UNIVERSITY OF THE WITWATERSRAND

Reviving Beta?

Another look at the cross-section of average share returns on the JSE

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041772H

TITLE OF PROPOSAL: Reviving Beta?: Another look at the Cross-section of Average Returns on the JSE

A 50% dissertation to be submitted in partial fulfilment for the degree of:

MASTERS OF COMMERCE (FINANCE)

UNIVERSITY OF THE WITWATERSRAND

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DATE: 29 February 2012

Declaration

I hereby declare that this is my own unaided work, the substance of or any part of which has not been submitted in the past or will be submitted in the future for a degree in to any university and that the information contained herein has not been obtained during my employment or working under the aegis of, any other person or organization other than this university

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ABSTRACT

Van Rensburg and Robertson (2003a) stated that the CAPM beta has little or no relationship with returns generated by size and price to earnings sorted portfolios. This study intends to demonstrate that a reformulated CAPM beta, estimated using return on equity as opposed to share returns, unravels the size and value premium. The study proves that the "cash-flow" generated beta partially explains the cross-sectional variation in share returns when measured over the long run, specifically when portfolios are sorted on book to market, however the cash flow beta is less successful when attempting to explain the small size premium. The premise of the study is that the cash flow dynamics of share returns eventually dominate the first and second moments and thus result in cash flow based measures of risk and return that should succeed in explaining the cross-sectional variation in share returns. The study makes use of vector autoregressive models in order to examine the short term effect of structural shocks to the cash flow fundamentals of a stock or portfolio through impulse response functions as well as quantifying a long-term relationship between cash flow fundamentals and share returns using a VECM specification. The study further uses fixed effects, random effects and GMM/dynamic panel data cross-sectional regressions in order to examine the ability of the cash flow beta explaining the value and size premium. The results of the study are mixed. The cash flow beta does well in explaining the returns of portfolios sorted on book to market, but fails to do the same with size sorted portfolios. In the cash flow betas favour, it performs far better than the conventionally measured CAPM beta throughout the study.

Definition of Terms

CAPM: The capital asset pricing model of Sharpe (1964), Lintner (1965) and later Black (1972). The model states that under rational and homogenous expectations with regards to risk and return, the market risk of an asset, proxied by the market beta is the sole determinant of an assets expected return.

Cash flow beta: The cash flow beta per Cohen, Polk and Voulteenaho (2008) where beta is estimated using cash flow fundamentals of the underlying asset in question

ROE: The return on equity of a share is considered by Cohen, Polk and Voulteenaho (2008) as the monthly change in book value per share (inclusive of gross dividend payments)

VAR: Vector autoregressive models are multivariate time-series models that utilise both lagged independent as well as dependent variables in explaining time-series data

IRF: Impulse response functions utilise the estimated VAR's as a system and allow one to study the interaction between variables within a VAR. This involves tracing the marginal effect of a shock in one variable and its effect on another

Variance Decompositions: Otherwise known as the forecast error variance decomposition – Allows one to decompose the variation in a forecasted variable due to a shock in another variable

VECM: Vector Error Correction Model allows for the estimation of long term relationships in non-stationary data based on cointegration between the variables in a VAR

I(1): A non-stationary variable is said to be integrated of order one if it is stationary after being differenced once, this implies that if a variable is I(n), it is only stationary after being differenced n times

Cointegration: Variables are said to be cointegrated of order one if a combination of the non-stationary variables yields a stationary time series

LR test: A statistical test that determines whether a VECM restriction is binding

B/M: Book to market is the book value of a share scaled by the market price of the share. The book to market ratio is the inverse of the popularised price to book ratio

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A. Introduction

The CAPM in its current form presents a logical conundrum. Markowitz (1959) stated that the risk of an asset should be the sole determinant of expected return. The theory was further extended by Sharpe (1964), Lintner (1965) and Black (1972) to consider the effects of diversification and the result was a two-parameter model that consisted of a risk-free or zero beta asset and an ex-ante efficient market portfolio. Their combined findings led to the capital asset pricing model, where risk (and therefore expected return) is explained by a single factor, the CAPM beta, which is the covariance of an assets return to that of the market portfolio, scaled by the variance of the market portfolios return. The fields of financial economics, investment and corporate finance are plagued with inconsistency as one is introduced to the theory of CAPM and the concept of market efficiency as if they are gospel, yet the natural progression of a financial economist is to learn that the CAPM and market efficiency only hold in theory, and that in the 'real world' CAPM fails in explaining the cross-sectional variation in historical share returns and therefore, the model is relegated to the annals of theoretical history. There have been a number of attempts to salvage the CAPM by making modifications (varying from slight to extreme) both to the theory as well as the composition of the asset pricing model, yet the general consensus holds that CAPM in its original form is void, albeit theoretically appealing. The purpose of this study is to consider and test a variation of the CAPM and identify whether the modified CAPM has the ability to succeed where others have failed.

