact measures, however, inclusion of liquidity weakens the effect of momentum for illiquid stocks.

The findings here, although not directly comparable to those of other studies, do seem somewhat at odds to previous findings. In particular, the inclusion of liquidity appears to have produced contradictory results. However, it is unlikely that this is due to the inclusion of liquidity in the model, but rather due to the use of an entirely different sample. The JSE, being an emerging market, is expected to behave very differently to the developed US market for example. In addition, the sample used in this research is a far more recent sample that includes the financial crisis of 2008, whereas most previous studies have made use of earlier periods. Lastly, the portfolio formation method employed here is different to other studies, in particular with the inclusion of momentum as a base factor.

Before concluding that liquidity is indeed an insignificant factor, two additional statistics should be analysed: the R^2 value (that gives an indication of the goodness of fit of a model) and the Durbin-Watson statistic (that gives an indication as to the autocorrelation in the residuals). Comparing the R^2 values of Fama and French (1993: 3) with those of this research, a difference was found. Fama and French (1993: 3) found R^2 values of 0.95 and upwards for their three-factor model, whereas this research found R^2 values of around 0.45 for its five-factor model. In fact, this was the highest average obtained, with all other models showing R^2 values between 0.25 and 0.35. The worst coefficient of determination was obtained by the standard CAPM (around 0.25) which improved marginally to around 0.3 when a liquidity factor was added to the model. The same was found for the momentum-augmented Fama-French model, which showed an R^2 of around 0.35 but increased to an average value of 0.45 when a liquidity factor was added. But, when comparing these values to those of Lesmond (2005: 411), it was found that they were similar in magnitude. Lesmond (2005: 411) found R^2 coefficients for the South African market to lie between 0.31 and 0.37. This is directly comparable with the results of this research, with some models showing even higher coefficients. In fact, according to Lesmond's (2005: 411) results, most emerging markets appear to demonstrate coefficients of determination of less than 0.5. The difference between the Fama and French (1993: 3) results and those of this paper might be due to the difference in the sorting of the portfolios. Fama and French sorted their portfolios according to two variables only (size and value), whereas this research sorted the portfolios according to four variables (liquidity, size, value and momentum). This higher level of sorting led to a lower number of stocks in each portfolio, and, as a result, a higher level of noise in the regression. This, in turn, can lead to a reduction in the R^2. This is also a possible explanation for the lower value of R^2 in Lesmond's (2005: 411) regressions, since emerging markets tend to have fewer stocks listed on their exchanges.

However, as mentioned earlier, R^2 can be somewhat misleading since it can increase by chance and not due to the new term actually improving the model. Therefore, it is important to also determine the adjusted R^2, and see if the same results are found there. When considering the adjusted R^2 for the results of this research, it is found that it also increase from the models with no liquidity factor to those that include the factor. Hence, it can be concluded that the addition of the liquidity factor improves the model fit. This result is somewhat at odds with the results obtained earlier, that stated that liquidity is in fact not a significant factor. However, the R^2 and adjusted R^2 values obtained are, on average, less than 50%, so, although the inclusion of the liquidity factor improved the models' fits, it is still too small a value to be able to conclude that these models explain all the variation in excess stock returns. If anything, the results show that there are other factors that have not been taken into account as yet that would explain most of the excess returns.

Lastly, the Durbin-Watson statistics of all models lie between an acceptable band of 1.9 and 2.2. Hence, there does not appear to be any autocorrelation in the residuals. This is as expected since the use of the Newey-West method should have eliminated any such effects.

Therefore, it seems that the inclusion of liquidity in the model affects, if anything, the strength of the effect of the size, value and momentum factors on illiquid firms, while the only effect that is felt by liquid firms is in respect of the size factor. This is in contrast to its effect on the estimated market betas, where there is no impact on illiquid firms, but only on liquid firms. However, these effects are felt mainly by the bid-ask spread, turnover and price impact measures, with the zeros measures showing virtually no change in coefficients. It must be pointed out though, that these effects are all fairly weak, so in general, it is concluded that liquidity does not influence excess returns.

4.4 SUMMARY

The results demonstrate that liquidity does not influence excess stock returns on the JSE. Therefore it can be concluded that liquidity is not a priced factor on the South African market. This is a surprising result. Liquidity is expected to be particularly important on emerging markets, although the opposite is found here. The South African stock market is by far the largest and most developed stock market in Africa, and one of the largest amongst emerging economies. It is easily accessible to foreign investors, with many South African based stocks also having dual-listings on other well-developed markets (such as the NYSE and the LSE). Therefore, amongst emerging economies at the very least, the JSE can be regarded as a liquid stock market. It is surprising then, to find that liquidity is not only not a priced factor, but that it has no effect on generating excess returns whatsoever. Several reasons that may assist in explaining this finding are outlined below.

As outlined in Chapter 1, the South African stock market is defined by a high level of concentration in terms of its constituents. As at the end of July 2011 (and hence the end of the sample period used in this research), in excess of 20% of the FTSE JSE All Share Index was represented by only two mining companies. This was an especially high concentration if one considers that the index consisted of around 165 shares in total. Additionally, the next 30% was represented by only another five companies, meaning that half of the index was represented by only seven companies. This means that, despite the construction of value-weighted portfolios that should, in theory, take account of the market capitalisation of the firms, any excess return generation could only be considered asymmetrically. Due to the small weighting of the other 158 shares, their excess return generation is impeded. Hence, although the portfolios may include a large number of shares, it may in fact be only a very small subsample that is actually generating the alpha returns. And since the stocks in this research are sorted into a considerable number of portfolios according to the intersection of four factors, several of these portfolios did not include one of the larger shares and therefore had diminished alpha generation powers. Therefore the effect of liquidity could not be gauged properly.

The period used for this research (2003 to 2011) included a highly volatile time in financial markets – namely the financial crisis of 2008. Liquidity of stock markets dropped as investors came under pressure. Government attempted to restore investor confidence through their introduction of the 2009 *Framework for South Africa's response to the international economic crisis*. In it, they set out their response to the issues at hand in an effort to strengthen the capacity of the economy to grow, which would stimulate investment and hence restore liquidity. However, the initial crisis was followed by the European debt crisis, which put further strain on the stock market and the liquidity issue that was still not resolved. Therefore, a big portion of the period used for the analysis showed uncharacteristically low levels of liquidity, which, when analysed in conjunction with the earlier bull market, may have distorted the results somewhat. However, as mentioned in Chapter 3, the period chosen was deliberate since it covers all possible cycles of the market and therefore should be representative of long term market behaviour. Hence, the regression analyses should correspond to the average stock performance.

Lastly, it is always important to also consider the robustness of the particular models employed. Several studies have been published that tested various models on the JSE. Reddy and Thomson (2011: 43) tested the empirical validity of the CAPM on the South African stock market. They found that, although the model could be rejected for most twelve-month periods between 2000 and 2009, for all periods combined (so over a longer time horizon) its use could be reasonably justified. Similarly, Basiewicz and Auret (2010: 13) tested the feasibility of the Fama-French three-factor model in explaining returns on the JSE. They found that, although the results they obtained differed from the US, it did provide an adequate means to predict expected returns for stocks on the JSE. Hence, both the standard CAPM and the Fama-French three-factor models are feasible models to employ in testing returns on the JSE, which indicates that the unexpected results are not due to model error.

Hence, results would suggest the existence of some other factor/s that influence excess stock returns on the JSE. Further research is required to investigate this assumption.

CHAPTER 5

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 INTRODUCTION

This paper investigates the effect of liquidity on stock returns on the Johannesburg Stock Exchange (JSE). In particular, it examines whether liquidity is a priced factor that needs to be taken into account explicitly when devising investment strategies. It is analysed in conjunction with the effects of size, value and momentum, all of which are found to be significant to a certain extent in explaining excess stock returns over the period 2003 to 2008. Liquidity, however, is not found to be significant for the same period.

A carefully selected dataset, spanning 2003 to 2011, is used to perform the analysis. It is carefully examined to remove the effects of potential biases. Two size, two value and two momentum measures are first combined to determine the most efficient measure for each effect. Results suggested that the log of the stock's market value best captured the size effect, the earnings yield best captured the value effect and the previous three month's returns best captured the momentum effect. These three measures are subsequently combined with five liquidity proxies: the bid-ask spread first proposed by Amihud (1986: 223), turnover, the price impact measure of Amihud (2002: 31) and two zero return measures proposed by Lesmond *et al.* (1999: 1113). Numerous portfolios are created, based on their intersection of the various effects, after which a regression analysis is performed on each portfolio in turn.

The effect of liquidity on stock returns is especially important in an emerging economy such as that of South Africa. Not only are emerging markets generally regarded as illiquid, but the JSE has another peculiarity that may affect the liquidity levels of its stocks, namely that it is a highly skewed market. The JSE is highly concentrated, dominated by only a couple of mining shares. The biggest index on the JSE, the FTSE/JSE All Share Index (ALSI), consists of around 164 stocks representing around 99% of the total market capitalisation of all tradable ordinary stocks in South Africa. As at July 2011, 20% of the ALSI was represented by only two mining companies, with the next 30% being represented by only another five companies. Hence half of the index was represented by only seven companies. This asymmetry in market constituents can lead to liquidity problems, especially for the remaining 50% of the index which consists of 157 shares. As a result, the effect of liquidity on stock returns should be analysed in detail for this market, to determine if it is as influential a factor as it may appear to be.

5.2 SUMMARY OF MAIN FINDINGS

The analysis is carried out by performing an Ordinary Least Squares (OLS) regression on each portfolio, in turn. First, the shares are sorted into portfolios according to the intersection of the size, value and momentum effects, after which the effect of liquidity is analysed. Four factors are included in the models. The SMB (Small-Minus-Big) size factor and HML (High-Minus-Low) value factor, both originally introduced by Fama and French (1993: 3), as well as a momentum factor GMP (Good-Minus-Poor) are constructed. In addition, in order to take account of the effect of liquidity, a liquidity factor is also included in the models in the form of IMV (Illiquid-Minus-Very liquid).

Similar to the results of previous studies, the presence of size, value and momentum factors was shown to be influential in explaining excess stock returns. Nevertheless, since many of the estimated intercepts still showed statistical significance when the three effects above were included in the model, this suggested that there might be another factor influencing the excess returns on the South African market. In order to determine if liquidity might be this factor, the portfolios were reformed and the models re-estimated, taking account of liquidity. However, the results indicate that it is not a priced factor on the JSE. This result remains robust, irrespective of the type of liquidity measure used.

The strongest effect was found to be the momentum effect. It suggested that the higher the stocks' momentum (i.e. the higher its previous 3 month's returns), the higher the subsequent portfolio returns. Therefore, by including these types of stocks in a portfolio, it can be expected to outperform the market and hence generate excess returns. This is in accordance with the overreaction hypothesis and therefore also indicates that momentum investment strategies may indeed generate positive excess returns. Although the size and value effects did show some significance, no definite pattern emerged as to the direction of the effects. However, when the above mentioned models were expanded by the inclusion of a liquidity factor, no significant difference in results was found. This would indicate that liquidity does not affect excess stock returns and therefore is not an influencing factor. This suggests that it is also not a priced factor on the JSE, unlike size, value and momentum. However, since many of the estimated intercepts remained significant, this suggests that explanatory variables remain omitted from the model.

No single measure of liquidity emerged as superior in gauging its effects on stock returns. While the bid-ask spread, turnover and price impact measures did tend to indicate the presence of liquidity in explaining returns, these effects were very weak and rather insignificant overall. The most insignificant effect was shown by both of both measures of zero returns. Therefore, overall, it was concluded that the presence of liquidity did not affect and explain returns over and above that explained by the size, value and momentum effects. Consequently, liquidity does not appear to be a priced factor on the JSE.

The results were rather surprising, given the nature and time period of the data set in question. As mentioned earlier, this data set incorporated the financial crisis, a highly volatile period that led to immense losses worldwide. Although South Africa was not as badly affected as the US or UK, the effects did not go by unnoticed, with the repercussions being felt in every asset class. In particular, liquidity was found to be a very important factor, with illiquid assets being a large explanatory part of the losses. Since then, research in this area has increased. In particular, emerging markets have always been regarded as particularly illiquid, hence the effects of liquidity would be expected to be rather severe. Therefore the results obtained in this thesis are quite surprising, since the opposite was found to be the case.

5.3 PRIORITIES GOING FORWARD

The effect of liquidity on stock portfolio returns was found to be insignificant. However this might be due to the particular period used, or possibly the types of measures employed. It is therefore important to determine whether these results remain consistent over other periods too. Secondly, the analysis was performed using an Ordinary Least Squares (OLS) regression technique. Perhaps the use of a different modelling technique may provide more insight into the importance of each of the effects. Similarly, since the results indicate that there are other factors influencing returns that have not yet been taken into account in the model, further research is required to discover what these factors may be. Lastly, if liquidity is definitely found to be an insignificant factor, even when extending the analysis as suggested above, it would be of importance to find out why it is not an influencing factor on the JSE.

5.4 FURTHER RESEARCH

Although the time period was deliberately chosen to cover an entire investment cycle, a large part of the 8.5 year period was dominated by the financial crisis and subsequent European Debt crisis. These extreme events may have distorted the results somewhat. Therefore, this analysis should be repeated on a data set that either spans a different time period entirely or, alternatively, spans a longer time period.

It may also be of importance to analyse whether the measures employed in this analysis are indeed suitable as proxies for the respective effects. Although this thesis attempted to determine the most appropriate measures to capture the effects of size, value and momentum, further research may be required. The list of possible measures for each of these effects was by no means exhaustive. Hence it may be of importance to extend this list, thereby verifying if the measures used in this analysis are indeed the most fitting in capturing the effects.

Similarly, the range of liquidity measures employed was in no way complete. The most effective measures, as indicated by previous literature, were included in this analysis. Nevertheless, the analysis should be extended to include other proxies for liquidity since the range of literature on this topic is not very extensive. It is a relatively new area, especially for the South African market, for which the author was not able to find any published studies. This led to the decision to test the original measures, with no transformations applied, so as to determine their effects as is on stock returns. However, the descriptive statistics applied on the original measures indicated that the majority of liquidity proxies exhibited skewness. The bid-ask spread displayed the most normalised distribution, while turnover displayed a positive skewness and the remaining variables (price impact, as well as both zeros measures) displayed negative skewness. Hence the analysis should be extended to include new liquidity proxies, as well as the transformed versions of the four proxies that exhibited skewness.

The use of OLS regressions has often been criticised as too simplistic. In particular, the effects of autocorrelation on returns may lead to inefficiency the results. Although a Newey-West estimator was applied in an attempt to take this into account, a more sophisticated modelling technique may be required.

Lastly, the results indicate that there are other factors influencing returns that have not yet been taken into account in the model. Further research is required to discover what these factors may be.

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APPENDIX A
DATA ANALYSIS

This appendix refers to Chapter 3: Research Methodology. It provides an overview of the shares and variables used in this thesis, as well as any transformations performed on the variables, where applicable. Detailed illustrations of the descriptive statistics are also provided.

A.1 DELISTED SHARES AND THOSE WITH IMCOMPLETE DATA

The table lists those shares that have been delisted during the period January 2003 to May 2011 or for which data until the end of the period under review is not available. Inclusion of these shares eliminates the potential effect(s) of survivorship bias.

Table A.1 Delisted shares and those with incomplete data

The table reports those shares that have been delisted during the period January 2003 to May 2011 or for which data until the end of the period under review is not available.

Share code	Firm name	Last date of available data	Share code	Firm name	Last date of available data
AHV	African Harvest	2003/07	GNN	Grindrod	2004/02
AFI	African Life Assurance	2006/02	GNK	Grintek	2005/05
AOD	African Rainbow Minerals	2003/09	HCI	Hosken Consolidated Investments	2011/04
AFL	Aflease Gold and Uranium Resources	2005/12	ISC	Iscor	2011/04
AGI	AG Industries	2010/11	JCD	JCI	2005/08
ABI	Amalgamated Beverage Industries	2004/12	JNC	Johnnic Holdings	2008/09
AMB	AMB Holdings	2003/10	MPL	Metboard Properties	2006/08
AVG	Avgold	2004/05	MTC	Metro Cash & Carry	2004/11
AVS	Avis Southern Africa	2004/03	MEL	Mettle	2003/06
APL	Applied Technology Holdings	2004/06	NWL	Nu-World Holdings	2011/04
BJM	Barnard Jacobs Mellot Holdings	2011/01	PEP	Pepkor	2004/03
BDS	Bridgestone Firestone Maxiprest	2005/09	RNG	Randgold & Exploration	2011/04
CPT	Capital Alliance	2005/04	RBV	Reserve Holdings	2004/12
CHE	Chemical Services	2003/12	SGG	Sage Group	2005/09
CRH	Coronation Holdings	2003/08	SIS	Sun International South Africa	2004/08
CPA	Corpcapital	2005/07	TDH	Tradehold	2011/04
DLV	Dorbyl	2011/04	USV	United Service Technologies	2004/12
ENR	Energy Africa	2004/07	VNF	Venfin	2006/04
GMB	Glenrand M.I.B.	2011/04	WET	Wetherlys Investment Holdings	2003/10

A.2 VARIABLE TRANSFORMATIONS

The table shows those variables that were transformed through the use of a natural logarithmic transformation. It was applied to those variables for which it would make statistical sense to do so, i.e. to remove the effect of significant positive skewness.

Table A.2 Variable transformations

The table reports those variables that were transformed through the use of a natural logarithmic transformation.

Code before transformation	**Variable**	**Code after transformation**
mv	Market value	mvlog
bvtm	Book value to market	bvtmlog

A.3 CORRELATION MATRIX, HISTROGRAMS AND DESCRIPTIVE STATISTICS OF MONTHLY LIQUDIDITY PROXIES

The correlation matrix of the liquidity proxies considered is reported first. Most of the variables show low correlation coefficients with each other. This would indicate that the different proxies capture different effects. The two zeros measures, however, are highly correlated with each other. This is not surprising since they are directly linked by definition.

Table A.3 Correlation matrix of liquidity proxies

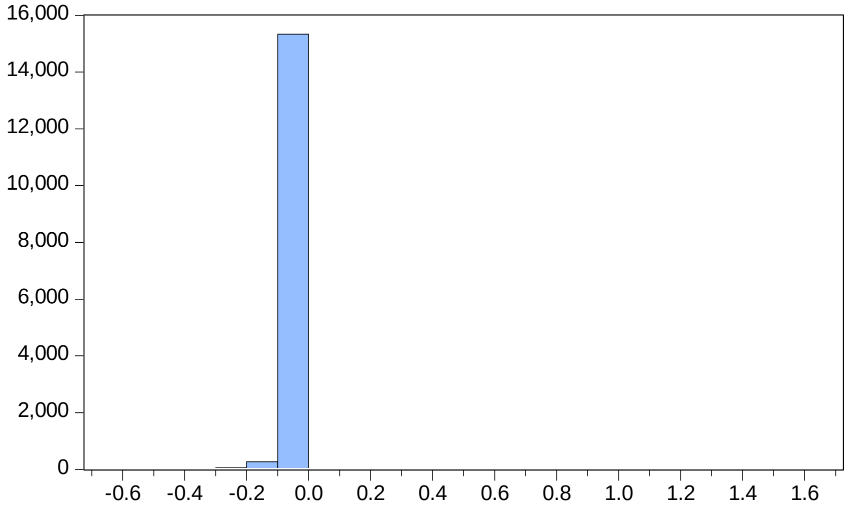
The table reports the correlation matrix of all five liquidity proxies for the ALSI over the period January 2003 to May 2011.

	BID_ASK_SPREAD	TURNOVER	PRICE_IMPACT	ZEROS_1	ZEROS_2
BID_ASK_SPREAD	1.00	0.40	0.04	0.55	0.44
TURNOVER	0.40	1.00	0.07	0.43	0.42
PRICE_IMPACT	0.04	0.07	1.00	0.02	0.01
ZEROS_1	0.55	0.43	0.02	1.00	0.90
ZEROS_2	0.44	0.42	0.01	0.90	1.00

Histograms of all liquidity proxies are reported next. Visual inspection of the histograms shows that the majority of proxies exhibit skewness. The bid-ask spread displays the most normalised distribution, although some outliers do seem to be present. Turnover displays a positive skewness, whilst the remaining variables (price impact, as well as both zeros measures) display a negative skewness. This would suggest that a transformation is required for all four variables that exhibit skewness, whilst the bid-ask spread measure needs to be analysed for the possibility of outliers.

Figure A.3.1 Histogram of the bid-ask spread measure

This figure depicts the histogram of the bid-ask spread measure for the ALSI over the period January 2003 to May 2011.