The methodology of Cohen, Polk and Vuolteenaho (2008) is employed in order to derive a "cash-flow" beta, where beta is estimated using cash flow returns proxied by monthly changes in book equity (referred to as return on equity or ROE), as opposed to dividend adjusted share returns. The central hypothesis of the study is to identify whether the cash flow beta is more successful than the conventional CAPM beta in explaining the cross-sectional variation in returns of shares listed on the Johannesburg Stock Exchange ("JSE"). The study employs an assortment of econometric methodologies in order to determine the effectiveness of the proposed cash flow beta and offer additional robustness. A number of sub-hypotheses are presented that extend to the central hypothesis of the study.

The sample period of the study is from January 1995 to June 2009 (fourteen and a half years) and includes all shares listed on the JSE over the period. As with most studies of this nature, data are sorted into portfolios based on independent size and value criteria, where value is proxied by the book value per share scaled by the market value per share (book to market ratio) and size by the natural logarithm of market capitalisation of the share in question. The study is split into two sub-studies where the first employs time-series based econometric tests while the second, cross-sectional regressions. All the methodologies employed find that there is both an persistent size effect and value premium present on the JSE, in line with the findings of Van Rensburg and Robertson (2003a), Graham and Uliana (2000), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011).

In the time-series experiments, VAR's are estimated and impulse response functions as well as variance decompositions are conducted in order to decompose the effect of different factors on the value and size sorted portfolio returns. The results indicate that the ROE of the extreme size and value portfolios contribute minimally to monthly return and the variation in return of the extreme value and small cap portfolio. The tests also include the ROE market proxy as well as the JSE All share index. The results of the impulse response functions are mixed. The value portfolio seems to be very sensitive to a shock to the overall cash flow return of the market, while the small size portfolio is more sensitive to a shock to the JSE. The variance decompositions indicate that a shock to the ROE of the market seems to contribute more to the variation in the size and value portfolio returns. A VECM is then estimated in order to compare the long-run relationships between the different portfolios and the JSE as well as the ROE market proxy. The findings indicate that the extreme value and small size portfolios have positive long run relationships with the ROE market proxy, strengthening the notion that the size and value effect is affected by the overall cash flow return of the market, contributing to the case for the cash flow beta. However, when estimating VECM's based on the excess returns earned by the high minus low and small minus big trading strategies, the ROE market proxy fails to maintain a significant long run relationship with the level excess returns.

The second part of the study focuses on the cross-sectional properties of the different portfolios sorted on value and size. Portfolios are sorted yearly and are held for 60 months post sort. Initially, value and size sorts are conducted separately where nine portfolios are constructed on book to market and ten on size. The second sort is a simultaneous size and value sort consistent with the methodology employed by Basiewicz and Auret (2009). Cohen, Polk and Voulteenaho (2008) considered estimating a cash flow beta based on accounting data and employed an arithmetic book value return referred to as return on equity ("ROE"). The ROE of a share is defined as the natural logarithm of a shares arithmetic book value holding period return, while the ROE of the market is the natural logarithm of the arithmetic book value holding period return of the value weighted market portfolio. Using a similar procedure to that employed by Cohen, Polk and Vuolteenaho (2008), cash flow betas are calculated over different holding periods for each of the portfolios and estimated using rolling window OLS regressions. The purpose of the exercise is to identify the evolution of the cash flow beta over time.

The findings are similar to that of Cohen, Polk and Vuolteenaho (2008) as the cash flow betas of the value portfolios are initially low, yet increase monotonically over time and eventually overtake the cash flow betas of the growth portfolios. The same phenomenon is not apparent for the portfolios sorted on size as the small size portfolios cash flow betas fail to increase over time and do not surpass the cash flow betas of the large capitalization portfolios. In this study, regressions are run using both fixed effects and GMM regressions and the results are once again consistent with the findings of Van Rensburg and Robertson (2003a), as there is both a significant value and size premium when shares are simultaneously sorted on size and value criteria[1]. The initial cross-sectional tests indicate that the conventionally measured CAPM beta fails to explain the cross-sectional variation in share returns and is consistently negative and significant. The cash flow betas performance is mixed as it succeeds in explaining the cross-sectional variation in the returns of portfolios sorted on value, but not on size. In the simultaneous value and size sort, the cash flow beta is significant when using the GMM specification, while the fixed effects regression finds the cash flow beta to be significant, but only at the 10% level. The success of the cash flow beta explaining the value premium may be attributed to the cash flow beta being a construct of the book to market ratio. A further interesting finding is that throughout the univariate and multivariate regressions, the CAPM beta produces a consistently negative coefficient, in line with the recent findings of Strugnell, Gilbert and Kruger (2011). In order to comprehensively test the cash flow beta, a price filter is applied in order to determine whether the failure of the cash flow beta in explaining the size premium is attributable to illiquidity. The results indicate that

[1] Also seen in Basiewicz and Auret (2009)

illiquidity is not the cause of the cash flow betas poor performance. Cash flow and CAPM betas are also estimated using equally-weighted market proxies in order to test whether the cash flow betas failure is attributable to concentration found in the JSE ALSI and the ROE market proxy. The results indicate that the failure of the cash flow beta in explaining the small size premium is not attributable to the concentration or inefficiency of the market proxy.

B. **Literature Review**

a) International Literature

Two popular phenomena in asset pricing theory that have received much attention are the small size effect and the value premium. The size effect can be summarized as the excess return earned by low capitalization stocks over large capitalization stocks. Banz (1981) was credited with the identification of the size effect or small firm premium and found that the presence of the size effect is persistent and fails to reconcile with CAPM as large capitalization shares tend to have larger betas yet achieve lower average returns than small capitalization shares. Reinganum (1981) concluded that the presence of an unquestionable and consistent size effect is in direct contravention with the theory of efficient markets and the CAPM.

The value effect entails that firms with a higher ratio of accounting based share value or earnings scaled by the firms market price per share tend to outperform shares at the other end of the spectrum, aptly named ‘growth’ shares due to their relatively high market value. Basu (1983) found that the earnings-to-price (“E/P”) ratio helped to explain the cross-sectional variation in share returns. Rosenberg, Reid and Lanstein (1985) found that the book-to-market ratio (“B/M”) has a significantly positive relationship with the average return. Chan, Hamao and Lakonishok (1991) found that B/M is a significant variable when attempting to explain the cross-sectional variation in returns of Japanese stocks.

A number of other less popular anomalies that have received international attention are the ‘leverage effect’ of Bhandari (1988), where leverage was found to have a positive relationship with average returns. Rozeff and Kinney (1976) found that the risk-adjusted returns of shares in January where significantly higher than returns achieved in any other calendar month. Debondt and Thaler (1985) found that past long-term losers consistently outperformed past long-term winners, while Jegadeesh and Titman (1993) found that past short-term winners outperformed past short-term losers, otherwise known as the "momentum" effect.

Fama and French (1992) conducted a comprehensive study and tested a number of conventionally used value and size proxies in order to isolate which was the most accurate and to determine whether size and value possess independent explanatory power on a cross-section of US listed stocks. The authors found that size (proxied by the natural log of market capitalization) and value (proxied by B/M) where both significantly powerful when explaining the cross-sectional variation in share returns. Fama and French (1993) concluded that risk is multidimensional and developed a pricing model that incorporates variables that represent both the value and size premium independently. The proposed model proved powerful in explaining the cross-sectional variation in share returns yet lacked a meaningful theoretical motivation for incorporating additional factors within a pricing model. Fama and French (1995) hypothesized that both the size and value premium are related to profitability, therefore the conventional CAPM beta fails to capture information regarding earnings potential and profitability. The authors acknowledged that their findings leave a number of central issue unanswered, namely; why does the CAPM beta, which in theory should be the sole determinant of risk and therefore return, fail to explain the variation in return.

Roll (1977) held that the CAPM in its current form cannot be tested and that any attempt to disprove or even test the validity of the CAPM would result in a type 1 or type 2 error, ie accepting the CAPM when it is false or rejecting the CAPM when it is true. In lieu of such opinion, the CAPM actually stood as untestable and in some sense unusable. Ross (1976) and later Chen, Roll and Ross (1986) developed arbitrage pricing theory ("APT"), where based on the lack of usability or testability of the CAPM, an asset pricing model was developed that utilises a number of macroeconomic factors that are tested to find a contemporaneous relationship with returns .On the basis of significant contemporaneous relationships, macroeconomic factors are incorporated into a pricing model. The APT, much like the Fama-French three factor model, lacks the theoretical foundation of the CAPM, yet succeeds in explaining a larger portion of the cross-sectional variation in share returns. The model of Fama and French (1993) is not dissimilar to the APT, as the model utilises variables that aid in the explanation of the cross-sectional variability in returns yet are solely based on consistent empirical relationships.