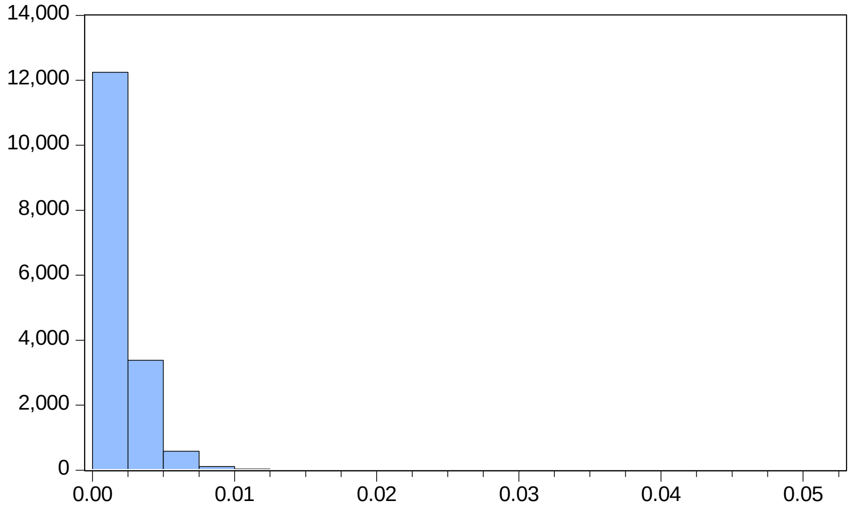


Series: BID_ASK_SPREAD
Sample 2003M01 2011M05
Observations 15718

Mean	-0.021338
Median	-0.012397
Maximum	1.626505
Minimum	-0.653642
Std. Dev.	0.036935
Skewness	3.561282
Kurtosis	396.9758
Jarque-Bera	1.02e+08
Probability	0.000000

Figure A.3.2 Histogram of the turnover measure

This figure depicts the histogram of the turnover measure for the ALSI over the period January 2003 to May 2011.



Series: TURNOVER
Sample 2003M01 2011M05
Observations 16390

Mean	0.001844
Median	0.001423
Maximum	0.050133
Minimum	0.000000
Std. Dev.	0.001833
Skewness	5.396380
Kurtosis	87.30814
Jarque-Bera	4933627.
Probability	0.000000

Figure A.3.3 Histogram of the price impact measure

This figure depicts the histogram of the price impact measure for the ALSI over the period January 2003 to May 2011.

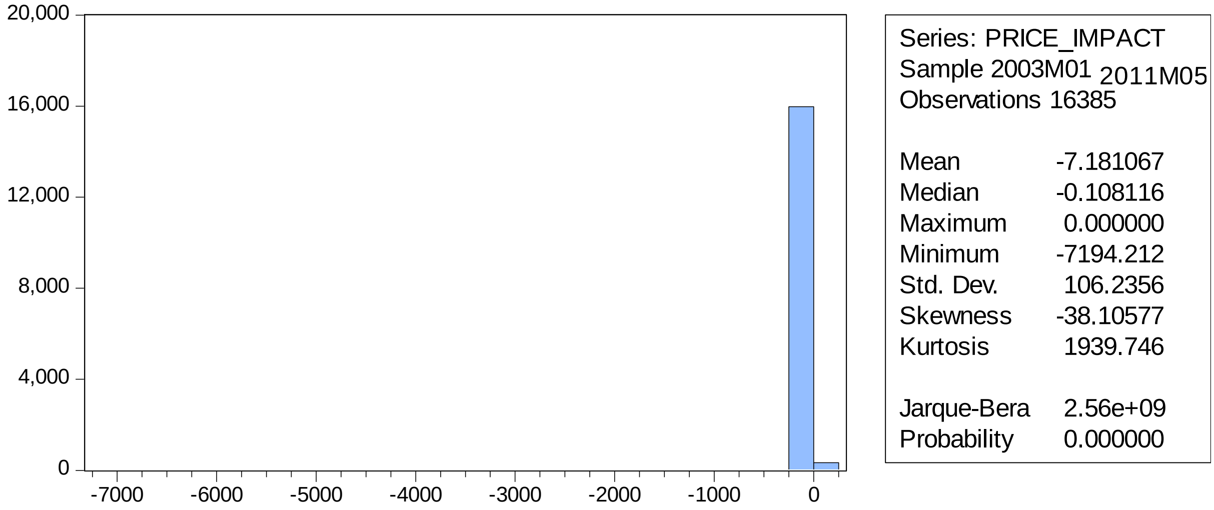


Figure A.3.4 Histogram of the zeros1 measure

This figure depicts the histogram of the zeros1 measure for the ALSI over the period January 2003 to May 2011.

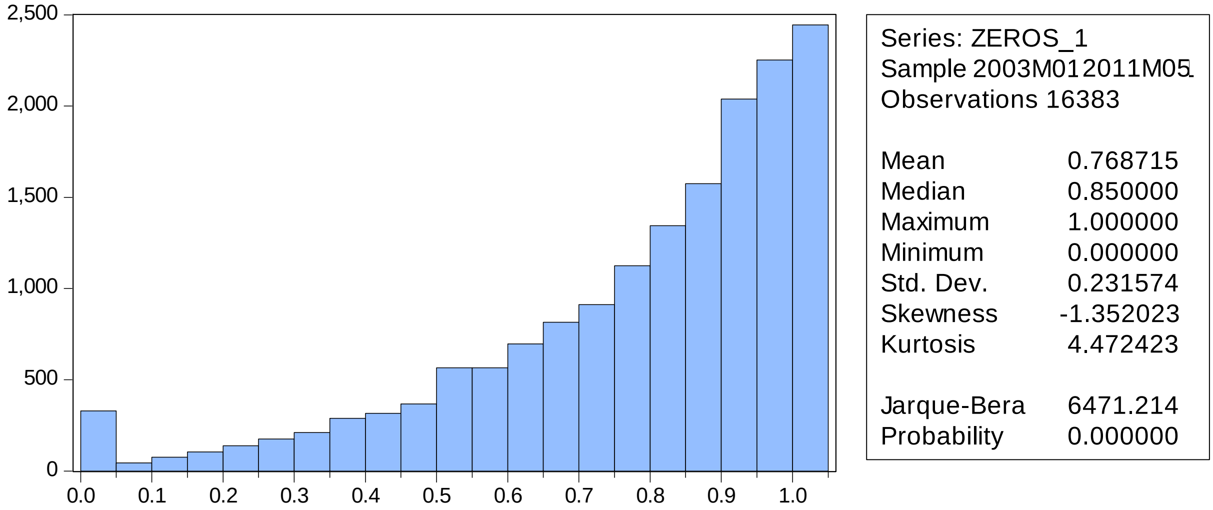
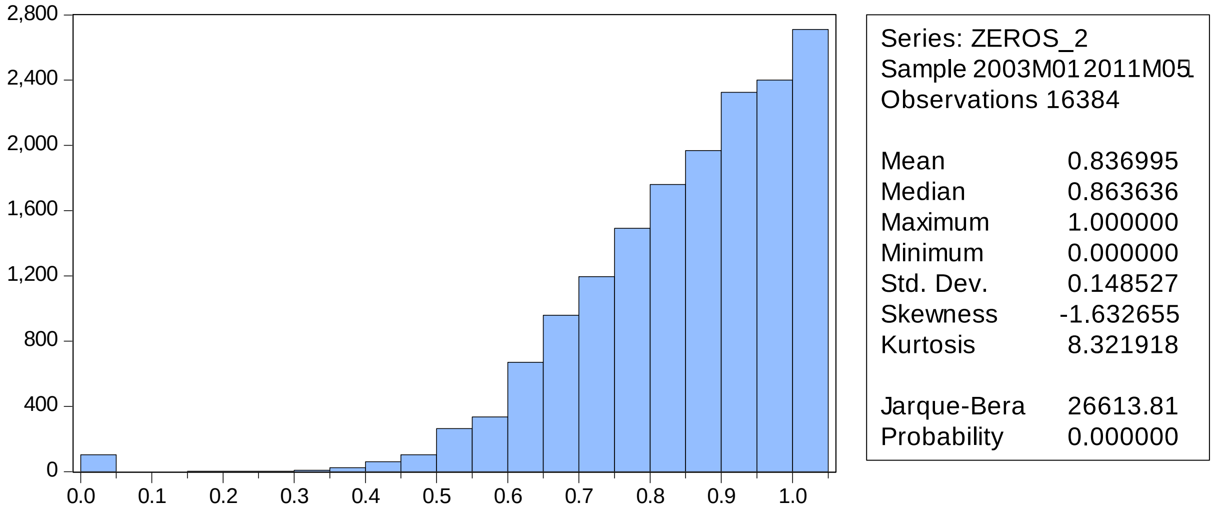


Figure A.3.5 Histogram of the zeros2 measure

This figure depicts the histogram of the zeros2 measure for the ALSI over the period January 2003 to May 2011.



A.4 CORRELATION MATRIX, HISTOGRAMS AND DESCRIPTIVE STATISTICS OF MONTHLY SIZE, VALUE AND MOMENTUM VARIABLES

The correlation matrix of the list of size, value and momentum variables considered is reported first. None of the variables shows a particularly high correlation coefficient with each other. This suggests that similar effects are not captured by different variables resulting in inaccurate conclusions.

Table A.4 Correlation matrix of size, value and momentum variables

The table reports the correlation matrix of the size, value and momentum variables.

	MVLOG	EPS	EY	BVTMLOG	MOM3	MOM12
MVLOG	1.00	0.46	-0.35	-0.38	0.01	0.02
EPS	0.46	1.00	0.00	-0.14	0.02	0.08
EY	-0.35	0.00	1.00	0.47	-0.13	-0.10
BVTMLOG	-0.38	-0.14	0.47	1.00	-0.10	-0.21
MOM3	0.01	0.02	-0.13	-0.10	1.00	0.50
MOM12	0.02	0.08	-0.10	-0.21	0.50	1.00

Histograms of all size, value and momentum variables after the winzorising and transformation (where applicable) process are reported here. Visual inspection of the histograms shows that the winzorising process eliminated extreme outliers, while the natural logarithmic transformation process (where applicable) resulted in more normally distributed variables. Positively skew distributions are evident for those variables that were not transformed.

Figure A.4.1 Histogram of the log of the share's market value size measure

This figure depicts the histogram of the log of the share's market value measure for the ALSI over the period January 2003 to May 2011. It is the first size measure being analysed.

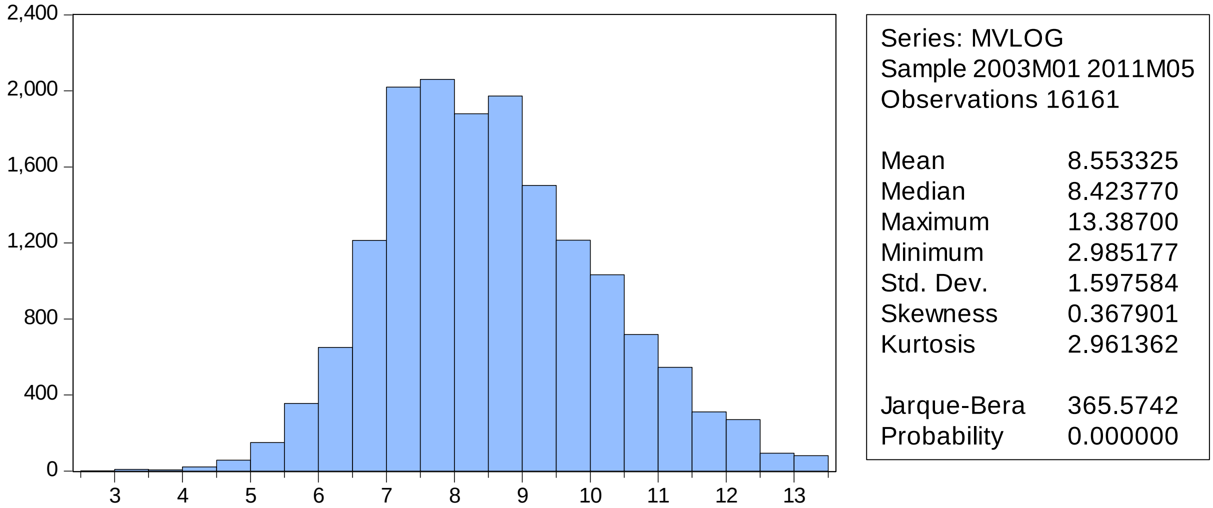


Figure A.4.2 Histogram of the earnings per share size measure

This figure depicts the histogram of the earnings per share measure for the ALSI over the period January 2003 to May 2011. It is the second size measure being analysed.

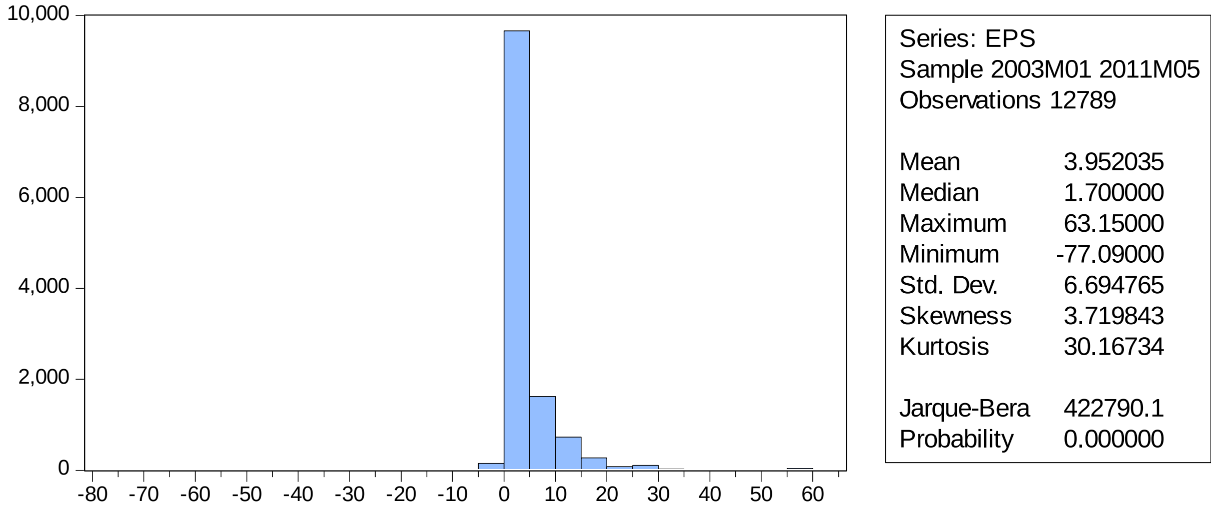
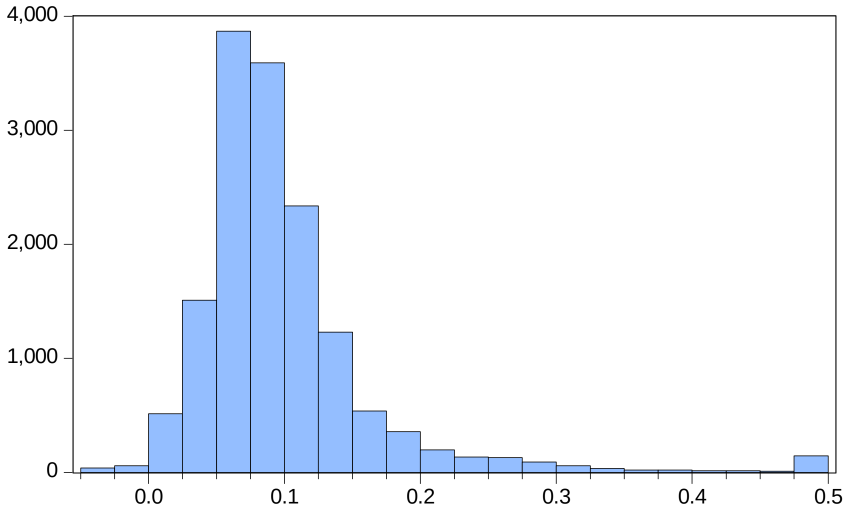


Figure A.4.3 Histogram of the earnings yield value measure

This figure depicts the histogram of the earnings yield measure for the ALSI over the period January 2003 to May 2011. It is the first value measure being analysed.

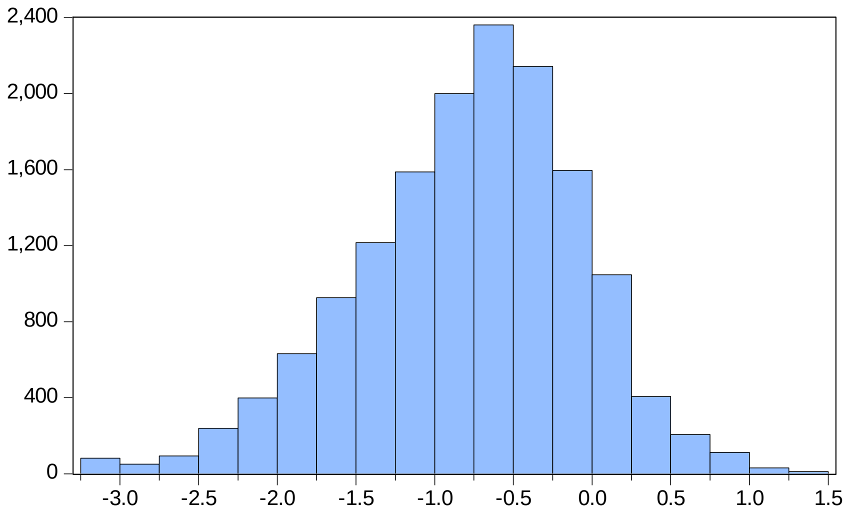


Series: EY
Sample 2003M01 2011M05
Observations 14907

Mean	0.098252
Median	0.084000
Maximum	0.479000
Minimum	-0.050000
Std. Dev.	0.067397
Skewness	2.764831
Kurtosis	14.31442
Jarque-Bera	98506.29
Probability	0.000000

Figure A.4.4 Histogram of the log of the book value to market value measure

This figure depicts the histogram of the log of the book value to market measure for the ALSI over the period January 2003 to May 2011. It is the second value measure being analysed.

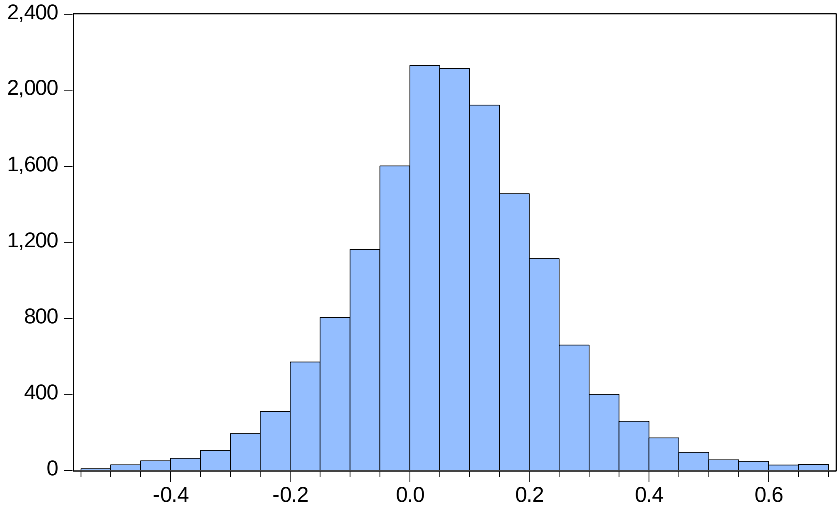


Series: BVTMLOG
Sample 2003M01 2011M05
Observations 15140

Mean	-0.785217
Median	-0.708036
Maximum	1.386294
Minimum	-3.210000
Std. Dev.	0.712659
Skewness	-0.426552
Kurtosis	3.340462
Jarque-Bera	532.2348
Probability	0.000000

Figure A.4.5 Histogram of the previous 3-month's returns momentum measure

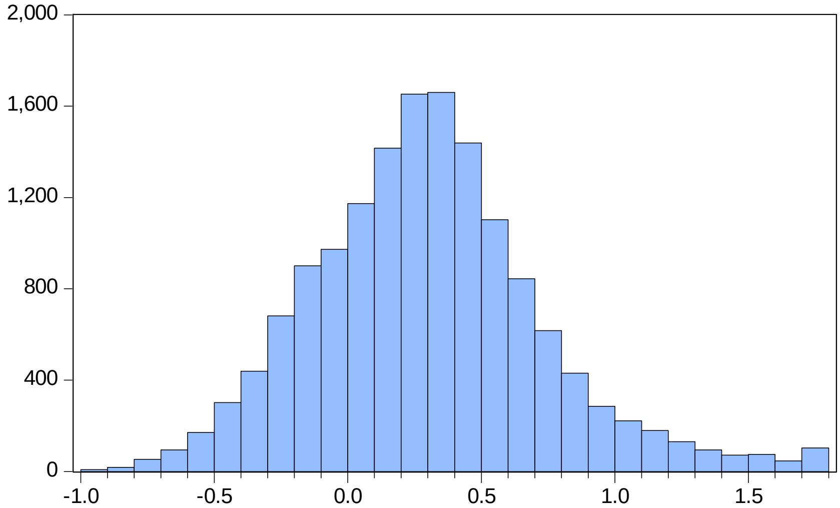
This figure depicts the histogram of the previous 3-month's returns measure for the ALSI over the period January 2003 to May 2011. It is the first momentum measure being analysed.