A fundamental problem when considering both the size and value premium is that their presence on an international scale is actually a joint rejection of the CAPM and the efficient market hypothesis. Without a meaningful explanation of the risks inherent in high value or small size firms, one is left to conclude that such anomalies are a rejection of market efficiency. If risks are not priced, then the market should not reward an investment or an asset with a higher return. In light of this, a number of financial economists endeavoured to explain the size and value premiums in order to salvage both the CAPM and the theory of efficient markets.

A stream of literature has emerged that considers cash flow fundamentals as a key in explaining the variation in share returns. Da (2009) builds on the consumption based CAPM or CCAPM of Rubinstein (1976), Lucas (1978), and Breeden (1979) and successfully decomposes share returns into a cash flow duration and cash flow covariance with aggregate consumption. The author found that the variation in share returns over long periods can be directly linked to fundamental cash flow fundamentals. Nekrasof and Shroff (2006) found that that a single-factor risk measure, based on the accounting beta estimated from cash flow fundamentals (accounting data) was able to largely explain the “mispricing” in value and growth stocks.

Campbell and Vuolteenaho (2004a) propose a version of Merton’s (1973) Intertemporal Capital Asset Pricing Model (ICAPM), in which investors care more about permanent cash-flow-driven movements than about temporary discount-rate-driven movements in the aggregate stock market. The theory relies on the logic that cash flow innovations should have a greater and more permanent effect on share returns as investors will naturally be more concerned with a cash flow change to an investment than a discount rate change. Considering a simple dividend paying asset, a negative shock to the cash flow component would result in a decrease in the present value, as would an increase to the discount rate, yet an increase to the discount rate would be compensated in the long run with a higher return. The authors decomposed beta into a ‘good’ and ‘bad’ beta, where the bad beta relates to a shares cash flow beta. The authors found that including both betas within in an asset pricing framework, greatly improved the performance of the standard CAPM.

Campbell (1991) and Campbell and Ammer (1993) use the dividend growth model proposed by Campbell and Shiller (1998a) to decompose share returns into news about cash flows and discount rates using vector auto-regressions (VAR). The process involves modelling discount rate news and backing out the cash flow related news as a residual. Voulteenaho (2000) developed a present value model that utilised ROE instead of dividend growth. Voulteenaho (2002) utilised the ROE based model and a VAR variance decomposition in order to determine the relative effect of cash flow innovations on the variation in share returns. The author found that firm level share returns are predominantly driven by cash flow fundamentals. A further finding was that a positive shock to the cash flow or good news attributable to cash flow is followed by a positive shock to return.

Campbell, Polk and Voulteenaho (2009) employed a similar methodology to that of Campbell (1991) and estimated a VAR in order to decompose firm-level stock returns of value and growth stocks into components driven by cash-flow shocks and discount-rate shocks. The authors found that both the variation in growth and value stocks is explained by the cash flow components derived from the VAR model. The authors further employed a cash flow based measure of ROE and regressed the ROE's of growth and value shares on the two components of the market return estimated by Campbell and Vuolteenaho (2003). The authors found that value stocks' ROE is more sensitive to market's cash-flow news than that of growth stocks and that growth stocks' ROE is more sensitive to the market's discount-rate news than that of value stocks.

Chen and Zhoa (2009) considered the methodology prescribed by Campbell and Shiller (1988a) and Campbell (1991) and found that the method of estimating discount rate news using VAR and backing out cash flow news as a residual carries a significant amount of imprecision. The authors noted that from a theoretical standpoint, the methodology would work, if and only if the model used perfectly replicated the data generating process of returns, which is never the case. The authors found that when attempting to replicate the results of Campbell, Polk and Voulteenaho (2009), they found that value shares did not have significantly higher cash flow betas nor did growth shares have significantly higher discount rate betas.

Cohen, Polk and Voulteenaho (2008) found that using the cash flow based measure of profitability (ROE) proposed by Voulteenaho (2000) in order to estimate beta, resulted in a cash flow beta estimation that monotonically increases for high value shares and decreases for growth shares. The authors noted that previous joint tests of market efficiency and CAPM lack power as they employ the estimation of profits/returns earned from dynamic trading strategies and reject the joint hypothesis based on economically high Sharpe ratios. The authors hypothesized that a buy-and-hold methodology of estimating portfolio returns was more theoretically appealing as it allowed for the examination of the long run behaviour of share returns. Convention dictates that a rational investor would not act like a trader and engage in extreme trading strategies that could potentially result in extreme losses and significant trading costs. Long-term investors or mutual funds are generally constrained from participating in extreme trading; therefore the authors employed a methodology that they considered a more accurate real-time test of the CAPM as it would mimic the possible actions of a conventional buy-and-hold investor.

The authors hypothesized that the cash flow fundamentals of an asset begin to dominate the first and second moments of returns in the long run, therefore the imprecision of the conventionally estimated CAPM beta is due to the inherent noise that plagues high frequency share returns. The authors conjectured that by estimating long run cash flow beta’s using the discounted ROE of a share and the discounted ROE of the market, one would derive a beta estimation that succeeds in explaining the value premium. The authors found that consistent with the results of Fama and French (1992, 1993,1996) and Lakonishok, Shleifer, and Vishny (1994), growth stocks have higher CAPM betas than value stocks.

The authors proposed a methodology of constructing portfolios yearly based on a price-to-book sort and holding the portfolios for 15 years post sort. The authors then calculated the persistence of the price to book value within portfolios and also estimated the evolution of conventional CAPM betas and cash flow betas over time. The authors found that within five years post sort, on average the cash flow betas of the value portfolios increased significantly and were higher than the cash flow betas of the growth portfolios. The authors confirmed their findings by running cross-sectional regressions and found that the estimated cash flow beta succeeded in explaining the cross-sectional variation in share returns.

The thematic similarity between the above paper and that of Campbell and Shiller (1988a) is that the cash flow fundamentals play a significantly larger role in the determination of risk premia. The general theme of the study implies that the joint hypothesis of market efficiency and the CAPM hold approximately in the long-run. This implies that the excess return earned on high minus low value or small minus big investment strategies can be successfully explained by cash-flow risk and the risk inherent in such strategies is priced (eventually). The findings emphasize the notion that the cash-flow based methodology of estimating beta delivers a ‘good’ approximation of price level returns. The implications of such findings are that a slight methodological change to the CAPM may be able to rationalize the conflict between investment and corporate finance as areas of study and reconcile the usage of CAPM in capital budgeting and valuation. Furthermore, the findings imply that markets are actually efficient in the long-run as cash-flow risks are priced into the excess returns of value and small cap shares.

b) South African Literature

The evidence of both the size and value premia in South African literature is mixed. De Villiers, Pettit and Affleck-Graves (1986), Bradfield, Barr and Affleck-Graves (1988), Page and Palmer (1993) and more recently Auret and Cline (2011) found no significant size effect on the JSE. Page (1996),Van Rensburg (2001),Van Rensburg and Robertson (2003a), Auret and Sinclaire (2006), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011) found both a significant size and value effect on the JSE. Notably, Van Rensburg and Robertson (2003a) stated that previous studies that failed to detect the small size effect were biased due to the small sample sizes and time frames employed.

Van Rensburg and Robertson (2003a) concluded their study with the statement that their findings were an unambiguous contradiction of the CAPM as they found that CAPM beta had a negative relationship with average returns over the sample period. Strugnell, Gilbert and

Kruger (2011) considered the results of Van Rensburg and Robertson (2003a) and conducted a similar study over a longer time frame and similarly concluded that there is both a significant size and value effect found on the cross-section of share returns on the JSE. More importantly, the authors found that beta "is irrelevant as far as return generation on the JSE is concerned, at least based on the possibly inefficient market proxy of the FTSE-JSE All – Share Index. Basiewicz and Auret (2009) conducted a similar study to Fama and French (1992) and found that there is both a significant and independent value and size effect on the JSE and that B/M is the best proxy for value, in line with the findings of Auret and Sinclaire (2006).

Van Rensburg and Robertson (2003a) considered the variation in share returns when sorting portfolios based on size, price-to-earnings (P/E) and pre-ranking beta. The authors conducted a two way sort where stocks were sorted (monthly) initially based on size and then on P/E. Basiewicz and Auret (2009) considered the findings and the methodology of Van Rensburg and Robertson (2003a) and conducted a study where portfolios were sorted yearly as opposed to monthly and the size and value sort was conducted simultaneously in order to allow for independent variation based on size and value. The authors found both a significant size and value effect and that B/M was the best proxy for value. These findings were consistent, if not less extreme, than Auret and Sinclaire (2006) as the latter found that B/M, when included in multivariate regressions, subsumed the size effect.

Basiewicz and Auret (2009) conducted an intensive study that considered the effects of a number of methodological variations as well as practical constraints applied to a typical investor. The study considered the effects of transaction costs, liquidity constraints and returns calculated using both equally and value weighted portfolios. The authors found that the application of price and liquidity restrictions resulted in dampening on the size and value premium. The authors also found that equally-weighted portfolio returns generally exceeded value-weighted returns.