Series: MOM3	
Sample 2003M01 2011M05	
Observations 15381	
Mean	0.066773
Median	0.066099
Maximum	0.665000
Minimum	-0.550000
Std. Dev.	0.164429
Skewness	0.087342
Kurtosis	3.909739
Jarque-Bera	549.9599
Probability	0.000000

Figure A.4.6 Histogram of the previous 12-month's returns momentum measure

This figure depicts the histogram of the previous 12-month's returns measure for the ALSI over the period January 2003 to May 2011. It is the second momentum measure being analysed.



Series: MOM12	
Sample 2003M01 2011M05	
Observations 15182	
Mean	0.296975
Median	0.283771
Maximum	1.764000
Minimum	-0.933721
Std. Dev.	0.432451
Skewness	0.487658
Kurtosis	3.790296
Jarque-Bera	996.8293
Probability	0.000000

APPENDIX B
NEWEY-WEST METHOD

Newey and West (1987, 1994) developed an autocorrelation-consistent as well as heteroskedasticity-consistent estimator of the variance-covariance matrix of the Ordinary Least Squares (OLS) estimator. This is especially useful since many estimators are based on sample averages. However, unless the underlying series is known to be i.i.d., an estimator of the variance of the sample series needs to be determined that takes account of serial correlation. The Newey-West estimator is one of the most popular such estimators, especially in the field of econometrics.

B.1 REASONING BEHIND THE NEWEY-WEST ESTIMATORS

Consider the following equation

$$\boldsymbol{Y} = \boldsymbol{X}\beta + \boldsymbol{U}$$

where $\boldsymbol{Y}$ is the N×1 dependent variable vector;

$\boldsymbol{X}$ is the N×(k+1) independent variable matrix;

β is a (k+1)×1 vector of coefficients; and

$\boldsymbol{U}$ is an N×1 vector of error terms.

The Newey-West technique is based on the knowledge that in the presence of heteroskedasticity and/or autocorrelation the error covariance matrix $\boldsymbol{UU'}$ cannot be written in the form $\sigma^2\boldsymbol{I}$, where σ^2 is a constant error variance and $\boldsymbol{I}$ is an N×N identity matrix. Instead, the variance-covariance matrix of coefficients is written in the form $\boldsymbol{X'UU'X} = \boldsymbol{X'}\sigma^2\boldsymbol{IX}$, where both matrices are (k+1)×(k+1).[6] The coefficient estimates obtained using this method are identical to those obtained using OLS.

Newey and West (1987: 703) therefore provided a method for calculating consistent estimators that resulted in positive semidefinite covariance matrices. The resulting standard errors are called the HAC, or heteroskedasticity and autocorrelation consistent, standard errors. In effect, this was done by filling the diagonal of $\boldsymbol{G} = \boldsymbol{UU'}$ with the squares of the residuals and then estimating the first couple of elements next to the diagonal with the products of the residuals. Lastly, the off-diagonal elements were shrunk towards zero with the use of a shrinking factor that increased with the distance from the diagonal.

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[6] Refer to Baker (2007: 1) for further information.

B.2 THEORY BEHIND THE NEWEY-WEST STANDARD ERRORS

Consider the model

$$y_t = X_t'\theta_0 + u_t$$

where y_t and u_t are scalars and X_t and θ_0 are vectors. Assume a r×1 vector of instruments Z_t is available, where $EZ_tu_t = 0$ and Z_tu_t has serial correlation and heteroskedasticity of unknown form.

Hence the following needs to be estimated (see Hansen (1982: 1029)):

$$S = \sum_{j=-\infty}^{\infty} EZ_tu_tZ_{t-j}'u_{t-j} \equiv \sum_{j=-\infty}^{\infty} \Omega_j = \Omega_0 + \sum_{j=0}^{\infty}(\Omega_j + \Omega_j')$$

Let T be the sample size; and $\hat{\theta}$ be an estimate such that $T^{1/2}(\theta - \theta_0)$ is asymptotically normal. In addition, let $\hat{u}_t = y_t - X_t\hat{\theta}$ and define the j[th] sample autocovariance of $Z_t\hat{u}_t$ as $\widehat{\Omega}_t = T^{-1}\sum_{t=j+1}^{T} Z_t\hat{u}_tZ_{t-j}\hat{u}_{t-j}$ for $j \geq 0$, $\widehat{\Omega}_j = \widehat{\Omega}_{-j}$ for $j < 0$. The estimators of S may be written as the weighted sums of the $\widehat{\Omega}_j$'s.

For the majority of weighting schemes the weights are zero for all $j \geq m+1$ for some bandwidth $m + 1 \ll T$. In this case, an estimate $\bar{S}$ of S is constructed as follows:

$$\bar{S} = \widehat{\Omega}_0 + \sum_{j=1}^{m} w(j,m)\left(\widehat{\Omega}_j + \widehat{\Omega}_j'\right)$$

where $w(\cdot)$ is a kernel representing the weights. Newey and West chose to use the Bartlett kernel[7], in which case the weights became

$$w(j,m) = 1 - \frac{j}{m+1}$$

However, the choice of m is not arbitrary. To determine it, let the weight vector be

$$w = (0\ \ 1\ \ 1\ \ \ldots\ \ 1)'\ .$$

In addition, let

$$\hat{h}_t = Z_t\hat{u}_t\ ,\quad \hat{A} = \sum_{t=2}^{T}\hat{h}_t\hat{h}_t'\left(\sum_{t=2}^{T}\hat{h}_{t-1}\hat{h}_{t-1}'\right)^{-1}\ ,\quad \hat{h}_t' \equiv \hat{h}_t - \hat{A}\hat{h}_{t-1}\ ,$$

---

[7] In fact, Newey and West (1994: 631) showed that the choice of kernel did not matter. They compared three kernels, namely the Barlett, Parzen and QS kernels, and found that the results were similar.

$$n = \left[4(T/100)^{2/9}\right] \ ,$$

$$\hat{\sigma}_j = (T-1)^{-1} \sum_{t=j+2}^{T} \left\{ \left(w'\hat{h}_t^+\right)\left(w'\hat{h}_{t-j}^+\right) \right\} \ , \ j = 0, \dots, n \ ,$$

$$\hat{s}^{(1)} = 2\sum_{j=1}^{n} j\hat{\sigma}_j \quad , \quad \hat{s}^{(0)} = \hat{\sigma}_0 + 2\sum_{j=1}^{n} \hat{\sigma}_j \quad , \quad \hat{\gamma} = 1.1447\left(\left\{\hat{s}^{(1)}/\hat{s}^{(0)}\right\}^2\right)^{1/3} \ .$$

where, as above, $\hat{u}_t$ is the scalar regression residual, Z_t is the r×1 vector of instruments and T is the sample size.

In the above equations, n is called the *lag selection parameter* and is used to estimate $\hat{s}^{(0)}$ and $\hat{s}^{(1)}$, which in turn are used to establish the bandwidth m. Newey and West recommended initially setting $m = \left[\hat{\gamma}T^{1/3}\right]$ and then increasing or decreasing n to examine its effect on m and hence the sensitivity of the results. Refer to Newey and West (1994: 631) for further details and discussions of this method.

Previous studies have found a lag parameter of 6 to be the most effective for the type of research conducted in this thesis.

APPENDIX C
REGRESSION RESULTS

C.1 INTRODUCTION

This appendix refers to Chapter 4: Empirical Findings. It provides detailed results of all regressions performed.

C.2 REGRESSION RESULTS FOR THE STANDARD CAPM

A standard CAPM model was run on portfolios set up according to the various size, value and momentum variables according to equation 3.5:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + \varepsilon_{jt}$$

All possible combinations of the two value variables (log of book value to market and earnings yield), two size variables (log of the market value and earnings per share) and two momentum variables (previous 3- and 12-month's returns) were applied to set up the different portfolios. The results of the regressions are presented below.

C.2.1 EY, MVLOG, MOM3

Table C.2.1 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.249 (-1.651)	0.869 (6.487)*	0.3068	0.2993	2.6838	-0.629 (-0.676)	0.872 (6.918)*	0.3692	0.3624	2.4514
	Small (S)	-4.788 (-3.640)*	0.564 (4.053)*	0.1398	0.1305	1.9599	0.278 (0.319)	1.019 (9.737)*	0.3564	0.3494	2.3355
Medium (M)	Big (B)	-2.585 (-3.015)*	0.679 (5.188)*	0.2723	0.2644	2.4516	-0.262 (-0.218)	0.999 (4.558)*	0.4274	0.4212	2.6033
	Small (S)	11.417 (0.825)	2.010 (1.477)	0.0252	0.0146	2.3212	-1.339 (-1.772)	0.815 (5.115)*	0.3685	0.3616	2.0135
High (H)	Big (B)	-2.536 (-2.653)*	0.705 (4.550)*	0.2724	0.2645	2.1335	-2.047 (-2.421)**	0.786 (7.582)*	0.3855	0.3788	2.1112
	Small (S)	-3.977 (-3.849)*	0.617 (3.661)*	0.2120	0.2034	1.8602	12.577 (1.043)	2.088 (1.768)	0.0340	0.0235	2.3581

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.2 EY, MVLOG, MOM12

Table C.2.2 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-0.693 (-0.782)	0.935 (8.068)*	0.3251	0.3177	2.6942	-1.172 (-1.430)	0.812 (5.731)*	0.3510	0.3440	2.7451
	Small (S)	-1.859 (-1.601)	0.829 (5.942)*	0.3032	0.2956	1.8630	-3.954 (-3.600)*	0.469 (3.422)*	0.1320	0.1226	2.1819
Medium (M)	Big (B)	-0.851 (-1.192)	0.830 (8.792)*	0.4202	0.4139	2.6844	-0.134 (-0.103)	1.061 (4.103)*	0.3707	0.3639	2.2191
	Small (S)	-3.932 (-5.382)*	0.555 (6.451)*	0.2521	0.2440	2.3693	13.446 (0.827)	2.186 (1.339)	0.0226	0.0120	2.2850
High (H)	Big (B)	-3.364 (-3.421)*	0.652 (4.473)*	0.2805	0.2727	2.0055	1.231 (0.874)	1.229 (5.888)*	0.4316	0.4254	2.1086
	Small (S)	-2.879 (-2.985)*	0.707 (5.365)*	0.2815	0.2737	1.9202	6.317 (0.668)	1.372 (1.443)	0.0235	0.0129	2.4039

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.3 EY, EPS, MOM3

Table C.2.3 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.496 (-1.705)	0.939 (8.513)*	0.3351	0.3279	2.5194	-0.285 (-0.280)	0.861 (6.020)*	0.3149	0.3075	2.3088
	Small (S)	-4.295 (-2.864)*	0.490 (4.059)*	0.0598	0.0496	2.0741	-3.104 (-2.591)**	0.574 (3.271)*	0.1257	0.1162	2.2557
Medium (M)	Big (B)	-2.952 (-3.489)*	0.628 (5.522)*	0.2477	0.2395	2.4286	0.694 (0.506)	0.999 (4.436)*	0.3797	0.3730	2.4318
	Small (S)	-1.163 (-1.470)	0.793 (5.870)*	0.3131	0.3057	2.3017	0.855 (0.684)	1.334 (6.031)*	0.4361	0.4300	1.9583
High (H)	Big (B)	-2.730 (-2.531)**	0.653 (3.693)*	0.2193	0.2109	2.1173	-0.942 (-1.358)	0.784 (9.666)*	0.4312	0.4251	2.2790
	Small (S)	-3.536 (-4.272)*	0.686 (4.689)*	0.2791	0.2713	1.9564	12.555 (1.015)	2.310 (1.937)	0.0390	0.0286	2.3802

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.4 EY, EPS, MOM12

Table C.2.4 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\bar{R}^2$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\bar{R}^2$	Durbin-Watson	α_j	β_{jm}	R^2	$\bar{R}^2$	Durbin-Watson
Low (L)	Big (B)	-1.370 (-1.648)	0.963 (8.505)*	0.3500	0.3429	2.4300	-0.600 (-0.656)	0.844 (6.573)*	0.3231	0.3158	2.4286
	Small (S)	-2.674 (-2.093)	0.645 (4.525)*	0.1487	0.1394	2.4811	-1.282 (-0.927)**	0.978 (3.556)*	0.2928	0.2851	2.2318
Medium (M)	Big (B)	-0.701 (-0.897)	0.830 (7.445)*	0.4169	0.4105	2.6241	-0.144 (-0.107)	1.066 (4.149)*	0.3696	0.3627	2.2211
	Small (S)	-2.832 (-3.695)*	0.743 (9.055)*	0.3153	0.3079	2.4823	-3.420 (-3.138)*	0.563 (3.177)*	0.2289	0.2205	2.1147
High (H)	Big (B)	-2.751 (-2.916)*	0.614 (3.781)*	0.2044	0.1958	2.1852	0.985 (0.620)	1.125 (4.470)*	0.3793	0.3725	2.0258
	Small (S)	-3.527 (-4.190)*	0.725 (5.899)*	0.2276	0.2192	1.8513	7.089 (0.611)	1.479 (1.289)	0.0193	0.0087	2.3535

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.5 BVTMLOG, MVLOG, MOM3

Table C.2.5 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\bar{R}^2$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\bar{R}^2$	Durbin-Watson	α_j	β_{jm}	R^2	$\bar{R}^2$	Durbin-Watson
Low (L)	Big (B)	-2.152 (-2.845)*	0.813 (12.231)*	0.3317	0.3244	2.4170	-1.042 (-0.962)	0.827 (4.895)*	0.3236	0.3163	2.3910
	Small (S)	-6.581 (-3.648)*	0.395 (2.277)**	0.0463	0.0360	2.1378	-1.243 (-1.666)	0.748 (5.941)*	0.2526	0.2445	2.2392
Medium (M)	Big (B)	-2.725 (-3.722)*	0.690 (7.089)*	0.3132	0.3057	2.3353	1.257 (2.149)**	1.137 (12.376)*	0.5156	0.5103	2.3982
	Small (S)	24.593 (0.914)	3.414 (1.291)	0.0219	0.0113	2.2044	-1.683 (-2.121)**	0.737 (7.130)*	0.3616	0.3546	1.7896
High (H)	Big (B)	-1.069 (-1.214)*	1.039 (5.675)*	0.3102	0.3027	2.1499	-1.598 (-2.571)**	0.750 (6.122)*	0.2782	0.2704	2.3673
	Small (S)	-3.669 (-4.193)	0.560 (4.450)*	0.2601	0.2521	2.0135	8.482 (1.049)	1.941 (2.406)**	0.0543	0.0440	2.4628

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.6 BVTMLOG, MVLOG, MOM12

Table C.2.6 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.758 (-1.793)	0.798 (7.940)*	0.2746	0.2667	2.5069	-1.174 (-1.581)	0.884 (7.016)*	0.4479	0.4419	2.4976
	Small (S)	-5.022 (-5.330)*	0.533 (6.214)*	0.1327	0.1232	1.9562	-2.909 (-2.855)*	0.557 (3.682)*	0.1640	0.1549	2.0215
Medium (M)	Big (B)	-1.058 (-1.197)	0.930 (9.208)*	0.4104	0.4040	2.1168	-0.232 (-0.238)	0.997 (5.569)*	0.3619	0.3550	2.1988
	Small (S)	-2.519 (-2.846)*	0.787 (7.726)*	0.3235	0.3162	2.1565	14.662 (0.780)	2.283 (1.223)	0.0193	0.0087	2.2460
High (H)	Big (B)	-1.017 (-1.533)	0.864 (6.523)*	0.3084	0.3008	2.0285	-2.305 (-2.418)**	0.766 (5.797)*	0.2476	0.2394	2.5132
	Small (S)	-2.687 (-2.934)*	0.736 (4.759)*	0.3197	0.3123	1.9210	2.856 (0.447)	1.162 (1.721)	0.0322	0.0216	2.4851

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.7 BVTMLOG, EPS, MOM3

Table C.2.7 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-2.442 (-3.671)*	0.757 (9.588)*	0.3023	0.2947	2.3468	-0.832 (-0.730)	0.877 (5.867)*	0.3354	0.3281	2.2637
	Small (S)	-2.519 (-3.326)*	0.707 (7.167)*	0.2656	0.2577	2.1567	-1.070 (-1.482)	0.796 (4.246)*	0.1980	0.1893	2.4029
Medium (M)	Big (B)	-2.847 (-3.319)*	0.648 (5.158)*	0.2543	0.2462	2.3892	2.360 (1.538)	1.094 (3.196)*	0.1997	0.1910	2.2588
	Small (S)	-4.678 (-2.897)*	0.509 (2.567)*	0.0462	0.0359	1.9705	-0.747 (-0.505)	0.898 (4.708)*	0.3167	0.3092	2.1572
High (H)	Big (B)	-0.890 (-1.142)	0.877 (5.629)*	0.2741	0.2662	2.2661	-0.564 (-0.725)	0.798 (6.259)*	0.2674	0.2595	2.1767
	Small (S)	-4.179 (-4.582)*	0.461 (3.305)**	0.1769	0.1679	1.6343	4.610 (0.939)	1.370 (2.928)*	0.0557	0.0455	2.5526

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.2.8 BVTMLOG, EPS, MOM12

Table C.2.8 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-0.512 (-0.564)	0.929 (10.594)*	0.3521	0.3451	2.4210	-1.137 (-1.308)	0.856 (7.128)*	0.3992	0.3927	2.2572
	Small (S)	-4.337 (-3.469)*	0.459 (3.356)*	0.0806	0.0706	2.5979	2.076 (1.025)	1.090 (1.897)	0.0841	0.0741	1.9717
Medium (M)	Big (B)	-1.797 (-1.885)	0.796 (6.293)*	0.3037	0.2961	2.1556	-0.944 (-0.564)	0.719 (1.982)	0.0850	0.0751	2.2095
	Small (S)	-1.886 (-1.636)	0.834 (5.801)*	0.3361	0.3289	2.3687	-1.313 (-1.199)	0.965 (4.421)*	0.2987	0.2910	2.1126
High (H)	Big (B)	-1.780 (-1.953)	0.804 (6.688)*	0.4258	0.4195	1.9880	-1.381 (-1.743)	0.764 (5.361)*	0.2538	0.2457	2.2994
	Small (S)	-2.677 (-2.201)**	0.641 (4.261)*	0.1950	0.1862	2.1703	2.607 (0.351)	1.059 (1.417)	0.0207	0.0101	2.4684

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3 REGRESSION RESULTS FOR THE MOMENTUM-AUGMENTED FAMA-FRENCH MODEL

A momentum-augmented Fama-French model was run on portfolios set up according to the various size, value and momentum variables according to equation 3.6:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + s_{jSMB} SMB_t + h_{jHML} HML_t + g_{jGMP} GMP_t + \eta_{jt}$$

The results for the different portfolios are presented below.