Strugnell, Gilbert and Kruger (2011) questioned whether the findings of Van Rensburg and Robertson (2003a) where sample specific and whether the conventional method of estimating the CAPM beta using ordinary least squares contributed to the poor performance of the

CAPM beta in explaining the cross-sectional variation in share returns on the JSE. Cloete, De Jongh and De Wet (2002) found that by combining the estimation techniques developed by Vasicek (1973) and Williams (1977) resulted in estimations of beta that performed better when compared to other beta estimation methodologies. Strugnell, Gilbert and Kruger (2011) considered a larger sample period and utilised a number of methodologies when estimating beta in order to correct for thin trading. Betas were estimated using at least 60 months of historical return as described by Bradfield (2003). In line with the findings of Cloete, De Jongh and De Wet (2002), the authors hypothesized that the negative relationship found between beta and average returns in Van Rensburg and Robertson (2003a) may have been partially due to methodological bias in estimating beta.

The size and value effect as well as the testing of the joint-hypothesis of the CAPM and market efficiency have received much attention in South African literature; however the usage of accounting based return measures in order to explain the return data generating process as well as the cross-sectional variation in returns has received little attention. Taylor (1995) considered the potential lack of precision in estimating accounting based return, specifically accounting rate of return, return on assets, return on equity and earnings yield and proposed that accounting measures of return contain important informational content despite the inherent bias and potential estimation error related to accounting data.

Bergesen and Ward (1996) conducted a thorough study on the descriptive power of financial ratios and their relationship with beta. The authors found that beta possessed a positive relationship with firm growth, profitability and size. The authors further found that the cash flow and profitability measures used where significant throughout the study yet, the estimated cash flow beta was insignificant throughout the study. The findings of the authors seem to be consistent with later literature as the results imply a size and value effect. The study differs methodologically to later studies as the authors tested the significance of accounting based ratios in relation to beta as opposed to actual returns. The finding of beta possessing a positive relationship with size and profitability implies that both growth and large cap firms should have higher CAPM betas. Furthermore, the accounting measures used to proxy cash flow and profitability seemed to possess a positive relationship with returns over the period of study

C. Data

The time period of the study conducted is January 1995 to June 2009 and the Findata@Wits database was the sole data source used. All shares listed on the Johannesburg Stock Exchange ("JSE") over the time period were considered. Findata@Wits database utilises a number of data and information sources. I-Net Bridge and McGregor BFA were the main sources of price, dividend and accounting data. In order to account for corporate actions, JSE monthly bulletins were used. Shares that exit the sample due to delisting or suspension are given a zero return and are deemed not listed in order to account for potential survivorship bias. The FTSE-JSE ALSI ("JSE") is used as the market proxy, consistent with similar studies conducted on the JSE.

The results are split into two separate sets of tests that utilise differing methodologies. In order to accommodate the time-series properties of the data, time-series econometric tests are employed in order to determine whether the proposed cash-flow beta and its construction are viable when employing a time-series based approach. The second set of tests relies on the panel properties of the data. Cross-sectional regressions are run using fixed effects and GMM/dynamic panel regressions in order to correct for the potential estimation bias that can occur when data has both cross-sectional and time-series properties. The utilization of two different regression procedures allows for comparisons to be drawn between the estimations, while consistent results across specifications adds further robustness to the study. As mentioned previously, the central hypothesis of the study is to determine whether a modified methodology of estimating beta results in a measure that successfully describes the cross-sectional variation in average returns on the JSE.

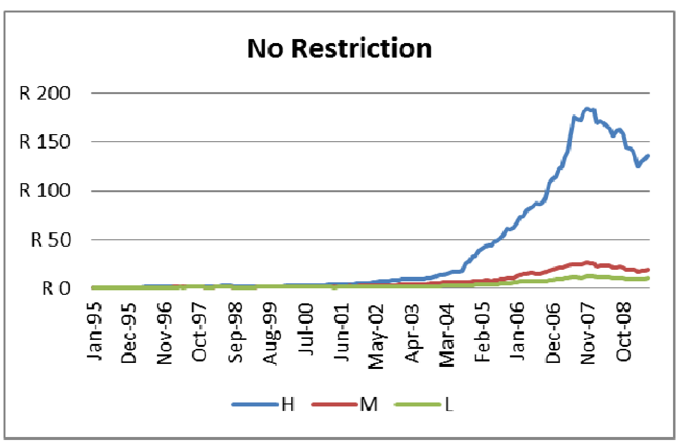
D. Time-Series Tests

a) Preliminary Tests

Data is initially sorted according to size and value separately, where size is proxied by the natural log of market capitalization and value by the book-value per share scaled by the market-value per share. Shares are sorted into one of three portfolios based on their previous year's median book to market or average size. Portfolio break points, based on the lower 33rd and upper 66th percentile, are inserted at each sorting point and stocks are categorised accordingly. The average equally weighted returns are calculated for each portfolio assuming three long-term strategies where holding periods are three, five and seven years. The portfolio construction is intended to mimic medium-term (three year), long-term (five year) and extra-long term (seven year) buy-and-hold investment strategy.[2]