C.3.1 EY, MVLOG, MOM3

Table C.3.1 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	0.313 (0.268)	1.014 (5.540)*	-0.073 (-0.492)	-0.002 (-0.013)	-0.620 (-2.827)*	0.3768	0.3488	2.6469	-1.342 (-1.733)	0.813 (7.724)*	-0.195 (-1.519)	0.249 (1.470)	0.404 (2.385)**	0.4487	0.4239	2.5136
	Small (S)	-2.510 (-3.090)*	0.761 (6.653)*	0.296 (2.125)**	-0.506 (-2.539)**	-1.035 (-4.950)*	0.4430	0.4180	2.2729	-1.264 (-1.276)	0.857 (5.728)*	0.567 (4.215)*	-0.752 (-4.252)*	0.625 (2.543)**	0.5236	0.5022	2.0503
Medium (M)	Big (B)	-1.007 (-1.600)	0.832 (9.239)*	-0.244 (-3.839)*	0.272 (3.174)*	-0.650 (-4.634)*	0.3919	0.3646	2.5331	-0.978 (-0.849)	0.937 (4.836)*	-0.111 (-1.082)	0.159 (1.118)	0.359 (2.278)**	0.4654	0.4414	2.6849
	Small (S)	0.451 (0.257)	1.009 (3.490)*	2.253 (9.759)*	1.131 (3.776)*	-0.386 (-1.422)	0.9811	0.9802	2.3829	-1.429 (-1.348)	0.806 (4.011)*	0.026 (0.299)	-0.006 (-0.054)	0.002 (0.006)	0.3727	0.3445	2.0225
High (H)	Big (B)	-1.102 (-1.279)	0.849 (6.807)*	-0.352 (-4.137)*	0.435 (3.740)*	-0.580 (-2.848)*	0.4019	0.3750	2.1580	-2.168 (-2.973)*	0.792 (7.692)*	-0.468 (-5.269)*	0.654 (5.280)*	0.123 (0.798)	0.5825	0.5637	2.1786
	Small (S)	-2.430 (-2.930)*	0.772 (5.212)*	-0.323 (-2.697)*	0.437 (2.872)*	-0.693 (-2.640)*	0.3834	0.3557	2.0523	0.897 (0.586)	1.032 (3.984)*	1.738 (8.162)*	1.462 (5.311)*	0.524 (1.446)	0.9779	0.9769	2.5165

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.2 EY, MVLOG, MOM12

Table C.3.2 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-0.581 (-0.776)	0.947 (9.051)*	-0.011 (-0.079)	-0.106 (-0.659)	0.031 (0.233)	0.3377	0.3080	2.7105	-2.475 (-3.504)*	0.665 (6.363)*	-0.441 (-4.465)*	-0.208 (-2.131)**	0.545 (4.968)*	0.5010	0.4785	2.7073
	Small (S)	-0.438 (-0.558)	1.020 (12.317)*	0.576 (5.256)*	-0.658 (-3.761)*	-0.227 (-1.902)	0.5280	0.5068	2.0751	-4.164 (-4.150)*	0.478 (3.352)*	0.110 (0.958)	-0.688 (-2.175)**	0.314 (1.412)	0.2847	0.2525	2.0651
Medium (M)	Big (B)	-1.233 (-1.651)	0.781 (9.145)*	-0.152 (-1.293)	0.095 (0.672)	0.098 (0.602)	0.4364	0.4110	2.5396	-2.386 (-2.521)	0.804 (5.841)*	-0.749 (-4.476)*	-0.176 (-0.827)	0.852 (3.092)*	0.6039	0.5861	1.9802
	Small (S)	-3.398 (-4.087)*	0.613 (4.892)*	0.175 (1.619)	0.118 (0.790)	-0.236 (-2.470)**	0.2935	0.2618	2.5303	1.264 (0.835)	1.235 (7.059)*	1.896 (9.903)*	0.502 (2.570)**	1.479 (7.002)*	0.9867	0.9861	2.1526
High (H)	Big (B)	-3.081 (-3.740)*	0.659 (5.566)*	-0.029 (-0.259)	0.520 (3.002)*	-0.285 (-1.571)	0.3772	0.3492	2.2100	-0.778 (-0.951)	0.971 (11.439)*	-0.799 (-6.322)*	0.484 (1.805)	0.519 (3.887)*	0.6393	0.6231	2.0805
	Small (S)	-1.804 (-2.228)**	0.806 (7.465)*	0.260 (2.170)**	0.641 (4.512)*	-0.622 (-4.127)*	0.4864	0.4633	2.3999	-1.994 (-2.444)**	0.674 (6.475)*	0.801 (7.043)*	0.695 (4.577)*	1.050 (8.770)*	0.9832	0.9824	2.5844

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.3 EY, EPS, MOM3

Table C.3.3 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.241 (-1.324)	0.956 (8.585)*	0.171 (0.753)	-0.144 (-1.043)	0.002 (0.018)	0.3517	0.3225	2.5191	-1.744 (-1.915)	0.737 (5.727)*	-0.327 (-2.791)*	-0.264 (-2.614)**	0.672 (4.751)*	0.4906	0.4677	2.3926
	Small (S)	-1.441 (-1.833)	0.691 (5.601)*	1.598 (4.161)*	-0.667 (-3.560)*	-0.656 (-4.713)*	0.6236	0.6066	2.0852	-3.233 (-3.038)*	0.533 (3.148)*	0.609 (2.081)**	-0.678 (-3.031)*	0.387 (1.969)	0.4006	0.3736	2.1503
Medium (M)	Big (B)	-1.957 (-3.260)*	0.726 (10.196)*	-0.010 (-0.095)	0.291 (3.015)*	-0.471 (-4.107)*	0.3800	0.3521	2.6182	-0.484 (-0.410)	0.904 (5.122)*	-0.407 (-2.583)**	0.014 (0.134)	0.402 (2.698)*	0.4572	0.4328	2.4587
	Small (S)	-0.055 (-0.087)	0.889 (9.713)*	0.215 (1.312)	0.233 (2.239)**	-0.527 (-4.950)*	0.4383	0.4130	2.6536	0.380 (0.382)	1.270 (6.492)*	0.327 (1.778)	-0.369 (-2.320)**	0.306 (1.478)	0.4985	0.4760	1.9096
High (H)	Big (B)	-1.922 (-2.237)**	0.735 (5.920)*	-0.082 (-0.412)	0.369 (2.081)**	-0.469 (-2.889)*	0.3501	0.3209	2.4075	-1.369 (-2.454)**	0.754 (9.229)*	-0.232 (-1.909)	0.065 (0.671)	0.125 (1.169)	0.4644	0.4404	2.3432
	Small (S)	-2.100 (-2.794)*	0.815 (5.949)*	0.221 (1.694)	0.250 (2.508)**	-0.619 (-4.329)*	0.4669	0.4430	2.2918	-2.268 (-1.590)	0.614 (3.091)*	2.143 (11.752)*	1.564 (11.332)*	1.369 (7.771)*	0.9729	0.9716	2.3818

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.4 EY, EPS, MOM12

Table C.3.4 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the earnings yield (EY) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-0.645 (-0.792)	1.019 (9.390)*	0.370 (1.859)	-0.350 (-2.614)**	0.028 (0.298)	0.4308	0.4053	2.4530	-1.879 (-2.775)*	0.710 (7.009)*	-0.339 (-3.531)*	-0.157 (-1.894)	0.533 (4.519)*	0.4847	0.4615	2.5535
	Small (S)	-0.583 (-0.558)	0.834 (7.565)*	0.885 (3.947)*	-0.449 (-2.750)*	-0.335 (-2.712)*	0.4215	0.3955	2.6599	-1.723 (-1.782)	0.902 (5.151)*	0.410 (3.077)*	-0.819 (-5.009)*	0.788 (4.152)*	0.5848	0.5661	2.1225
Medium (M)	Big (B)	-0.918 (-1.081)	0.814 (7.872)*	-0.243 (-1.625)*	0.177 (1.454)	-0.076 (-0.833)	0.4515	0.4268	2.5381	-2.036 (-2.355)**	0.871 (6.406)*	-0.438 (-3.786)	-0.207 (-1.154)	0.779 (2.762)*	0.5921	0.5737	2.2384
	Small (S)	-1.879 (-2.660)*	0.839 (8.349)*	0.353 (2.382)**	0.008 (0.105)	-0.309 (-3.114)*	0.4193	0.3932	2.6553	-3.701 (-3.755)*	0.536 (3.201)*	-0.038 (-0.278)	0.007 (0.070)	0.092 (1.082)	0.2434	0.2094	2.0668
High (H)	Big (B)	-2.561 (-3.101)*	0.650 (5.205)*	-0.276 (-2.942)*	0.459 (4.027)*	-0.426 (-3.533)*	0.3616	0.3329	2.3439	-1.058 (-1.123)	0.932 (6.930)*	-0.930 (-4.875)*	0.295 (1.786)	0.419 (2.296)**	0.6086	0.5910	2.2192
	Small (S)	-2.511 (-3.114)*	0.840 (6.015)*	0.053 (0.409)	0.373 (2.317)**	-0.625 (-2.782)*	0.4030	0.3762	2.0757	1.300 (1.009)	1.044 (5.353)*	2.479 (7.533)*	1.100 (4.277)*	1.647 (8.679)*	0.9683	0.9669	2.4334

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.5 BVTMLOG, MVLOG, MOM3

Table C.3.5 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.280 (-1.944)	0.862 (13.729)*	-0.249 (-3.221)*	-0.042 (-0.339)	-0.562 (-4.640)*	0.4291	0.4034	2.5123	-1.478 (-1.537)	0.809 (5.907)*	0.144 (1.087)	0.014 (0.082)	0.373 (1.686)	0.3757	0.3477	2.4802
	Small (S)	-4.239 (-3.566)*	0.616 (4.974)*	-0.094 (-0.839)	-0.753 (-2.187)**	-0.797 (-3.215)*	0.3183	0.2877	1.9100	-1.146 (-1.454)	0.807 (5.976)*	0.317 (1.904)	-0.389 (-2.295)**	0.364 (1.513)	0.3211	0.2906	2.1769
Medium (M)	Big (B)	-2.104 (-3.062)*	0.721 (7.549)*	-0.220 (-2.758)*	0.028 (0.215)	-0.402 (-3.248)*	0.3785	0.3506	2.3446	0.971 (1.411)	1.097 (11.504)*	-0.095 (-0.878)	0.224 (1.834)	0.028 (0.148)	0.5382	0.5175	2.4595
	Small (S)	5.077 (1.834)	1.386 (4.003)*	2.977 (10.733)*	1.465 (3.362)*	-1.683 (-3.899)*	0.9862	0.9856	2.3886	-2.171 (-2.515)**	0.714 (6.186)*	0.168 (2.208)**	-0.010 (-0.114)	0.339 (2.996)*	0.4062	0.3795	1.8513
High (H)	Big (B)	-1.201 (-1.543)	0.901 (8.046)*	-0.825 (-3.604)*	0.985 (4.147)*	-0.897 (-2.766)*	0.5922	0.5739	2.0890	-2.163 (-3.346)*	0.662 (5.764)*	-0.223 (-1.856)	0.475 (2.180)**	-0.021 (-0.125)	0.3770	0.3490	2.4749
	Small (S)	-3.509 (-5.110)*	0.566 (5.174)*	-0.058 (-0.954)	0.001 (0.007)	-0.140 (-1.186)	0.2722	0.2395	2.0271	-1.268 (-1.254)	0.963 (7.342)*	1.222 (10.325)*	1.370 (5.010)*	0.435 (2.221)**	0.9744	0.9733	2.3934

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.6 BVTMLOG, MVLOG, MOM12

Table C.3.6 **Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum**

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.741 (-1.603)	0.810 (7.552)*	-0.058 (-0.399)	-0.366 (-1.854)	0.193 (1.290)	0.3038	0.2725	2.4574	-2.143 (-3.629)*	0.803 (11.347)*	-0.489 (-5.521)*	-0.227 (-1.294)	0.572 (5.301)*	0.6252	0.6083	2.2752
	Small (S)	-3.698 (-6.297)*	0.666 (6.669)*	0.512 (3.268)*	-0.435 (-1.704)	-0.361 (-1.867)	0.2834	0.2512	2.0095	-2.737 (-2.494)**	0.603 (3.291)*	0.022 (0.167)	-0.925 (-3.076)**	0.377 (2.432)**	0.3609	0.3322	1.7565
Medium (M)	Big (B)	-0.780 (-0.816)	0.951 (8.964)*	0.065 (0.420)	0.079 (0.443)	-0.135 (-0.786)	0.4246	0.3988	2.1798	-1.480 (-2.365)**	0.889 (7.947)*	-0.599 (-4.021)*	-0.152 (-0.845)	0.657 (3.573)*	0.5158	0.4941	2.1553
	Small (S)	-1.727 (-2.179)**	0.854 (8.428)*	0.378 (2.826)*	0.161 (0.863)	-0.446 (-2.462)**	0.4189	0.3928	2.2296	1.463 (0.635)	1.259 (4.581)*	2.089 (6.879)*	0.405 (0.728)	1.987 (9.448)*	0.9806	0.9798	1.8710
High (H)	Big (B)	-1.641 (-2.042)**	0.788 (6.264)*	-0.291 (-1.778)	0.574 (2.139)**	0.023 (0.137)	0.3946	0.3673	1.9535	-3.796 (-4.840)*	0.618 (5.264)*	-0.675 (-5.126)*	0.384 (1.731)	0.503 (3.097)*	0.4569	0.4325	2.4804
	Small (S)	-1.994 (-3.065)*	0.790 (6.988)*	0.347 (2.252)**	0.279 (2.495)**	-0.462 (-2.909)*	0.4310	0.4054	2.1993	-2.889 (-2.337)**	0.687 (5.545)*	0.606 (3.362)*	0.808 (2.730)*	0.717 (4.173)*	0.9679	0.9664	2.3898

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.7 BVTMLOG, EPS, MOM3

Table C.3.7 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	-1.775 (-2.146)**	0.824 (8.843)*	-0.220 (-2.130)**	0.231 (2.126)**	-0.318 (-2.811)*	0.3835	0.3558	2.3758	-3.093 (-3.238)*	0.670 (6.316)*	-0.368 (-2.045)**	-0.194 (-1.809)	0.658 (3.429)*	0.5162	0.4944	2.3392
	Small (S)	-1.335 (-2.075)**	0.820 (10.259)*	0.113 (0.662)	0.233 (1.650)	-0.411 (-2.360)**	0.3627	0.3340	2.3376	-2.538 (-2.818)*	0.641 (3.558)*	0.304 (2.992)*	-0.732 (-5.387)*	0.762 (4.086)*	0.4896	0.4667	2.1939
Medium (M)	Big (B)	-2.346 (-2.646)*	0.695 (5.540)*	-0.114 (-0.844)	0.088 (0.987)	-0.195 (-1.484)	0.2880	0.2560	2.3983	0.305 (0.240)	0.950 (5.045)*	-1.329 (-3.095)*	1.082 (2.225)**	-0.076 (-0.216)	0.5217	0.5002	2.3220
	Small (S)	-0.625 (-0.410)	0.891 (3.611)*	0.422 (0.660)	0.693 (1.964)	-1.359 (-2.283)**	0.3822	0.3545	2.0531	-1.009 (-0.810)	0.864 (5.255)*	0.272 (1.637)	-0.326 (-2.459)**	0.250 (1.320)	0.3835	0.3558	2.1990
High (H)	Big (B)	-1.447 (-1.853)	0.853 (7.408)*	-0.766 (-5.570)*	0.719 (5.866)*	-0.260 (-1.649)	0.5540	0.5340	2.4253	-2.223 (-2.887)*	0.663 (4.689)*	-0.748 (-4.106)*	0.380 (3.516)*	0.193 (1.193)	0.4465	0.4217	2.1244
	Small (S)	-3.051 (-3.925)*	0.572 (5.166)*	0.019 (0.124)	0.343 (3.802)*	-0.456 (-4.070)*	0.3985	0.3714	1.9300	-2.020 (-1.459)	0.867 (5.944)*	1.324 (10.738)*	2.095 (14.590)*	1.214 (6.408)*	0.9256	0.9223	2.2891

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.3.8 BVTMLOG, EPS, MOM12

Table C.3.8 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the log of the book value to market (BVTMLOG) as a proxy for the value effect, earnings per share (EPS) as a proxy for the size effect and the previous 12-month's returns (MOM12) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Low (L)	Big (B)	0.010 (0.011)	0.963 (10.046)*	0.241 (1.191)	-0.146 (-1.950)	-0.269 (-1.959)	0.4305	0.4049	2.4818	-1.752 (-2.327)**	0.810 (8.839)*	-0.409 (-3.162)*	-0.024 (-0.402)	0.352 (3.767)*	0.5375	0.5167	2.3858
	Small (S)	-3.541 (-3.959)*	0.503 (3.912)*	1.114 (6.655)*	-0.407 (-5.596)*	-0.513 (-6.002)*	0.4349	0.4096	2.6920	-1.035 (-0.767)	0.799 (4.286)*	0.984 (4.199)*	-1.616 (-8.041)*	1.421 (7.425)*	0.8347	0.8272	2.1017
Medium (M)	Big (B)	-1.673 (-1.673)	0.806 (6.427)*	-0.048 (-0.242)	0.005 (0.040)	-0.050 (-0.350)	0.3121	0.2812	2.1430	-3.256 (-2.196)**	0.523 (2.658)*	-0.117 (-0.436)	-0.632 (-3.052)*	1.144 (5.700)*	0.6366	0.6203	2.3929
	Small (S)	-2.012 (-1.934)	0.689 (5.392)*	0.487 (2.166)**	-0.032 (-0.261)	-0.383 (-2.416)**	0.3296	0.2995	2.3952	-2.130 (-2.190)**	0.896 (5.678)*	-0.043 (-0.326)	-0.226 (-1.619)	0.405 (2.594)**	0.4342	0.4088	2.0328
High (H)	Big (B)	-1.946 (-2.135)**	0.793 (7.256)*	-0.205 (-1.968)	0.034 (0.759)	0.107 (1.620)	0.4485	0.4237	2.0759	-1.915 (-3.034)*	0.727 (6.108)*	-0.398 (-2.150)**	0.070 (0.872)	0.306 (2.913)*	0.3291	0.2990	2.4222
	Small (S)	-2.012 (-1.934)	0.689 (5.392)*	0.487 (2.166)**	-0.032 (-0.261)	-0.383 (-2.416)**	0.3296	0.2995	2.3952	-0.445 (-0.300)	0.867 (5.611)*	2.047 (7.940)*	1.735 (15.007)*	0.962 (5.675)*	0.9433	0.9408	2.2566

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.4 REGRESSION RESULTS FOR THE STANDARD CAPM (FOR PORTFOLIOS THAT TAKE ACCOUNT OF LIQUIDITY)

A standard CAPM model was run on portfolios set up according to five liquidity variables: the bid-ask spread, turnover, the Amihud price impact measure and the two zeros measures, namely zeros1 and zeros2. The size, value and momentum variables were held constant. Equation 3.5 provides a mathematical description of this particular model:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + \varepsilon_{jt}$$

The results from the two earlier regression analyses (which can be found in Appendix C.2 and C.3) were used to determine which measures best describe the respective size, value and momentum effects. They were found to be the earnings yield (EY) for the value effect, the log of the firm’s market value (MVLOG) for the size effect and, lastly, the previous 3-month’s returns (MOM3) for the momentum effect. These three measures were applied together with the various liquidity measures to determine their significance in setting up portfolios and hence generating excess returns. This was done by running regressions on the various portfolios.

As can be seen, this model is identical to that in Appendix C.2. The aim of performing this regression again was to compare it to the results of equation 3.5 that were obtained earlier. The difference between these two regression analyses is the way in which the portfolios were set up. The portfolios from the earlier regression analysis were set up according to different size, value and momentum variables, whilst in this analysis the portfolios were set up according to five different liquidity variables, while the size, value and momentum variables were held constant (namely EY, MVLOG and MOM3). Therefore these results are compared to the results found in Table C.2.1. If liquidity is indeed an influencing factor, then we would expect the significance of the factors to differ from those obtained earlier.

The results of the standard CAPM regressions (equation 3.5) are presented below.

C.4.1 BID-ASK- SPREAD

Table C.4.1 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the bid-ask spread as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms											
Low (L)	Big (B)	-1.311 (-1.682)	0.859 (6.176)*	0.2904	0.2827	2.6850	-0.534 (-0.579)	0.870 (6.734)*	0.3708	0.3640	2.4715
	Small (S)	-2.521 (-2.426)**	0.735 (3.983)*	0.1239	0.1144	2.0815	-2.912 (-3.344)*	0.706 (7.760)*	0.2316	0.2233	2.2273
Medium (M)	Big (B)	-2.522 (-2.817)*	0.690 (5.129)*	0.2716	0.2637	2.4207	-0.270 (-0.213)	1.004 (4.320)*	0.4160	0.4096	2.6006
	Small (S)	-2.043 (-1.310)	0.926 (4.899)*	0.2274	0.2190	1.8463	-2.402 (-1.218)	0.698 (2.370)**	0.1226	0.1130	2.0790
High (H)	Big (B)	-2.554 (-2.692)*	0.700 (4.685)*	0.2657	0.2577	2.1777	-2.219 (-2.579)**	0.755 (6.772)*	0.3570	0.3500	2.1268
	Small (S)	-5.055 (-3.524)*	0.312 (2.462)**	0.0355	0.0250	2.3797	-2.427 (-2.147)**	0.538 (3.480)*	0.1525	0.1433	2.0252
Panel B: Liquid firms											
Low (L)	Big (B)	-3.760 (-3.474)*	0.545 (3.055)*	0.1580	0.1489	2.0529	-1.682 (-1.393)	0.832 (6.099)*	0.3212	0.3138	1.8411
	Small (S)	-4.356 (-3.920)*	0.591 (4.326)*	0.1540	0.1448	2.1229	0.515 (0.465)	1.050 (7.438)*	0.2707	0.2627	2.4165
Medium (M)	Big (B)	-3.228 (-3.723)*	0.619 (5.923)*	0.1955	0.1868	2.0181	-3.084 (-3.676)*	0.725 (6.070)*	0.4723	0.4666	1.5183
	Small (S)	-5.612 (-2.439)**	0.411 (1.797)	0.0341	0.0236	2.0393	-1.241 (-1.986)	0.782 (6.888)*	0.3296	0.3223	2.0562
High (H)	Big (B)	-4.205 (-2.809)*	0.353 (1.765)	0.0419	0.0315	2.1846	-0.837 (-0.452)	1.022 (3.738)*	0.2565	0.2484	2.0776
	Small (S)	-2.404 (-3.791)*	0.793 (6.247)*	0.3920	0.3853	1.5388	-2.896 (-1.071)	0.663 (2.538)**	0.0745	0.0644	2.0691

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.4.2 TURNOVER

Table C.4.2 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to turnover as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms											
Low (L)	Big (B)	-1.786 (-2.104)**	0.860 (6.723)*	0.3388	0.3316	2.5587	-1.114 (-1.208)	0.782 (6.140)*	0.3124	0.3050	2.4642
	Small (S)	-4.012 (-5.335)*	0.535 (4.031)*	0.1930	0.1842	1.8164	-3.446 (-2.755)*	0.483 (3.340)*	0.0966	0.0868	2.1897
Medium (M)	Big (B)	-2.800 (-2.802)*	0.623 (3.872)*	0.2149	0.2063	2.4736	-0.239 (-0.187)	1.018 (4.367)*	0.4072	0.4008	2.5658
	Small (S)	-5.778 (-4.207)*	0.475 (3.863)*	0.0567	0.0465	2.4887	-2.793 (-3.747)*	0.802 (6.484)*	0.4548	0.4488	1.9052
High (H)	Big (B)	-2.444 (-2.319)**	0.724 (4.610)*	0.2502	0.2420	2.2151	-3.153 (-3.149)*	0.691 (5.831)*	0.3114	0.3039	1.9527
	Small (S)	-4.497 (-2.157)	0.374 (1.656)	0.0344	0.0239	2.1022	-3.585 (-3.366)*	0.399 (4.334)*	0.1033	0.0936	1.7967
Panel B: Liquid firms											
Low (L)	Big (B)	-2.102 (-2.749)*	0.701 (5.232)*	0.2367	0.2284	2.7222	-0.024 (-0.023)	1.013 (7.479)*	0.4424	0.4363	2.2408
	Small (S)	-5.093 (-3.114)*	0.568 (3.631)*	0.0885	0.0786	2.1983	0.148 (0.191)	0.997 (11.685)*	0.4050	0.3985	2.2292
Medium (M)	Big (B)	-2.830 (-4.087)*	0.723 (8.295)*	0.2529	0.2447	2.2438	-1.597 (-1.687)	0.940 (5.677)*	0.4161	0.4097	2.2324
	Small (S)	-4.485 (-2.054)**	0.522 (2.463)**	0.0597	0.0495	2.0136	-1.316 (-1.129)	0.797 (3.101)*	0.2432	0.2350	1.9812
High (H)	Big (B)	-3.780 (-3.413)*	0.426 (3.589)*	0.0985	0.0887	2.5216	1.588 (1.066)	1.262 (6.252)*	0.4613	0.4554	2.1895
	Small (S)	-2.886 (-3.979)*	0.812 (4.651)*	0.2992	0.2915	1.9289	-2.348 (-1.026)	0.703 (2.972)*	0.0912	0.0813	2.2633

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.4.3 PRICE IMPACT

Table C.4.3 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to price impact as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms											
Low (L)	Big (B)	-1.310 (-1.659)	0.861 (6.106)*	0.2878	0.2800	2.6764	-0.532 (-0.581)	0.872 (6.804)*	0.3728	0.3659	2.4700
	Small (S)	-4.495 (-2.150)**	0.541 (2.574)**	0.0826	0.0727	1.8252	-4.368 (-3.513)*	0.429 (3.317)*	0.0812	0.0713	2.0411
Medium (M)	Big (B)	-2.469 (-2.597)**	0.694 (4.923)*	0.2532	0.2451	2.4588	-0.253 (-0.198)	1.004 (4.272)*	0.4156	0.4092	2.5918
	Small (S)	-4.812 (-4.328)*	0.658 (5.063)*	0.1290	0.1195	2.4406	-3.499 (-3.347)*	0.500 (3.357)*	0.1860	0.1772	1.6270
High (H)	Big (B)	-2.546 (-2.834)*	0.709 (4.964)*	0.2824	0.2746	2.1595	-2.265 (-2.495)**	0.757 (6.521)*	0.3388	0.3316	2.0653
	Small (S)	-5.503 (-3.554)*	0.358 (1.767)	0.0356	0.0251	2.2955	-0.724 (-0.220)	0.723 (2.323)**	0.0641	0.0540	2.0142
Panel B: Liquid firms											
Low (L)	Big (B)	-1.025 (-1.146)	0.889 (5.578)*	0.3117	0.3043	2.4102	-1.382 (-0.967)	0.754 (4.358)*	0.2667	0.2587	1.9086
	Small (S)	-4.386 (-3.801)*	0.582 (4.250)*	0.1347	0.1252	2.1382	-0.783 (-1.006)	0.926 (10.425)*	0.4005	0.3940	2.2842
Medium (M)	Big (B)	-2.498 (-3.434)*	0.781 (9.117)*	0.2272	0.2188	2.3627	-2.625 (-2.916)*	0.876 (7.462)*	0.4307	0.4245	1.8908
	Small (S)	-4.541 (-2.091)**	0.457 (2.268)**	0.0485	0.0381	2.0320	-1.243 (-1.340)	0.857 (4.082)*	0.3318	0.3246	2.1153
High (H)	Big (B)	0.854 (0.209)	0.785 (2.003)**	0.0286	0.0181	2.5206	0.211 (0.104)	1.118 (4.211)*	0.2613	0.2533	2.1754
	Small (S)	-2.072 (-2.924)*	0.846 (4.920)*	0.3542	0.3472	1.6798	-2.555 (-1.028)	0.675 (2.677)*	0.0790	0.0690	2.1998

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.4.4 ZEROS 1

Table C.4.4 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the zeros1 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms											
Low (L)	Big (B)	-1.469 (-1.755)	0.839 (5.634)*	0.2648	0.2568	2.7037	-0.564 (-0.613)	0.878 (7.116)*	0.3675	0.3606	2.4194
	Small (S)	-2.853 (-1.506)	0.749 (3.957)*	0.1307	0.1212	2.0259	-1.548 (-0.953)	0.740 (4.688)*	0.1498	0.1406	1.9770
Medium (M)	Big (B)	-2.518 (-2.627)**	0.685 (4.536)*	0.2538	0.2457	2.4314	-0.294 (-0.251)	1.016 (4.819)*	0.4231	0.4168	2.5875
	Small (S)	-4.493 (-3.639)*	0.604 (4.141)*	0.0787	0.0687	2.3703	-3.743 (-2.314)**	0.537 (2.800)*	0.1571	0.1480	1.8809
High (H)	Big (B)	-2.497 (-2.504)**	0.721 (4.610)*	0.2564	0.2483	2.2840	-2.293 (-2.452)**	0.768 (6.879)*	0.3298	0.3225	2.0463
	Small (S)	-3.071 (-3.878)*	0.549 (6.451)*	0.1876	0.1787	2.2588	-0.440 (-0.108)	0.717 (1.912)	0.0422	0.0318	2.0078
Panel B: Liquid firms											
Low (L)	Big (B)	-2.541 (-2.753)*	0.785 (4.819)*	0.2922	0.2845	1.8080	-0.248 (-0.135)	1.084 (2.963)*	0.2625	0.2545	2.0383
	Small (S)	-5.346 (-4.142)*	0.486 (3.528)*	0.0843	0.0744	2.1768	-0.423 (-0.469)	0.973 (8.977)*	0.3147	0.3072	2.5569
Medium (M)	Big (B)	-2.834 (3.800)*	0.668 (7.857)*	0.1804	0.1715	2.2125	-1.128 (-0.573)	0.791 (2.405)**	0.2211	0.2127	2.1021
	Small (S)	-4.529 (-2.084)**	0.487 (2.436)**	0.0537	0.0434	2.0586	-2.746 (-3.534)*	0.685 (4.868)*	0.3173	0.3099	1.9396
High (H)	Big (B)	-2.741 (-2.251)**	0.668 (2.692)*	0.1476	0.1383	1.6971	-3.126 (-1.949)	0.502 (3.335)*	0.0859	0.0760	2.0331
	Small (S)	-4.270 (-4.256)*	0.588 (3.664)*	0.1623	0.1531	2.0380	-2.624 (-1.129)	0.698 (2.979)*	0.0931	0.0832	2.2196

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.4.5 ZEROS 2

Table C.4.5 Regressions of excess stock returns on the excess market returns

The table reports the regression results for the standard CAPM for portfolios set up according to the zeros2 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while the t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) as well as the Durbin-Watson statistic.

		Momentum									
		Poor (P)					Good (G)				
Value	**Size**	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms											
Low (L)	Big (B)	-1.435 (-1.707)	0.840 (5.612)*	0.2632	0.2552	2.6927	-0.571 (-0.621)	0.878 (7.133)*	0.3671	0.3602	2.4236
	Small (S)	-3.116 (-1.570)	0.676 (2.829)*	0.0790	0.0690	1.7566	-2.106 (-0.980)	0.656 (3.076)*	0.0669	0.0567	1.8090
Medium (M)	Big (B)	-2.508 (-2.615)**	0.689 (4.575)*	0.2545	0.2464	2.4460	-0.207 (-0.172)	1.025 (4.776)*	0.4207	0.4144	2.5775
	Small (S)	-4.342 (-2.825)*	0.701 (3.619)*	0.0762	0.0662	2.2762	-2.510 (-1.492)	0.625 (3.079)*	0.1881	0.1793	2.0497
High (H)	Big (B)	-2.516 (-2.505)**	0.719 (4.564)*	0.2473	0.2391	2.3235	-3.107 (-2.095)**	0.719 (5.357)*	0.1819	0.1731	1.7726
	Small (S)	-1.719 (-1.234)	0.667 (5.015)*	0.1673	0.1583	2.0891	-1.257 (-0.402)	0.643 (2.215)**	0.0527	0.0424	2.0114
Panel B: Liquid firms											
Low (L)	Big (B)	-2.188 (-2.508)*	0.855 (5.626)*	0.2689	0.2610	2.0833	1.796 (1.027)	1.303 (4.293)*	0.3433	0.3362	2.0887
	Small (S)	-5.069 (-3.664)*	0.515 (3.775)*	0.1126	0.1030	2.2294	-0.674 (-0.813)	0.925 (9.941)*	0.3495	0.3424	2.3799
Medium (M)	Big (B)	-3.264 (-4.404)*	0.602 (7.378)*	0.1586	0.1495	2.2353	-0.714 (-0.559)	0.783 (3.890)*	0.2536	0.2455	2.1624
	Small (S)	-4.314 (-1.913)	0.510 (2.442)**	0.0584	0.0482	1.9994	-1.268 (-1.547)	0.808 (4.571)*	0.3455	0.3384	2.0446
High (H)	Big (B)	-2.586 (-2.101)**	0.703 (2.948)*	0.1598	0.1506	1.7311	-3.226 (-2.033)**	0.487 (3.306)*	0.0825	0.0726	2.0263
	Small (S)	-4.087 (-3.960)*	0.593 (3.673)*	0.1788	0.1699	1.9409	-2.441 (-1.037)	0.704 (2.972)*	0.0935	0.0837	2.2108

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.5 REGRESSION RESULTS FOR THE MOMENTUM-AUGMENTED FAMA-FRENCH MODEL (FOR PORTFOLIOS THAT TAKE ACCOUNT OF LIQUIDITY)

A momentum-and-augmented Fama-French model was run on portfolios set up according to the five liquidity variables: the bid-ask spread, turnover, the Amihud price impact measure and the two zeros measures, namely zeros1 and zeros2. The size, value and momentum variables are as in Appendix C.4. The following regression was run on these portfolios (i.e. according to equation 3.6):

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + s_{jSMB} SMB_t + h_{jHML} HML_t + g_{jGMP} GMP_t + \eta_{jt}$$

As can be seen, this model is identical to that in Appendix C.3. The aim of performing this regression again was to compare it to the results of equation 3.6 that were obtained earlier. The difference between these two regression analyses is the way in which the portfolios were set up. The portfolios from the earlier regression analysis were set up according to different size, value and momentum variables, whilst in this analysis the portfolios were set up according to five different liquidity variables, while the size, value and momentum variables were held constant (namely EY, MVLOG and MOM3). Therefore these results are compared to the results found in Table C.3.1. If liquidity is indeed an influencing factor, then we would expect the significance of the factors to differ from those obtained earlier.

The results for the different portfolios are presented below.

C.5.1 BID-ASK SPREAD

Table C.5.1 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the bid-ask spread as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																	
Low (L)	Big (B)	-0.334 (-0.301)	0.965 (5.275)*	-0.445 (-2.010)**	0.002 (0.011)	-0.760 (-3.463)*	0.3896	0.3621	2.5834	-0.774 (-0.867)	0.862 (7.289)*	-0.411 (-2.061)**	0.364 (1.860)	0.166 (0.858)	0.4330	0.4075	2.4676
	Small (S)	-1.634 (-1.312)	0.770 (4.685)*	1.242 (2.666)*	-1.197 (-2.931)*	-0.644 (-2.153)**	0.4357	0.4104	2.2631	-3.130 (-4.175)*	0.667 (7.920)*	0.478 (2.220)**	-0.310 (-1.779)	0.165 (0.771)	0.2790	0.2466	2.1982
Medium (M)	Big (B)	-1.288 (-1.763)	0.836 (7.549)*	-0.173 (-1.285)	0.254 (1.743)	-0.702 (-4.766)*	0.3837	0.3560	2.4054	-0.452 (-0.409)	0.998 (5.132)*	-0.250 (-1.221)	0.263 (1.744)	0.142 (0.616)	0.4416	0.4165	2.6115
	Small (S)	-0.185 (-0.132)	1.161 (5.143)*	0.158 (0.536)	0.706 (2.061)*	-0.754 (-2.075)**	0.3583	0.3295	1.9511	-1.880 (-0.969)	0.776 (2.636)*	0.140 (0.445)	0.441 (1.430)	-0.065 (-0.298)	0.1548	0.1168	2.0876
High (H)	Big (B)	-1.454 (-1.730)	0.836 (6.360)*	-0.014 (-0.114)	0.346 (1.972)	-0.519 (-3.102)*	0.3483	0.3190	2.2480	-1.896 (-2.488)**	0.817 (6.817)*	-0.168 (-1.012)	0.548 (6.248)*	-0.005 (-0.030)	0.4574	0.4330	2.2188
	Small (S)	-2.787 (-3.218)*	0.598 (4.841)*	0.951 (2.810)*	0.829 (2.898)*	-0.659 (-2.589)**	0.4150	0.3887	2.3266	-2.441 (-2.294)**	0.563 (3.784)*	0.319 (1.352)	0.536 (3.319)*	0.373 (1.863)	0.3039	0.2726	1.9998
Panel B: Liquid firms																	
Low (L)	Big (B)	-3.037 (-2.630)**	0.613 (3.495)*	-0.338 (-1.104)	-0.204 (-1.012)	-0.661 (-3.170)*	0.2804	0.2481	2.0115	-2.944 (-3.477)*	0.677 (5.886)*	-0.052 (-0.154)	-0.386 (-1.425)	0.576 (2.513)**	0.4133	0.3869	1.8481
	Small (S)	-2.939 (-3.650)*	0.732 (6.770)*	-0.041 (-0.232)	-0.218 (-1.144)	-0.983 (-3.336)*	0.3349	0.3050	2.3448	-0.560 (-0.463)	0.895 (6.089)*	1.152 (5.507)*	-0.773 (-3.594)*	0.722 (3.015)*	0.4389	0.4137	2.3459
Medium (M)	Big (B)	-1.947 (-3.434)*	0.770 (10.187)*	-0.409 (-2.293)**	0.258 (1.666)	-0.815 (-3.287)*	0.3352	0.3053	2.0099	-3.461 (-4.540)*	0.688 (6.132)*	-0.124 (-1.270)	0.062 (0.729)	0.214 (1.876)	0.4969	0.4743	1.5264
	Small (S)	-2.813 (-2.356)**	0.761 (3.814)*	1.890 (2.481)**	0.962 (2.347)**	-0.581 (-2.222)**	0.5010	0.4786	1.8981	-0.960 (-1.571)	0.815 (7.199)*	0.350 (1.989)**	0.058 (0.346)	-0.017 (-0.126)	0.3562	0.3273	2.2477
High (H)	Big (B)	-1.853 (-1.508)	0.644 (3.862)*	-0.611 (-2.128)**	0.744 (3.704)	-1.320 (-3.760)*	0.3244	0.2940	2.0739	-2.406 (-1.885)	0.880 (4.767)*	-0.629 (-2.833)*	0.529 (2.182)**	0.976 (2.612)**	0.4283	0.4026	2.1431
	Small (S)	-1.575 (-2.728)*	0.898 (6.410)*	0.166 (0.639)	0.298 (2.107)**	-0.310 (-1.415)	0.4562	0.4318	1.5866	-0.941 (-0.642)	0.946 (4.382)*	1.570 (1.968)	1.448 (3.343)*	0.045 (0.155)	0.4948	0.4720	1.8708

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.5.2 TURNOVER

Table C.5.2 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to turnover as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																	
Low (L)	Big (B)	-1.602 (-1.768)	0.862 (7.201)*	-0.785 (-3.536)*	-0.031 (-0.135)	-0.728 (-2.633)*	0.5011	0.4786	2.3656	-2.297 (-2.681)*	0.650 (5.251)*	-0.694 (-3.307)*	0.194 (1.020)	0.062 (0.311)	0.4228	0.3968	2.3327
	Small (S)	-2.035 (-3.009)*	0.735 (7.599)*	0.217 (1.616)	-0.416 (-3.065)*	-0.882 (-5.364)*	0.4926	0.4698	2.1019	-4.214 (-2.936)*	0.394 (2.190)**	0.186 (1.048)	-0.636 (-3.036)*	0.381 (1.441)	0.1821	0.1454	2.1251
Medium (M)	Big (B)	-1.522 (-2.180)**	0.753 (5.839)*	-0.398 (-2.861)*	0.286 (1.915)	-0.879 (-3.779)*	0.3666	0.3381	2.5507	-1.399 (-1.238)	0.890 (4.915)*	-0.625 (-2.758)*	0.204 (0.945)	0.108 (0.534)	0.4811	0.4577	2.4532
	Small (S)	-2.176 (-2.106)**	0.848 (5.907)*	0.190 (0.749)	-0.138 (-0.551)	-1.634 (-3.775)*	0.3306	0.3006	2.5531	-2.040 (-2.148)**	0.887 (6.163)*	0.197 (1.327)	0.101 (0.662)	-0.186 (-1.300)	0.4871	0.4641	1.9888
High (H)	Big (B)	-1.767 (-1.821)	0.800 (5.546)*	-0.339 (-2.122)**	0.598 (2.602)**	-0.469 (-2.112)**	0.3484	0.3191	2.2373	-3.605 (-4.101)*	0.651 (4.785)*	-0.363 (-2.638)*	0.680 (4.285)*	0.080 (0.403)	0.4714	0.4476	2.2493
	Small (S)	-1.173 (-0.918)	0.744 (4.900)*	0.224 (0.665)	1.041 (4.259)*	-1.207 (-2.925)*	0.3029	0.2716	2.2691	-2.850 (-2.747)*	0.492 (4.807)*	0.429 (2.016)**	0.405 (2.552)**	0.077 (0.320)	0.2315	0.1970	1.9428
Panel B: Liquid firms																	
Low (L)	Big (B)	-1.688 (-1.660)	0.730 (4.431)*	-0.480 (-2.405)**	-0.167 (-0.849)	-0.626 (-3.053)*	0.3436	0.3140	2.6069	-1.290 (-1.228)	0.866 (8.437)*	-0.653 (-2.984)*	-0.129 (-0.529)	0.063 (0.336)	0.5400	0.5193	2.1055
	Small (S)	-2.450 (-2.169)*	0.838 (5.707)*	0.450 (1.889)	-0.601 (-2.324)**	-1.061 (-3.403)*	0.3021	0.2708	2.3900	-0.019 (-0.028)	0.991 (12.475)*	0.817 (3.759)*	-0.307 (-1.862)	0.670 (2.440)**	0.5353	0.5144	2.2372
Medium (M)	Big (B)	-1.653 (-2.403)**	0.837 (7.571)*	-0.265 (-1.339)	-0.083 (-0.484)	-0.806 (-4.219)*	0.3679	0.3395	2.2157	-2.271 (-2.506)**	0.868 (5.451)*	-0.286 (-1.659)	0.163 (0.904)	0.135 (0.599)	0.4426	0.4175	2.1325
	Small (S)	-1.707 (-1.201)	0.857 (4.118)*	1.168 (1.663)	1.130 (2.376)**	-0.161 (-0.410)	0.4003	0.3733	1.9970	-0.557 (-0.397)	0.889 (3.233)*	0.526 (1.770)	0.134 (0.668)	0.083 (0.414)	0.2974	0.2658	2.2135
High (H)	Big (B)	-2.933 (-2.741)*	0.508 (4.519)*	-0.743 (-2.998)*	0.461 (3.356)*	-0.908 (-3.103)*	0.3148	0.2840	2.4282	-0.231 (-0.273)	1.066 (9.695)*	-1.057 (-4.285)*	0.630 (2.679)*	0.177 (0.744)	0.6380	0.6217	2.1938
	Small (S)	-1.551 (-1.858)	0.967 (5.493)*	0.072 (0.392)	0.725 (3.306)*	-0.431 (-2.067)**	0.4444	0.4195	2.0348	-1.486 (-1.101)	0.838 (4.131)*	0.836 (1.145)	1.366 (2.516)**	0.559 (1.165)	0.3766	0.3485	2.2828