Various holding periods are used in order to simulate the methodology of Cohen, Polk and Voulteenaho (2008). Holding portfolio constituents constant over longer holding periods affords one the ability to identify whether both B/M and size values are persistent over time. The usage of three portfolios also allows for lower rate of migration of shares between the portfolios and should allow for each portfolio to contain a larger number of shares at the end of each holding period. Basiewicz and Auret (2009) utilised both price and liquidity filters to determine the effect of liquidity and transaction costs on the size and value premium. A price filter of 100, 75 and 50 cents is applied to the portfolio in order to ascertain the effect on each of the extreme portfolios. To make the study tractable, the results of the five year sorts with a 50 cent price filter are presented (See Appendix 1).

Figure 1: Value sorted portfolios using a 5 year holding period (No restriction and 50c restriction)



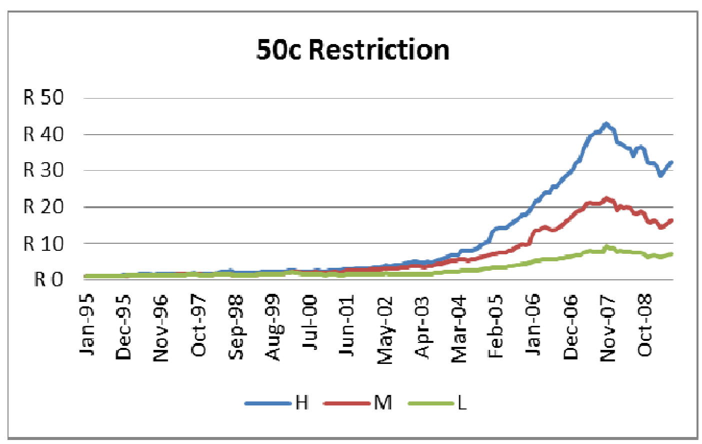
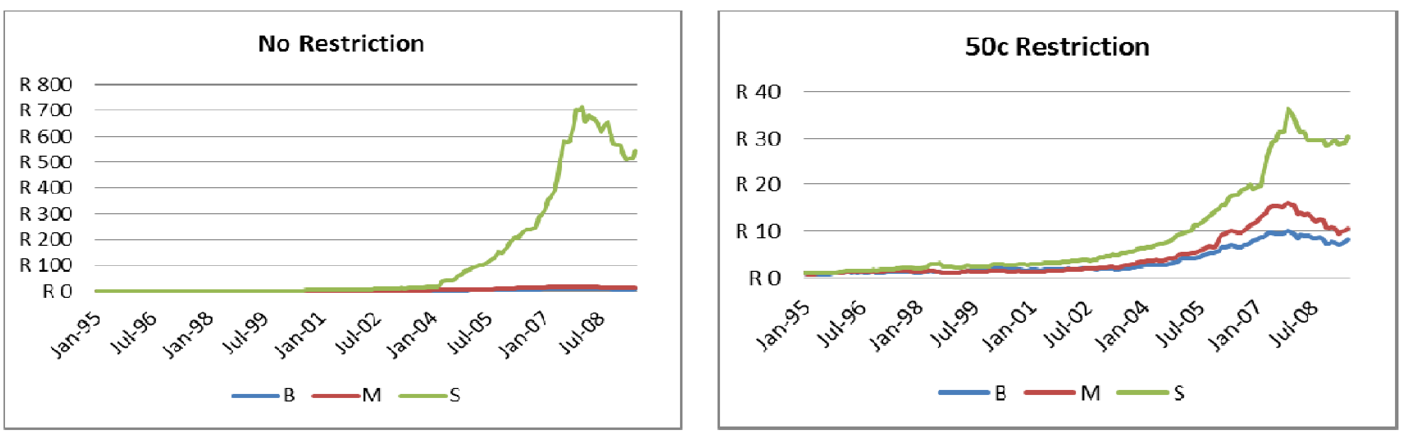