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.5.3 PRICE IMPACT

Table C.5.3 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the price impact measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																	
Low (L)	Big (B)	-1.642 (-1.619)	0.818 (5.085)*	-0.353 (-1.587)	-0.002 (-0.008)	-0.282 (-1.364)	0.3316	0.3016	2.6240	-1.802 (-2.003)**	0.745 (6.120)*	-0.414 (-2.313)**	0.128 (1.223)**	0.336 (2.375)**	0.4397	0.4145	2.4373
	Small (S)	-2.503 (-1.460)	0.721 (3.575)*	0.271 (1.881)	-0.346 (-2.473)	-1.063 (-3.318)*	0.2817	0.2494	1.8492	-4.589 (-3.520)*	0.396 (2.723)*	-0.136 (-0.809)	-0.294 (-2.279)	0.077 (0.538)	0.1284	0.0892	2.0316
Medium (M)	Big (B)	-1.952 (-2.043)**	0.740 (5.888)*	-0.026 (-0.138)	0.024 (0.219)	-0.469 (-2.265)**	0.3233	0.2929	2.5392	-1.337 (-1.311)	0.892 (4.942)*	-0.421 (-1.443)	0.056 (0.446)	0.200 (1.234)	0.4549	0.4304	2.5694
	Small (S)	-2.859 (-3.588)*	0.853 (5.295)*	0.536 (2.324)**	-0.086 (-0.448)	-0.713 (-2.495)**	0.2423	0.2082	2.5025	-2.650 (-2.663)*	0.597 (4.228)*	0.454 (2.562)**	0.115 (0.855)	-0.021 (-0.126)	0.2645	0.2314	1.8192
High (H)	Big (B)	-2.297 (-2.605)**	0.731 (5.279)*	-0.103 (-0.559)	0.124 (1.215)	-0.409 (-1.805)	0.3585	0.3297	2.2495	-2.752 (-2.939)*	0.719 (5.370)*	-0.116 (-0.719)	0.394 (5.099)	0.066 (0.421)	0.4377	0.4124	2.2313
	Small (S)	-2.591 (-3.254)*	0.683 (6.372)*	1.210 (3.655)*	0.615 (3.243)*	-0.699 (-2.623)**	0.4082	0.3816	2.6898	-2.023 (-1.271)	0.656 (3.742)*	0.326 (0.707)	1.385 (1.980)*	1.047 (1.462)	0.3588	0.3300	2.1166
Panel B: Liquid firms																	
Low (L)	Big (B)	-0.621 (-0.588)	0.915 (5.913)*	-0.179 (-0.822)	-0.154 (-1.070)	-0.550 (-2.234)**	0.3931	0.3658	2.2488	-2.027 (-1.979)	0.676 (5.601)*	-0.279 (-1.153)	-0.345 (-1.961)	0.216 (1.528)	0.3594	0.3307	2.0675
	Small (S)	-2.736 (-3.481)*	0.727 (7.483)*	0.122 (0.980)	-0.282 (-1.772)	-1.043 (-3.798)*	0.3910	0.3637	2.2453	-0.409 (-0.485)	0.962 (9.574)*	0.191 (1.379)	-0.169 (-1.012)	0.058 (0.361)	0.4251	0.3993	2.2561
Medium (M)	Big (B)	-1.997 (-2.795)*	0.822 (7.147)*	-0.043 (-0.223)	-0.061 (-0.261)	-0.452 (-1.556)	0.2718	0.2391	2.3347	-3.019 (-3.640)*	0.836 (6.754)*	-0.130 (-0.863)	0.020 (0.240)	0.109 (0.647)	0.4380	0.4128	1.8813
	Small (S)	-1.455 (-1.186)	0.814 (3.694)*	1.514 (2.192)**	0.776 (1.965)	-0.425 (-2.440)**	0.4575	0.4331	2.0746	-0.390 (-0.302)	0.948 (4.016)*	0.352 (1.733)	0.025 (0.265)	-0.151 (-0.989)	0.3611	0.3324	2.3397
High (H)	Big (B)	-2.087 (-1.565)	0.469 (2.651)*	-2.823 (-4.565)*	2.174 (4.061)*	-2.843 (-4.335)*	0.7621	0.7515	2.3999	-2.626 (-1.734)	0.849 (4.435)*	-0.772 (-2.205)**	0.612 (2.039)**	0.865 (3.847)*	0.4528	0.4282	2.1140
	Small (S)	-1.418 (-1.642)	0.918 (4.850)*	0.214 (0.775)*	0.189 (1.582)	-0.266 (-1.509)	0.4064	0.3797	1.8649	-0.535 (-0.368)	0.935 (3.372)*	1.288 (1.564)	1.044 (2.182)**	-0.013 (-0.040)	0.4038	0.3770	2.1373

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.5.4 ZEROS 1

Table C.5.4 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the zeros1 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																	
Low (L)	Big (B)	-1.288 (-1.171)	0.833 (5.243)*	-0.399 (-1.806)	-0.034 (-0.137)	-0.400 (-1.509)	0.3081	0.2770	2.6488	-1.485 (-1.810)	0.794 (8.130)*	-0.522 (-2.901)*	0.099 (0.609)	0.237 (1.456)	0.4487	0.4239	2.4106
	Small (S)	-0.303 (-0.260)	0.928 (8.057)*	0.542 (2.651)*	-0.409 (-2.521)**	-1.343 (-3.927)*	0.4702	0.4464	2.4168	-2.048 (-1.299)	0.671 (3.419)*	0.562 (2.669)*	-0.503 (-2.264)**	0.460 (1.210)	0.2195	0.1844	1.9743
Medium (M)	Big (B)	-1.577 (-2.409)**	0.773 (8.447)*	-0.547 (-3.243)*	0.3606 (3.381)*	-0.780 (-5.725)*	0.4087	0.3821	2.5871	-0.902 (-0.810)	0.952 (5.455)*	-0.460 (-2.539)**	0.030 (0.241)	0.060 (0.323)	0.4605	0.4363	2.5849
	Small (S)	-1.767 (-1.762)	0.844 (4.300)*	0.220 (0.895)	0.171 (0.788)	-1.406 (-3.347)*	0.2915	0.2596	2.3748	-2.995 (-1.945)	0.617 (3.494)*	0.358 (2.066)**	0.056 (0.491)	-0.176 (-0.862)	0.2033	0.1674	1.9698
High (H)	Big (B)	-1.524 (-1.970)	0.812 (8.351)*	-0.453 (-2.763)*	0.328 (2.163)**	-0.748 (-3.867)*	0.3791	0.3512	2.3923	-2.097 (-2.435)**	0.824 (8.153)*	-0.493 (-3.497)*	0.583 (3.715)*	-0.193 (-1.193)	0.4987	0.4762	2.1444
	Small (S)	-2.330 (-2.639)*	0.626 (6.333)*	-0.370 (-2.000)**	0.338 (2.552)**	-0.547 (-2.595)**	0.2882	0.2562	2.1872	0.321 (0.096)	1.001 (2.424)**	0.837 (0.929)	1.774 (2.398)**	0.930 (1.465)	0.4083	0.3817	2.0419
Panel B: Liquid firms																	
Low (L)	Big (B)	-2.459 (-2.699)*	0.763 (5.610)*	-0.690 (-2.912)*	0.016 (0.119)	-0.520 (-3.406)*	0.4040	0.3772	1.6618	-2.121 (-1.981)	0.831 (4.616)*	-0.827 (-2.333)**	-0.674 (-2.636)*	0.245 (0.972)	0.4518	0.4272	2.1763
	Small (S)	-3.888 (-4.177)*	0.579 (4.987)*	0.050 (0.182)	-0.219 (-1.186)	-0.940 (-2.768)*	0.2830	0.2507	2.2654	-0.977 (-1.114)	0.883 (6.789)*	0.228 (0.885)	-0.527 (-1.949)	0.251 (1.160)	0.3880	0.3605	2.1781
Medium (M)	Big (B)	-1.147 (-1.584)	0.805 (8.184)*	-0.168 (-0.904)	0.114 (0.920)	-1.077 (-3.836)*	0.3786	0.3507	2.2142	-2.649 (-1.808)	0.656 (2.820)*	-0.720 (-3.062)*	0.138 (0.805)	0.478 (1.631)	0.3676	0.3391	2.3538
	Small (S)	-2.037 (-1.644)	0.796 (3.620)*	1.352 (1.599)	0.541 (1.613)	-0.315 (-1.296)	0.3401	0.3104	2.0017	-1.713 (-2.915)	0.795 (9.223)*	-0.021 (-0.101)	0.289 (2.545)**	-0.503 (-3.276)*	0.4131	0.3867	2.1600
High (H)	Big (B)	-1.157 (-0.873)	0.842 (3.648)*	-0.873 (-3.063)*	0.836 (2.772)*	-1.174 (-2.744)*	0.4300	0.4044	2.0191	-3.556 (-2.899)*	0.515 (3.834)*	-0.897 (-3.119)*	0.802 (3.588)*	0.003 (0.016)	0.3437	0.3142	2.3051
	Small (S)	-2.484 (-2.901)*	0.799 (5.290)*	0.286 (1.184)	0.556 (3.022)*	-0.621 (-2.396)**	0.3762	0.3482	2.2193	-1.741 (-1.504)	0.862 (4.338)*	0.907 (0.953)	0.532 (1.537)	0.340 (1.077)	0.2399	0.2058	2.2378

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.5.5 ZEROS 2

Table C.5.5 Regressions of excess stock returns on the excess market returns and the mimicking returns for size, value and momentum

The table reports the regression results for the momentum-augmented Fama-French model for portfolios set up according to the zeros2 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum															
		Poor (P)								Good (G)							
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																	
Low (L)	Big (B)	-1.373 (-1.269)	0.805 (5.231)*	-0.302 (-1.443)	-0.201 (-0.840)	-0.325 (-1.413)	0.3105	0.2795	2.6558	-1.755 (-2.058)**	0.756 (7.360)*	-0.455 (-2.485)**	-0.100 (-0.682)	0.357 (2.541)**	0.4534	0.4289	2.3808
	Small (S)	-0.408 (-0.295)	0.850 (4.416)*	0.693 (2.673)*	-0.544 (-1.975)	-1.443 (-3.176)*	0.4006	0.3736	1.9069	-3.625 (-1.711)	0.510 (1.953)	1.340 (1.856)	-1.066 (-2.599)**	1.088 (2.681)*	0.2889	0.2569	1.7982
Medium (M)	Big (B)	-2.062 (-2.387)**	0.715 (5.322)*	-0.295 (-1.109)	0.102 (0.669)	-0.376 (-2.246)**	0.2960	0.2644	2.4093	-0.937 (-0.796)	0.937 (5.190)*	-0.424 (-2.102)**	-0.099 (-0.610)	0.115 (0.668)	0.4608	0.4365	2.5894
	Small (S)	-1.938 (-1.269)	0.904 (3.358)*	0.488 (1.632)	0.029 (0.098)	-1.077 (-2.540)**	0.1935	0.1573	2.2852	-2.022 (-1.304)	0.689 (3.627)*	0.456 (1.987)**	0.025 (0.197)	0.003 (0.014)	0.2320	0.1975	2.1827
High (H)	Big (B)	-1.869 (-2.027)**	0.766 (5.929)*	-0.331 (-1.388)	0.177 (1.006)	-0.472 (-2.790)*	0.3029	0.2715	2.3268	-3.081 (-2.089)**	0.771 (5.838)*	-0.474 (-2.108)**	0.714 (2.247)**	0.093 (0.333)	0.3533	0.3242	1.8911
	Small (S)	-0.724 (-0.442)	0.774 (4.727)*	-0.143 (-0.400)	0.411 (2.338)**	-0.434 (-2.042)**	0.2235	0.1886	1.9962	-0.508 (-0.184)	0.866 (2.637)*	0.790 (1.189)	1.139 (2.014)**	0.658 (1.165)	0.2621	0.2289	2.0736
Panel B: Liquid firms																	
Low (L)	Big (B)	-2.165 (-2.745)*	0.799 (6.976)*	-0.873 (-3.134)*	-0.061 (-0.439)	-0.564 (-3.608)*	0.4182	0.3921	1.8165	-0.356 (-0.297)	1.044 (7.160)*	-0.736 (-2.612)**	-0.579 (-2.102)**	0.486 (1.817)	0.4647	0.4406	2.0787
	Small (S)	-4.246 (-3.714)*	0.547 (4.046)*	0.015 (0.090)	-0.253 (-1.564)	-0.602 (-2.063)**	0.2290	0.1943	2.3096	-1.471 (-1.789)	0.837 (7.014)*	0.255 (1.671)	-0.430 (-2.427)**	0.375 (1.696)	0.4122	0.3858	2.2034
Medium (M)	Big (B)	-1.699 (-2.101)**	0.709 (8.743)*	-0.009 (-0.043)	-0.038 (-0.207)	-0.927 (-3.180)*	0.3442	0.3148	2.2099	-1.909 (-1.850)	0.680 (4.696)*	-0.796 (-3.916)*	0.260 (2.261)**	0.356 (1.471)	0.4436	0.4186	2.2369
	Small (S)	-2.076 (-1.539)	0.820 (4.185)*	1.327 (1.610)	0.673 (1.820)	-0.133 (-0.490)	0.3217	0.2913	2.0822	-1.073 (-1.140)	0.838 (4.282)*	0.044 (0.218)	0.125 (0.914)	-0.018 (-0.080)	0.3520	0.3229	2.1523
High (H)	Big (B)	-1.351 (-0.801)	0.818 (2.855)*	-0.471 (-1.483)	0.498 (1.437)	-0.718 (-1.712)	0.2659	0.2329	1.8332	-3.699 (-2.955)*	0.493 (3.464)*	-0.502 (-1.853)	0.632 (3.317)**	0.319 (1.662)	0.2669	0.2340	2.2629
	Small (S)	-2.344 (-2.692)*	0.787 (5.240)*	0.234 (1.335)	0.512 (3.067)**	-0.585 (-2.555)**	0.3400	0.3104	2.2627	-1.822 (-1.508)	0.872 (4.719)*	0.834 (0.918)	0.684 (1.677)	0.511 (1.584)	0.2524	0.2188	2.3436

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.6 REGRESSION RESULTS FOR THE LIQUIDITY-AUGMENTED STANDARD CAPM

A standard CAPM model, augmented for liquidity, was run on portfolios set up according to their levels of liquidity as well as size, value and momentum variables. Equation 3.6 provides a mathematical description of this particular model:

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + i_{jIMV} IMV_t + u_{jt}$$

The size, value and momentum variables are as in Appendix C.4. These three measures were applied together with the various liquidity measures to determine their significance in setting up portfolios and hence generating excess returns. This was done by running regressions on the various portfolios. The aim of this regression was to compare it to the results from equation 3.5 in order to determine if the added liquidity variable has any predictive power. The results of the standard CAPM regressions, augmented for liquidity, (i.e. equation 3.7) are presented below.

C.6.1 BID-ASK- SPREAD

Table C.6.1 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity

The table reports the regression results for the liquidity-augmented standard CAPM for portfolios set up according to the bid-ask spread as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm} and i_{jIMV} represent the coefficients of the market return and liquidity factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum											
		Poor (P)						Good (G)					
Value	**Size**	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms													
Low (L)	Big (B)	-1.714 (-2.078)**	0.832 (5.222)*	0.803 (3.311)*	0.3819	0.3683	2.4656	-0.913 (-0.938)	0.844 (5.605)*	0.756 (3.106)*	0.4722	0.4606	2.2811
	Small (S)	-2.927 (-2.959)*	0.707 (4.027)*	0.809 (1.565)	0.1782	0.1601	1.9596	-3.137 (-3.840)*	0.691 (7.859)*	0.448 (2.236)**	0.2653	0.2491	2.1435
Medium (M)	Big (B)	-2.769 (-3.803)*	0.673 (5.666)*	0.492 (3.195)*	0.3215	0.3066	2.3581	-0.550 (-0.386)	0.985 (3.908)*	0.559 (2.801)*	0.4626	0.4508	2.5099
	Small (S)	-2.630 (-1.969)	0.886 (4.975)*	1.170 (1.817)	0.3587	0.3446	1.7190	-2.781 (-1.608)	0.673 (2.478)**	0.756 (1.663)	0.1745	0.1563	1.9692
High (H)	Big (B)	-2.833 (-3.412)*	0.681 (5.076)*	0.557 (3.621)*	0.3264	0.3116	2.0888	-2.477 (-2.918)*	0.737 (7.074)*	0.516 (4.274)*	0.4173	0.4045	1.9611
	Small (S)	-5.065 (-3.753)*	0.312 (2.621)**	0.021 (0.035)	0.0356	0.0144	2.3754	-2.772 (-2.843)*	0.515 (3.632)*	0.686 (3.756)*	0.2421	0.2255	1.9805
Panel B: Liquid firms													
Low (L)	Big (B)	-3.584 (-2.977)*	0.557 (2.905)*	-0.352 (-1.436)	0.1818	0.1638	2.1034	-1.408 (-1.326)	0.850 (7.298)*	-0.547 (-2.236)**	0.3713	0.3575	1.9117
	Small (S)	-4.208 (-3.777)*	0.600 (4.170)*	-0.294 (-1.095)	0.1678	0.1495	2.1348	0.749 (0.754)	1.066 (7.795)*	-0.467 (-1.049)	0.2900	0.2744	2.3893
Medium (M)	Big (B)	-3.127 (-3.631)*	0.626 (5.655)*	-0.203 (-0.701)	0.2031	0.1856	2.0435	-2.950 (-3.701)*	0.734 (6.445)*	-0.267 (-2.432)**	0.4955	0.4844	1.6656
	Small (S)	-4.976 (-2.978)*	0.454 (2.685)*	-1.269 (-1.350)	0.1509	0.1323	2.1930	-1.178 (-1.804)	0.786 (6.780)*	-0.125 (-0.969)	0.3326	0.3179	2.0590
High (H)	Big (B)	-4.187 (-2.887)*	0.355 (1.811)	-0.036 (-0.136)	0.0420	0.0210	2.1907	-0.708 (-0.410)	1.031 (3.918)*	-0.257 (-0.841)	0.2624	0.2462	2.1111
	Small (S)	-2.592 (-5.099)*	0.781 (6.673)*	0.374 (2.993)*	0.4234	0.4108	1.4868	-2.401 (-1.176)	0.697 (3.499)*	-0.985 (-0.909)	0.1338	0.1148	2.1850

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.6.2 TURNOVER

Table C.6.2 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity

The table reports the regression results for the liquidity-augmented standard CAPM for portfolios set up according to turnover as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm} and i_{jIMV} represent the coefficients of the market return and liquidity factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum											
		Poor (P)						Good (G)					
Value	**Size**	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms													
Low (L)	Big (B)	-1.480 (-1.684)	0.908 (6.462)*	0.337 (1.924)	0.3543	0.3402	2.5210	-0.914 (-0.917)	0.813 (5.916)*	0.220 (0.962)	0.3198	0.3049	2.4381
	Small (S)	-3.597 (-4.639)*	0.599 (4.232)*	0.456 (1.766)	0.2351	0.2183	1.7420	-2.989 (-2.496)**	0.554 (4.013)*	0.503 (2.725)*	0.1281	0.1089	2.1907
Medium (M)	Big (B)	-2.582 (-2.772)*	0.657 (4.478)*	0.239 (1.315)	0.2243	0.2073	2.4718	-0.203 (-0.165)	1.024 (4.506)*	0.040 (0.224)	0.4074	0.3944	2.5650
	Small (S)	-4.908 (-3.921)*	0.610 (4.533)*	0.955 (1.915)	0.1257	0.1064	2.4910	-2.673 (-3.142)*	0.821 (5.919)*	0.132 (0.732)	0.4585	0.4466	1.8779
High (H)	Big (B)	-2.233 (-2.354)**	0.757 (5.343)*	0.232 (1.183)	0.2579	0.2416	2.2302	-3.154 (-3.201)*	0.691 (6.103)*	-0.001 (-0.011)	0.3114	0.2962	1.9531
	Small (S)	-3.552 (-2.662)*	0.521 (3.000)*	1.039 (2.163)**	0.1138	0.0944	2.1992	-3.542 (-3.200)*	0.406 (4.008)*	0.047 (0.218)	0.1038	0.0841	1.8004
Panel B: Liquid firms													
Low (L)	Big (B)	-1.995 (-2.564)**	0.717 (5.148)*	0.118 (0.729)	0.2387	0.2220	2.7134	-0.241 (-0.244)	0.979 (7.710)*	-0.239 (-1.485)	0.4497	0.4376	2.2684
	Small (S)	-5.720 (-2.804)*	0.470 (2.346)**	-0.689 (-1.233)	0.1276	0.1084	2.2097	-0.302 (-0.357)	0.927 (9.743)*	-0.495 (-3.133)*	0.4349	0.4225	2.2101
Medium (M)	Big (B)	-3.204 (-3.824)*	0.665 (6.909)*	-0.411 (-1.428)	0.2774	0.2615	2.2698	-2.070 (-2.320)**	0.866 (5.901)*	-0.520 (-2.533)**	0.4543	0.4423	2.2699
	Small (S)	-6.320 (-2.273)**	0.237 (0.738)	-2.017 (-1.628)	0.3269	0.3121	2.1480	-1.797 (-1.369)	0.722 (2.896)*	-0.528 (-1.854)	0.2752	0.2593	1.9460
High (H)	Big (B)	-3.892 (-3.391)*	0.409 (3.225)*	-0.123 (-0.860)	0.1009	0.0812	2.5150	1.186 (0.877)	1.200 (6.682)*	-0.442 (-2.482)**	0.4782	0.4668	2.2732
	Small (S)	-3.278 (-4.384)*	0.751 (4.709)*	-0.430 (-1.942)	0.3243	0.3095	1.9048	-4.192 (-1.525)	0.417 (1.275)	-2.026 (-1.564)	0.3179	0.3029	2.4034

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.6.3 PRICE IMPACT

Table C.6.3 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity

The table reports the regression results for the liquidity-augmented standard CAPM for portfolios set up according to the price impact measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm} and i_{jIMV} represent the coefficients of the market return and liquidity factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum											
		Poor (P)						Good (G)					
Value	**Size**	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms													
Low (L)	Big (B)	-0.769 (-0.947)	0.934 (6.272)*	0.605 (2.784)*	0.3581	0.3440	2.6036	-0.214 (-0.218)	0.914 (6.761)*	0.355 (2.017)**	0.4033	0.3902	2.3709
	Small (S)	-4.483 (-1.924)	0.542 (2.321)*	0.013 (0.042)	0.0827	0.0625	1.8278	-3.840 (-3.000)*	0.500 (3.737)*	0.591 (2.099)**	0.1574	0.1388	1.9271
Medium (M)	Big (B)	-2.293 (-2.400)**	0.718 (5.179)*	0.197 (1.235)	0.2633	0.2471	2.4400	-0.018 (-0.015)	1.035 (4.483)*	0.263 (1.527)	0.4296	0.4171	2.5700
	Small (S)	-4.127 (-4.123)*	0.750 (5.483)*	0.766 (2.446)**	0.2153	0.1980	2.3651	-3.363 (-3.171)*	0.518 (3.532)*	0.152 (1.238)	0.1945	0.1768	1.5929
High (H)	Big (B)	-2.434 (-2.758)*	0.724 (5.204)*	0.126 (0.900)	0.2868	0.2711	2.1403	-2.140 (-2.303)**	0.773 (6.639)*	0.140 (0.766)	0.3445	0.3301	2.0049
	Small (S)	-5.465 (-3.167)*	0.363 (1.591)	0.043 (0.104)	0.0359	0.0147	2.2887	0.535 (0.141)	0.892 (2.347)**	1.408 (1.442)	0.1845	0.1666	1.8351
Panel B: Liquid firms													
Low (L)	Big (B)	-1.108 (-1.262)	0.878 (5.498)*	-0.094 (-0.711)	0.3135	0.2984	2.4074	-1.615 (-1.245)	0.723 (4.595)*	-0.260 (-1.231)	0.2824	0.2667	1.8839
	Small (S)	-4.870 (-3.421)*	0.517 (3.394)*	-0.541 (-1.951)	0.1923	0.1746	2.1167	-1.193 (-1.460)	0.871 (9.606)*	-0.459 (-1.651)	0.4492	0.4370	2.1699
Medium (M)	Big (B)	-2.715 (-2.971)*	0.752 (7.827)*	-0.242 (-0.857)	0.2381	0.2213	2.3948	-2.749 (-3.126)*	0.859 (7.575)*	-0.139 (-1.055)	0.4361	0.4237	1.8877
	Small (S)	-5.400 (-2.141)**	0.342 (1.338)	-0.961 (-1.251)	0.1545	0.1359	2.1683	-1.462 (-1.625)	0.827 (4.118)*	-0.245 (-1.773)	0.3452	0.3308	2.1195
High (H)	Big (B)	-1.873 (-0.761)	0.420 (1.450)	-3.049 (-1.324)	0.2422	0.2256	2.6404	0.026 (0.011)	1.093 (3.787)*	-0.207 (-0.459)	0.2657	0.2496	2.1717
	Small (S)	-2.098 (-2.924)*	0.843 (5.166)*	-0.029 (-0.185)	0.3544	0.3403	1.6784	-3.552 (-1.265)	0.542 (1.812)	-1.116 (-1.297)	0.1857	0.1678	2.3524

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.6.4 ZEROS 1

Table C.6.4 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity

The table reports the regression results for the liquidity-augmented standard CAPM for portfolios set up according to the zeros1 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm} and i_{jIMV} represent the coefficients of the market return and liquidity factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum											
		Poor (P)						Good (G)					
Value	**Size**	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms													
Low (L)	Big (B)	-1.892 (-2.143)**	0.815 (4.724)*	0.749 (3.320)*	0.3785	0.3648	2.5896	-0.779 (-0.756)	0.865 (6.114)*	0.381 (2.316)**	0.4048	0.3918	2.2925
	Small (S)	-3.170 (-1.829)	0.731 (4.112)*	0.562 (1.585)	0.1702	0.1519	2.1130	-1.833 (-1.187)	0.723 (4.550)*	0.506 (1.515)	0.1877	0.1698	1.9726
Medium (M)	Big (B)	-2.620 (-2.832)*	0.679 (4.658)*	0.180 (1.830)	0.2632	0.2470	2.4293	-0.423 (-0.336)	1.008 (4.533)*	0.227 (1.093)	0.4345	0.4220	2.5468
	Small (S)	-4.929 (-3.885)*	0.579 (3.621)*	0.772 (2.864)*	0.1481	0.1293	2.3299	-3.877 (-2.630)**	0.529 (2.904)*	0.237 (1.021)	0.1736	0.1554	1.9158
High (H)	Big (B)	-2.592 (-2.608)**	0.716 (4.672)*	0.169 (0.991)	0.2639	0.2478	2.2541	-2.415 (-2.570)**	0.761 (6.804)*	0.217 (1.228)	0.3439	0.3295	1.9812
	Small (S)	-3.287 (-4.510)*	0.536 (6.985)*	0.383 (2.578)**	0.2368	0.2200	2.1607	-1.745 (-0.566)	0.642 (2.409)**	2.313 (1.510)	0.2788	0.2629	1.6856
Panel B: Liquid firms													
Low (L)	Big (B)	-2.470 (-2.607)**	0.789 (4.836)*	-0.126 (-1.035)	0.2962	0.2808	1.8115	-0.041 (-0.022)	1.096 (3.091)*	-0.367 (-1.502)	0.2786	0.2628	2.0377
	Small (S)	-5.215 (-3.936)*	0.494 (3.457)*	-0.231 (-1.290)	0.0946	0.0747	2.1412	0.024 (0.030)	0.998 (9.694)*	-0.792 (-2.558)**	0.4269	0.4143	2.3769
Medium (M)	Big (B)	-2.749 (-3.689)*	0.673 (7.708)*	-0.152 (-1.067)	0.1854	0.1675	2.2247	-0.879 (-0.489)	0.805 (2.631)*	-0.441 (-2.608)**	0.2581	0.2418	2.2770
	Small (S)	-3.859 (-2.562)**	0.525 (3.650)*	-1.188 (-1.327)	0.2260	0.2089	2.2041	-2.667 (-3.328)*	0.689 (4.753)*	-0.139 (-1.422)	0.3243	0.3095	1.9919
High (H)	Big (B)	-2.666 (-2.063)**	0.672 (2.636)*	-0.133 (-0.677)	0.1508	0.1321	1.7159	-2.956 (-1.790)	0.512 (3.250)*	-0.300 (-1.069)	0.1025	0.0828	2.0471
	Small (S)	-4.126 (-4.064)*	0.597 (3.615)*	-0.256 (-1.059)	0.1788	0.1608	2.0491	-1.960 (-1.181)	0.736 (4.244)*	-1.177 (-1.299)	0.2359	0.2191	2.4121

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.6.5 ZEROS 2

Table C.6.5 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity

The table reports the regression results for the liquidity-augmented standard CAPM for portfolios set up according to the zeros2 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm} and i_{jIMV} represent the coefficients of the market return and liquidity factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum											
		Poor (P)						Good (G)					
Value	**Size**	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms													
Low (L)	Big (B)	-1.596 (-1.749)	0.837 (4.786)*	0.731 (3.054)*	0.3749	0.3612	2.6095	-0.633 (-0.633)	0.877 (6.450)*	0.283 (1.716)	0.3884	0.3749	2.3410
	Small (S)	-3.304 (-1.853)	0.672 (2.901)*	0.852 (1.685)	0.1493	0.1306	1.8278	-2.307 (-1.161)	0.653 (3.483)*	0.913 (1.537)	0.1394	0.1205	1.8481
Medium (M)	Big (B)	-2.533 (-2.717)*	0.688 (4.660)*	0.115 (1.093)	0.2585	0.2422	2.4521	-0.246 (-0.194)	1.024 (4.565)*	0.178 (0.906)	0.4278	0.4152	2.5367
	Small (S)	-4.638 (-3.513)*	0.695 (3.654)*	1.343 (3.740)*	0.2331	0.2163	2.1915	-2.577 (-1.630)	0.624 (3.191)*	0.303 (1.187)	0.2129	0.1956	2.0523
High (H)	Big (B)	-2.546 (-2.593)**	0.719 (4.640)*	0.140 (0.855)	0.2525	0.2361	2.3104	-3.154 (-2.058)**	0.718 (5.219)*	0.217 (1.131)	0.1912	0.1735	1.7270
	Small (S)	-1.819 (-1.409)	0.665 (5.576)*	0.456 (1.898)	0.2110	0.1937	2.0843	-1.594 (-0.565)	0.637 (2.560)**	1.533 (1.638)	0.2207	0.2036	1.7401
Panel B: Liquid firms													
Low (L)	Big (B)	-2.121 (-2.358)**	0.856 (5.724)*	-0.307 (-1.784)	0.2884	0.2728	2.0688	1.835 (1.059)	1.304 (4.404)*	-0.177 (-0.759)	0.3469	0.3325	2.0978
	Small (S)	-5.009 (-3.579)*	0.516 (3.828)*	-0.272 (-1.449)	0.1302	0.1111	2.1644	-0.586 (-0.725)	0.927 (10.194)*	-0.401 (-1.681)	0.3863	0.3728	2.3168
Medium (M)	Big (B)	-3.307 (-4.521)*	0.601 (7.303)*	0.196 (0.928)	0.1680	0.1497	2.2483	-0.590 (-0.564)	0.785 (4.561)*	-0.565 (-2.653)*	0.3276	0.3128	2.3048
	Small (S)	-4.071 (-2.257)**	0.514 (2.929)*	-1.105 (-1.337)	0.2122	0.1949	2.1006	-1.194 (-1.398)	0.809 (4.579)*	-0.335 (-2.107)**	0.3787	0.3651	2.0744
High (H)	Big (B)	-2.528 (-2.014)**	0.705 (2.948)*	-0.262 (-1.452)	0.1722	0.1540	1.7484	-3.170 (-1.980)	0.488 (3.213)*	-0.254 (-0.929)	0.0951	0.0752	2.0575
	Small (S)	-4.020 (-3.821)*	0.595 (3.627)*	-0.302 (-1.709)	0.2048	0.1873	1.9477	-2.187 (-1.158)	0.709 (3.655)*	-1.153 (-1.408)	0.2340	0.2171	2.3841

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.7 REGRESSION RESULTS FOR THE LIQUIDITY-AND-MOMENTUM-AUGMENTED FAMA-FRENCH MODEL

A liquidity-and-momentum-augmented Fama-French model was run on portfolios set up according to the various liquidity variables, as well as fixed variables for the size, value and momentum effects. The following regression was run on these portfolios (i.e. according to equation 3.8):

$$r_{jt} = \alpha_j + \beta_{jm} r_{mt} + s_{jSMB} SMB_t + h_{jHML} HML_t + g_{jGMP} GMP_t + i_{jIMV} IMV_t + v_{jt}$$

The size, value and momentum variables are as in Appendix C.4. These three measures were applied together with the various liquidity measures to determine their significance in setting up portfolios and hence generating excess returns. This was done by running regressions on the various portfolios. The aim of this regression was to compare it to the results from equation 3.6 in order to determine if the added liquidity variable has any predictive power. The results for the different portfolios are presented below.

C.7.1 BID-ASK SPREAD

Table C.7.1 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity, size, value and momentum

The table reports the regression results for the liquidity-and-momentum-augmented Fama-French model for portfolios set up according to the bid-ask spread as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, i_{jIMV}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, liquidity factor, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum																	
		Poor (P)									Good (G)								
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																			
Low (L)	Big (B)	-0.763 (-0.723)	0.933 (5.012)*	-0.380 (-1.302)	0.002 (0.009)	-0.694 (-3.371)*	0.716 (3.056)*	0.4614	0.4308	2.3860	-1.230 (-1.553)	0.828 (6.897)*	-0.341 (-1.433)	0.364 (2.260)**	0.236 (1.697)	0.763 (3.581)*	0.5347	0.5083	2.3054
	Small (S)	-2.123 (-1.660)	0.734 (4.227)*	1.317 (2.737)*	-1.198 (-3.351)*	-0.568 (-2.022)**	0.818 (2.073)**	0.4904	0.4615	2.0470	-3.426 (-4.861)*	0.645 (7.930)*	0.523 (2.399)**	-0.310 (-1.509)	0.211 (1.002)	0.494 (2.449)**	0.3193	0.2806	2.0771
Medium (M)	Big (B)	-1.549 (-2.382)**	0.816 (7.758)*	-0.133 (-0.888)	0.254 (1.535)	-0.661 (-4.432)*	0.436 (2.374)**	0.4223	0.3895	2.3748	-0.793 (-0.697)	0.973 (4.836)*	-0.198 (-0.749)	0.262 (1.614)	0.195 (0.790)	0.570 (2.911)*	0.4893	0.4603	2.5398
	Small (S)	-0.879 (-0.728)	1.110 (5.346)*	0.264 (1.393)	0.706 (2.798)*	-0.647 (-2.470)**	1.161 (2.553)**	0.4857	0.4564	1.8757	-2.351 (-1.384)	0.742 (2.669)*	0.212 (0.904)	0.441 (1.513)	0.008 (0.028)	0.788 (1.909)	0.2104	0.1655	1.9810
High (H)	Big (B)	-1.772 (-2.187)**	0.812 (6.542)*	0.035 (0.338)	0.346 (2.188)**	-0.470 (-3.128)*	0.532 (3.435)*	0.4030	0.3691	2.1892	-2.213 (-2.939)*	0.793 (6.782)*	-0.120 (-0.708)	0.548 (6.190)*	0.044 (0.231)	0.530 (4.257)*	0.5200	0.4927	2.0824
	Small (S)	-2.827 (-2.929)*	0.595 (4.806)*	0.957 (2.712)*	0.829 (2.844)*	-0.653 (-2.718)*	0.067 (0.164)	0.4156	0.3824	2.3050	-2.902 (-3.310)*	0.529 (3.723)*	0.390 (2.389)**	0.535 (3.445)*	0.444 (2.181)**	0.771 (4.152)*	0.4154	0.3822	1.9257
Panel B: Liquid firms																			
Low (L)	Big (B)	-2.770 (-2.277)**	0.633 (3.453)*	-0.379 (-1.502)	-0.204 (-1.200)	-0.702 (-3.512)*	-0.446 (-1.869)	0.3180	0.2793	2.0691	-2.631 (-3.418)*	0.700 (6.910)*	-0.100 (-0.388)	-0.386 (-1.720)	0.527 (2.840)*	-0.524 (-2.624)**	0.4586	0.4279	1.9523
	Small (S)	-2.705 (-3.192)*	0.750 (6.750)*	-0.077 (-0.418)	-0.218 (-1.330)	-1.019 (-3.637)*	-0.392 (-1.769)	0.3590	0.3226	2.3597	-0.349 (-0.281)	0.911 (5.895)*	1.120 (5.953)*	-0.773 (-3.538)*	0.689 (2.791)*	-0.353 (-0.925)	0.4498	0.4185	2.3384
Medium (M)	Big (B)	-1.770 (-2.961)*	0.783 (9.476)*	-0.436 (-2.404)**	0.258 (1.791)	-0.842 (-3.364)*	-0.296 (-1.111)	0.3511	0.3142	2.0339	-3.305 (-4.313)*	0.699 (6.245)*	-0.148 (-1.566)	0.062 (0.740)	0.190 (1.656)	-0.260 (-2.647)*	0.5185	0.4911	1.6769
	Small (S)	-2.119 (-2.140)**	0.812 (4.526)*	1.784 (3.235)*	0.962 (3.071)*	-0.688 (-3.852)*	-1.159 (-3.261)*	0.5971	0.5742	2.1496	-0.900 (-1.454)	0.820 (7.098)*	0.341 (1.890)	0.058 (0.342)	-0.026 (-0.191)	-0.100 (-0.634)	0.3582	0.3217	2.2494
High (H)	Big (B)	-1.752 (-1.431)	0.652 (4.036)*	-0.627 (-2.093)**	0.744 (3.691)*	-1.336 (-3.634)*	-0.168 (-0.647)	0.3278	0.2896	2.0986	-2.282 (-1.975)	0.889 (4.997)*	-0.648 (-3.075)*	0.529 (2.142)**	0.957 (2.629)**	-0.207 (-0.709)	0.4321	0.3998	2.1765
	Small (S)	-1.800 (-3.258)*	0.881 (6.331)*	0.201 (1.011)	0.298 (2.425)**	-0.275 (-1.213)	0.377 (2.392)**	0.4876	0.4585	1.5401	-0.448 (-0.332)	0.983 (4.841)*	1.494 (2.332)**	1.448 (3.732)*	-0.031 (-0.102)	-0.825 (-1.718)	0.5358	0.5094	2.0140

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.7.2 TURNOVER

Table C.7.2 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity, size, value and momentum

The table reports the regression results for the liquidity-and-momentum-augmented Fama-French model for portfolios set up according to turnover as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, i_{jIMV}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, liquidity factor, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum																	
		Poor (P)									Good (G)								
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																			
Low (L)	Big (B)	-1.617 (-1.710)	0.860 (7.038)*	-0.788 (-3.935)*	-0.033 (-0.151)	-0.733 (-2.779)*	-0.020 (-0.077)	0.5011	0.4728	2.3670	-2.183 (-2.470)**	0.670 (5.362)*	-0.666 (-2.913)*	0.207 (1.081)	0.100 (0.466)	0.156 (0.508)	0.4260	0.3934	2.3350
	Small (S)	-1.885 (-2.597)**	0.762 (7.045)*	0.254 (1.895)	-0.398 (-3.011)*	-0.831 (-5.757)*	0.205 (1.055)	0.5001	0.4717	2.0749	-3.807 (-2.901)*	0.465 (2.866)*	0.285 (1.896)	-0.589 (-2.975)*	0.518 (1.926)	0.551 (3.323)*	0.2154	0.1708	2.1433
Medium (M)	Big (B)	-1.519 (-2.315)**	0.754 (6.321)*	-0.397 (-3.001)*	0.286 (1.897)	-0.878 (-3.440)*	0.004 (0.021)	0.3666	0.3306	2.5507	-1.411 (-1.305)	0.888 (5.105)*	-0.628 (-2.683)*	0.202 (0.974)	0.104 (0.527)	-0.017 (-0.060)	0.4811	0.4516	2.4521
	Small (S)	-1.714 (-1.618)	0.929 (5.875)*	0.302 (1.086)	-0.084 (-0.304)	-1.479 (-3.789)*	0.627 (2.011)**	0.3568	0.3202	2.5579	-1.913 (-1.880)	0.909 (5.796)*	0.228 (1.672)	0.116 (0.732)	-0.144 (-0.969)	0.171 (1.000)	0.4926	0.4638	1.9540
High (H)	Big (B)	-1.611 (-1.816)	0.827 (6.238)*	-0.302 (-2.083)**	0.616 (2.770)*	-0.417 (-1.704)	0.212 (1.052)	0.3540	0.3173	2.2555	-3.516 (-4.263)*	0.666 (5.222)*	-0.342 (-2.384)**	0.691 (4.287)*	0.110 (0.493)	0.120 (0.788)	0.4739	0.4440	2.2288
	Small (S)	-0.308 (-0.240)	0.896 (4.859)*	0.434 (1.633)	1.142 (4.084)*	-0.917 (-3.021)*	1.173 (2.907)*	0.3920	0.3574	2.3051	-2.638 (-2.739)*	0.529 (5.318)*	0.480 (2.262)**	0.430 (2.747)*	0.149 (0.548)	0.288 (1.753)	0.2457	0.2028	1.9842
Panel B: Liquid firms																			
Low (L)	Big (B)	-1.837 (-1.823)	0.704 (4.439)*	-0.516 (-2.962)*	-0.184 (-1.042)	-0.676 (-3.181)*	-0.203 (-0.869)	0.3488	0.3118	2.6116	-1.616 (-1.607)	0.809 (8.426)*	-0.732 (-4.527)*	-0.167 (-0.783)	-0.047 (-0.247)	-0.443 (-2.048)**	0.5623	0.5374	2.1371
	Small (S)	-3.293 (-2.683)*	0.691 (4.687)*	0.245 (1.144)	-0.700 (-2.975)*	-1.344 (-4.640)*	-1.143 (-2.261)**	0.3967	0.3625	2.4350	-0.211 (-0.291)	0.957 (11.134)*	0.770 (3.323)*	-0.330 (-1.926)	0.605 (2.122)**	-0.261 (-1.249)	0.5426	0.5166	2.2167
Medium (M)	Big (B)	-2.230 (-3.091)*	0.736 (7.473)*	-0.405 (-2.161)**	-0.150 (-1.116)	-0.999 (-5.669)*	-0.783 (-3.424)*	0.4461	0.4146	2.2210	-2.696 (-3.360)*	0.793 (6.090)*	-0.389 (-2.068)**	0.113 (0.752)	-0.008 (-0.031)	-0.576 (-2.748)*	0.4839	0.4546	2.1501
	Small (S)	-3.000 (-1.860)	0.630 (3.030)*	0.854 (2.618)**	0.979 (2.932)*	-0.595 (-2.413)**	-1.754 (-2.595)**	0.5781	0.5541	2.2445	-0.864 (-0.615)	0.835 (3.230)*	0.452 (1.629)	0.098 (0.437)	-0.019 (-0.080)	-0.415 (-1.160)	0.3149	0.2759	2.1737
High (H)	Big (B)	-3.264 (-2.939)*	0.450 (3.817)*	-0.823 (-3.299)*	0.422 (2.912)*	-1.019 (-3.150)*	-0.450 (-2.006)**	0.3437	0.3064	2.3864	-0.622 (-0.808)	0.997 (10.314)*	-1.152 (-4.594)*	0.584 (3.045)*	0.046 (0.178)	-0.530 (-2.396)**	0.6595	0.6401	2.3218
	Small (S)	-1.844 (-2.467)**	0.915 (5.805)*	0.001 (0.005)	0.691 (3.341)*	-0.529 (-2.113)**	-0.397 (-1.601)	0.4633	0.4328	2.0233	-2.646 (-1.650)	0.635 (3.010)*	0.555 (1.541)	1.231 (3.404)*	0.169 (0.470)	-1.573 (-2.045)**	0.4968	0.4683	2.4202

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.7.3 PRICE IMPACT

Table C.7.3 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity, size, value and momentum

The table reports the regression results for the liquidity-and-momentum-augmented Fama-French model for portfolios set up according to the price impact measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, i_{jIMV}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, liquidity factor, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum																	
		Poor (P)									Good (G)								
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																			
Low (L)	Big (B)	-0.941 (-1.036)	0.913 (5.489)*	-0.482 (-1.600)	0.123 (0.660)	-0.468 (-3.343)*	0.870 (3.657)*	0.4563	0.4254	2.4610	-1.459 (-1.727)	0.792 (6.459)*	-0.477 (-2.040)**	0.189 (1.580)	0.245 (1.895)	0.426 (2.260)**	0.4774	0.4477	2.3184
	Small (S)	-2.346 (-1.282)	0.742 (3.450)*	0.242 (1.694)	-0.319 (-2.301)**	-1.104 (-3.547)*	0.195 (0.865)	0.2863	0.2457	1.8357	-4.136 (-3.048)*	0.458 (3.145)*	-0.219 (-1.263)	-0.214 (-1.440)	-0.043 (-0.239)	0.562 (2.096)**	0.1875	0.1413	1.8963
Medium (M)	Big (B)	-1.621 (-1.678)	0.785 (6.338)*	-0.086 (-0.496)	0.083 (0.803)	-0.556 (-3.531)*	0.410 (2.139)**	0.3609	0.3246	2.5048	-1.065 (-1.148)	0.929 (5.312)*	-0.471 (-1.443)	0.104 (0.779)	0.128 (0.781)	0.337 (1.571)	0.4749	0.4450	2.5301
	Small (S)	-2.047 (-2.035)**	0.963 (4.887)*	0.387 (2.949)*	0.059 (0.409)	-0.929 (-2.937)*	1.007 (2.678)*	0.3706	0.3348	2.3957	-2.530 (-2.587)**	0.614 (4.383)*	0.432 (2.576)**	0.136 (0.902)	-0.053 (-0.355)	0.148 (0.915)	0.2714	0.2300	1.8107
High (H)	Big (B)	-2.006 (-2.506)**	0.771 (5.999)*	-0.156 (-0.910)	0.176 (1.455)	-0.486 (-2.577)**	0.362 (2.239)**	0.3897	0.3551	2.2160	-2.488 (-2.759)*	0.755 (5.829)*	-0.165 (-1.224)	0.441 (5.660)*	-0.004 (-0.026)	0.327 (3.862)*	0.4645	0.4341	2.1172
	Small (S)	-2.325 (-2.621)**	0.720 (5.396)*	1.161 (3.239)*	0.662 (2.697)*	-0.769 (-2.895)*	0.329 (0.804)	0.4210	0.3881	2.6505	-0.580 (-0.369)	0.853 (4.769)*	0.060 (0.293)	1.641 (2.918)*	0.664 (1.177)	1.791 (3.252)*	0.5261	0.4991	1.8947
Panel B: Liquid firms																			
Low (L)	Big (B)	-0.577 (-0.544)	0.921 (5.866)*	-0.187 (-0.842)	-0.146 (-1.047)	-0.562 (-2.498)**	0.055 (0.283)	0.3936	0.3591	2.2469	-2.408 (-2.938)*	0.624 (6.529)*	-0.209 (-1.231)	-0.412 (-2.851)*	0.317 (2.275)**	-0.472 (-2.418)**	0.4039	0.3701	2.1099
	Small (S)	-3.061 (-3.624)*	0.683 (7.235)*	0.181 (0.987)	-0.339 (-1.513)	-0.957 (-4.127)*	-0.402 (-1.468)	0.4184	0.3854	2.2632	-0.942 (-1.121)	0.890 (9.084)*	0.289 (2.438)**	-0.263 (-2.412)**	0.199 (1.306)	-0.661 (-2.848)*	0.5119	0.4841	2.0936
Medium (M)	Big (B)	-2.110 (-2.788)*	0.807 (7.180)*	-0.023 (-0.103)	-0.081 (-0.296)	-0.422 (-1.701)	-0.140 (-0.455)	0.2749	0.2337	2.3588	-3.154 (-3.938)*	0.818 (6.710)*	-0.105 (-0.730)	-0.004 (-0.047)	0.144 (0.813)	-0.168 (-1.402)	0.4447	0.4132	1.8892
	Small (S)	-2.200 (-1.850)	0.712 (3.641)*	1.650 (2.713)*	0.643 (2.508)**	-0.227 (-1.176)	-0.924 (-2.371)**	0.5418	0.5158	2.2304	-0.621 (-0.514)	0.916 (4.106)*	0.394 (1.617)	-0.017 (-0.171)	-0.090 (-0.573)	-0.287 (-1.836)	0.3769	0.3415	2.3194
High (H)	Big (B)	-2.973 (-2.127)**	0.348 (1.839)*	-2.660 (-4.855)*	2.017 (4.470)*	-2.608 (-4.986)*	-1.099 (-2.720)*	0.7860	0.7738	2.3873	-2.742 (-1.731)	0.833 (4.179)*	-0.751 (-2.333)**	0.592 (1.909)	0.896 (3.937)*	-0.145 (-0.479)	0.4546	0.4236	2.1137
	Small (S)	-1.338 (-1.613)	0.929 (5.160)*	0.199 (0.699)	0.204 (2.135)*	-0.288 (-1.887)	0.100 (0.525)	0.4085	0.3749	1.8793	-1.418 (-1.045)	0.814 (3.239)*	1.450 (2.010)**	0.887 (2.855)*	0.221 (0.650)	-1.095 (-2.292)**	0.4920	0.4632	2.2978

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.7.4 ZEROS 1

Table C.7.4 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity, size, value and momentum

The table reports the regression results for the liquidity-and-momentum-augmented Fama-French model for portfolios set up according to the zeros1 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, i_{jIMV}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, liquidity factor, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum																	
		Poor (P)									Good (G)								
Value	**Size**	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																			
Low (L)	Big (B)	-1.799 (-2.460)**	0.797 (5.808)*	-0.441 (-1.402)	-0.060 (-0.268)	-0.396 (-1.623)	0.773 (2.339)**	0.4284	0.3959	2.5095	-1.751 (-2.564)**	0.775 (8.015)*	-0.544 (-2.203)**	0.086 (0.559)	0.239 (1.610)	0.403 (1.767)	0.4902	0.4613	2.3120
	Small (S)	-0.672 (-0.637)	0.903 (7.320)*	0.512 (2.912)*	-0.427 (-3.159)*	-1.339 (-4.487)*	0.558 (3.860)*	0.5091	0.4812	2.4624	-2.390 (-1.524)	0.648 (3.236)*	0.534 (2.109)**	-0.520 (-2.108)**	0.463 (1.165)	0.517 (1.695)	0.2588	0.2166	1.9157
Medium (M)	Big (B)	-1.696 (-2.838)*	0.765 (8.771)*	-0.557 (-3.111)*	0.355 (3.349)*	-0.779 (-6.061)*	0.179 (1.498)	0.4180	0.3850	2.6047	-1.067 (-0.949)	0.940 (5.190)*	-0.474 (-2.033)**	0.022 (0.168)	0.061 (0.365)	0.249 (1.004)	0.4742	0.4443	2.5594
	Small (S)	-2.261 (-2.162)**	0.810 (4.025)*	0.180 (0.772)	0.146 (0.738)	-1.402 (-3.502)*	0.747 (4.209)*	0.3560	0.3194	2.2852	-3.138 (-2.208)**	0.607 (3.484)*	0.346 (1.893)	0.0495 (0.375)	-0.175 (-0.791)	0.216 (0.890)	0.2169	0.1724	1.9953
High (H)	Big (B)	-1.634 (-2.098)**	0.805 (8.267)*	-0.462 (-2.539)**	0.323 (2.033)**	-0.747 (-3.770)*	0.166 (0.961)	0.3864	0.3515	2.3728	-2.230 (-2.710)*	0.815 (8.107)*	-0.504 (-3.387)*	0.576 (3.542)*	-0.192 (-1.162)	0.202 (1.483)	0.5109	0.4831	2.1377
	Small (S)	-2.580 (-3.206)*	0.609 (6.516)*	-0.390 (-2.520)**	0.326 (2.886)*	-0.544 (-2.448)**	0.378 (2.693)*	0.3358	0.2981	2.1311	-1.114 (-0.468)	0.902 (3.137)*	0.720 (1.456)	1.703 (4.115)*	0.943 (1.853)	2.170 (2.917)*	0.6154	0.5936	1.8618
Panel B: Liquid firms																			
Low (L)	Big (B)	-2.395 (-2.653)*	0.768 (5.578)*	-0.684 (-3.052)*	0.019 (0.134)	-0.520 (-3.335)*	-0.097 (-0.489)	0.4064	0.3727	1.6598	-1.935 (-1.858)	0.844 (4.709)*	-0.812 (-2.569)**	-0.665 (-2.532)**	0.243 (1.058)	-0.282 (-0.908)	0.4613	0.4307	2.1928
	Small (S)	-3.740 (-4.005)*	0.589 (5.000)*	0.063 (0.224)	-0.211 (-1.111)	-0.941 (-2.832)*	-0.225 (-0.847)	0.2927	0.2525	2.2534	-0.467 (-0.535)	0.919 (7.184)*	0.270 (1.074)	-0.502 (-3.174)*	0.246 (1.306)	-0.770 (-3.611)*	0.4938	0.4650	2.0604
Medium (M)	Big (B)	-1.043 (-1.506)	0.812 (8.432)*	-0.160 (-0.792)	0.119 (0.915)	-1.078 (-3.771)*	-0.158 (-0.795)	0.3840	0.3490	2.2395	-2.375 (-1.773)	0.675 (3.109)*	-0.698 (-3.543)*	0.151 (0.952)	0.475 (1.642)	-0.414 (-3.081)*	0.4001	0.3660	2.5060
	Small (S)	-1.178 (-1.185)	0.856 (4.616)*	1.422 (2.524)**	0.583 (2.306)**	-0.323 (-1.438)	-1.298 (-2.396)**	0.5447	0.5188	2.2568	-1.607 (-2.863)*	0.802 (9.586)*	-0.013 (-0.053)	0.294 (2.681)*	-0.504 (-3.275)*	-0.161 (-1.118)	0.4224	0.3896	2.2254
High (H)	Big (B)	1.056 (-0.767)	0.849 (3.628)*	-0.865 (-3.117)*	0.841 (2.838)*	-1.175 (-2.790)*	-0.153 (-0.979)	0.4342	0.4020	2.0234	-3.350 (-2.848)*	0.530 (4.193)*	-0.880 (-3.409)*	0.812 (4.133)*	0.001 (0.004)	-0.311 (-1.381)	0.3614	0.3251	2.2474
	Small (S)	-2.277 (-2.690)*	0.813 (5.661)*	0.303 (1.485)	0.566 (3.597)*	-0.623 (-2.585)**	-0.312 (-2.458)**	0.4007	0.3666	2.2165	-0.907 (-0.716)	0.920 (5.067)*	0.975 (1.439)	0.573 (2.063)**	0.332 (1.022)	-1.261 (-1.928)	0.4030	0.3691	2.4432

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level

C.7.5 ZEROS 2

Table C.7.5 Regressions of excess stock returns on the excess market returns and the mimicking returns for liquidity, size, value and momentum

The table reports the regression results for the liquidity-and-momentum-augmented Fama-French model for portfolios set up according to the zeros2 measure as a proxy for liquidity, the earnings yield (EY) as a proxy for the value effect, the log of the market value (MVLOG) as a proxy for the size effect and the previous 3-month's returns (MOM3) as a proxy for the momentum effect. Regressions are run on portfolios set up according to the intersection of two liquidity groups, three value groups, two size groups and two momentum groups. The intercept (α) represents the average risk-adjusted return, while β_{jm}, i_{jIMV}, s_{jSMB}, h_{jHML} and g_{jGMP} represent the coefficients of the market return, liquidity factor, size factor, value factor and momentum factor respectively. The t-statistics are reported in parentheses below the coefficient estimates. The models are estimated using Newey-West standard errors with six lags. In addition, the table also reports the R^2, the adjusted R^2 ($\overline{R^2}$) and the Durbin-Watson statistic.

		Momentum																	
		Poor (P)									Good (G)								
Value	Size	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson	α_j	β_{jm}	s_{jSMB}	h_{jHML}	g_{jGMP}	i_{jIMV}	R^2	$\overline{R^2}$	Durbin-Watson
Panel A: Illiquid firms																			
Low (L)	Big (B)	-1.615 (-2.000)**	0.799 (5.560)*	-0.427 (-1.262)	-0.112 (-0.535)	-0.305 (-1.537)	0.742 (2.222)**	0.4206	0.3877	2.4909	-1.876 (-2.459)**	0.753 (7.232)*	-0.518 (-1.954)	-0.055 (-0.427)	0.367 (2.630)**	0.372 (1.675)	0.4889	0.4598	2.2728
	Small (S)	-0.596 (-0.427)	0.845 (4.097)*	0.595 (2.698)*	-0.475 (-1.841)	-1.428 (-3.501)*	0.577 (2.623)**	0.4315	0.3992	1.8851	-3.852 (-1.898)	0.504 (1.999)**	1.222 (1.835)	-0.982 (-2.569)**	1.106 (2.561)**	0.699 (1.973)	0.3296	0.2915	1.7537
Medium (M)	Big (B)	-2.109 (-2.525)**	0.713 (5.386)*	-0.319 (-1.222)	0.119 (0.837)	-0.372 (-2.199)**	0.142 (1.150)	0.3018	0.2622	2.4092	-1.014 (-0.842)	0.935 (4.963)*	-0.464 (-1.692)	-0.070 (-0.482)	0.121 (0.760)	0.237 (0.979)	0.4729	0.4429	2.5326
	Small (S)	2.344 (-1.821)	0.893 (3.607)*	0.279 (0.940)	0.178 (0.729)	-1.045 (-2.942)*	1.244 (3.998)*	0.3225	0.2840	2.1223	-2.106 (-1.417)	0.687 (3.582)*	0.412 (2.098)**	0.056 (0.382)	0.009 (0.046)	0.260 (0.990)	0.2494	0.2068	2.1681
High (H)	Big (B)	-1.926 (-2.139)**	0.764 (5.977)*	-0.361 (-1.520)	0.198 (1.154)	-0.468 (-2.634)*	0.176 (1.044)	0.3108	0.2717	2.3087	-3.216 (-2.194)**	0.767 (5.767)*	-0.544 (-2.659)*	0.763 (2.281)**	0.103 (0.379)	0.415 (2.036)**	0.3858	0.3509	1.8819
	Small (S)	-0.894 (-0.584)	0.770 (4.975)*	-0.231 (-0.773)	0.473 (2.670)*	-0.420 (-1.770)	0.522 (2.024)**	0.2785	0.2375	1.9900	-1.075 (-0.495)	0.852 (3.285)*	0.497 (1.437)	1.347 (3.006)*	0.704 (1.490)	1.741 (2.638)*	0.4694	0.4393	1.8481
Panel B: Liquid firms																			
Low (L)	Big (B)	-2.079 (-2.410)**	0.801 (6.503)*	-0.828 (-3.422)*	-0.093 (-0.632)	-0.571 (-3.774)*	-0.265 (-1.421)	0.4321	0.3999	1.8117	-0.311 (-0.267)	1.045 (7.179)*	-0.712 (-2.768)*	-0.596 (-2.011)**	0.482 (1.785)	-0.137 (-0.442)	0.4667	0.4364	2.0925
	Small (S)	-4.122 (-3.820)*	0.550 (4.376)*	0.079 (0.423)	-0.299 (-1.658)	-0.612 (-2.304)**	-0.382 (-1.561)	0.2622	0.2203	2.2843	-1.311 (-1.680)	0.841 (7.478)*	0.337 (1.576)	-0.488 (-3.240)*	0.363 (1.883)	-0.489 (-2.157)**	0.4645	0.4340	2.1528
Medium (M)	Big (B)	-1.737 (-2.173)**	0.708 (8.701)*	-0.029 (-0.146)	-0.024 (-0.137)	-0.924 (-3.270)*	0.115 (0.907)	0.3474	0.3103	2.2036	-1.776 (-1.969)	0.683 (5.290)*	-0.728 (-4.471)*	0.212 (1.747)	0.346 (1.572)	-0.408 (-2.854)*	0.4806	0.4511	2.2956
	Small (S)	-1.674 (-1.447)	0.830 (5.239)*	1.535 (2.496)**	0.526 (1.951)	-0.165 (-0.649)	-1.234 (-2.398)**	0.5054	0.4773	2.2931	-0.963 (-1.006)	0.841 (4.404)*	0.100 (0.424)	0.085 (0.625)	-0.027 (-0.135)	-0.337 (-2.048)**	0.3842	0.3492	2.1755
High (H)	Big (B)	-1.288 (-0.764)	0.820 (2.892)*	-0.438 (-1.419)	0.475 (1.421)	-0.724 (-1.767)	-0.194 (-1.199)	0.2725	0.2312	1.8445	-3.677 (-2.933)*	0.494 (3.475)*	-0.490 (-1.962)	0.624 (3.366)*	0.317 (1.627)	-0.066 (-0.338)	0.2677	0.2261	2.2595
	Small (S)	-2.241 (-2.640)*	0.790 (5.614)*	0.287 (1.828)	0.474 (3.142)*	-0.593 (-2.864)*	-0.316 (-2.294)**	0.3673	0.3313	2.2853	-1.444 (-1.155)	0.881 (5.526)*	1.029 (1.427)	0.546 (1.909)	0.481 (1.323)	-1.158 (-1.907)	0.3880	0.3532	2.5187

** indicates statistical significance at the 1% level
** indicates statistical significance at the 5% level