Figure 1 indicates that there is a significant value effect when sorting portfolios based on median B/M and holding portfolios for five years post sort. Such findings are consistent with the findings of Van Rensburg and Robertson (2003a), Auret and Sinclaire (2006), Basiewicz

[2] This implies that the medium term investment results in three sorts over the sample period

and Auret (2009) and Strugnell, Gilbert and Kruger (2011). The results indicate that a R1 investment in the extreme value portfolio at the beginning of the sample period would result in a portfolio end value of R140.38. When applying a price filter of 50c, the final investment value for the extreme value portfolio is R33.17, which is consistent with the findings of Basiewicz and Auret (2009) as they found that when applying a proxy for transaction costs and liquidity, the value and size premium are diminished, yet throughout the value portfolio outperforms the growth portfolio. Interestingly, when using a three year holding period, the final value of a R1 investment in the extreme value portfolio results in a portfolio value of R211.25 with no price restriction applied, yet when applying a 50c restriction, the extreme value portfolio final value falls to R60.19 at the end of the sample period. When using a seven year holding period, the final value of the extreme value portfolio with no price restriction is R136.05. When applying the 50c price filter, the portfolio value drops to R50.33. The results seem to imply that the seven year filter achieves the lowest final value when no restriction is applied but also seems to be the least sensitive to a price filter as it experiences the lowest decrease when applying the price filter (See appendix 1 for the results of applying a 75c and 100c filter).

Figure 2: Size sorted portfolios using a 5 year holding period (No restriction and 50c restriction)



When sorting portfolios based on size, the results are consistent with the findings of Van Rensburg and Robertson (2003a), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011). Figure 2 presents the results of a R1 investment in each of the size sorted portfolios sorted every 60 months. The final investment value for the small cap portfolio over the sample period, without considering liquidity and transaction costs, is R554.99. When accounting for liquidity and transaction costs, the final investment value of the small cap portfolio drops to R31.10. The incorporation of a proxy for transaction costs does not result in the disappearance of the size effect, therefore implying that there is a robust size and value effect on the JSE, and even when proxying for illiquidity and transaction costs, the small cap and value portfolios achieve superior returns when compared to the large cap and growth portfolios. Considering the results of the size sorts when applying a three year holding period, the small size portfolio final value is R511.92 while when applying a 50c filter, the value drops to R21.60. The seven year holding period results are even more interesting as the final portfolio value, when no restriction is applied is R399.37 and when applying a 50c filter the portfolio value drops to R32.63. The results seem to imply that an unrestricted size sort achieves a higher nominal return than a value filter yet the value sort is less sensitive to the application of a price filter. Another interesting finding is that the longer holding period sorts generally achieve lower final portfolio values yet are far less sensitive to the application of price restrictions. More importantly, the above evidence indicates that there is both a significant size and value effect on the JSE even when using abnormally long holding periods.

b) Vector Autoregressive Analyses (VAR)

VARs can be used to extract information from financial time series. Impulse responses determine the effect of a structural innovation or shock and its effect on a variable within an estimated system. Impulse response analysis may be based on the counterfactual experiment of tracing the marginal effect of a shock to one variable through the system. Stock and Watson (2001) stated that variance decomposition allows for the decomposition of the variation in a variable, given a shock or innovation experienced by another variable within an estimated VAR. A VAR is estimated for both the value and size sorted portfolio using the five year sorts. Since the time series data does not overlap, the five year sort is superior as the three year holding period is too short to be considered a “long” holding period, while the sample period only allows for two seven year sorts. In order to ascertain whether the VAR is stable and therefore whether the variables are stationary with in the VAR, a joint test of stationarity is run. For all variables considered within each of the VARs, all are stationary and the VARs themselves are stable using both individual dickey-fuller GLS and combined tests of stationarity. Appendix 2 produces the graphical representation of the inverse roots of the characteristic polynomial. Since all the roots fall within the unit circle, this implies that all the variables within the VAR have roots that are less than one, indicating a stationary VAR.

For each VAR the basic equation estimated can be represented by

$$Y_t = A_0 + A_q Y_{t-q} + e_t \qquad (\mathbf{1})$$

Where Y_t is a vector of dependent variables including the monthly returns of the size sorted portfolios[3], value sorted portfolios, the JSE ALSI return over the period, the ROE of the market, and finally the respective ROE's of the size and value portfolios. The ROE of each share is calculated using the following formulae:

$$ROE_t = \frac{X_t}{BE_{t-1}} \qquad (\mathbf{2})$$

$$X_t = BE_t - BE_{t-1} + Div_t^{gross} \qquad (\mathbf{3})$$

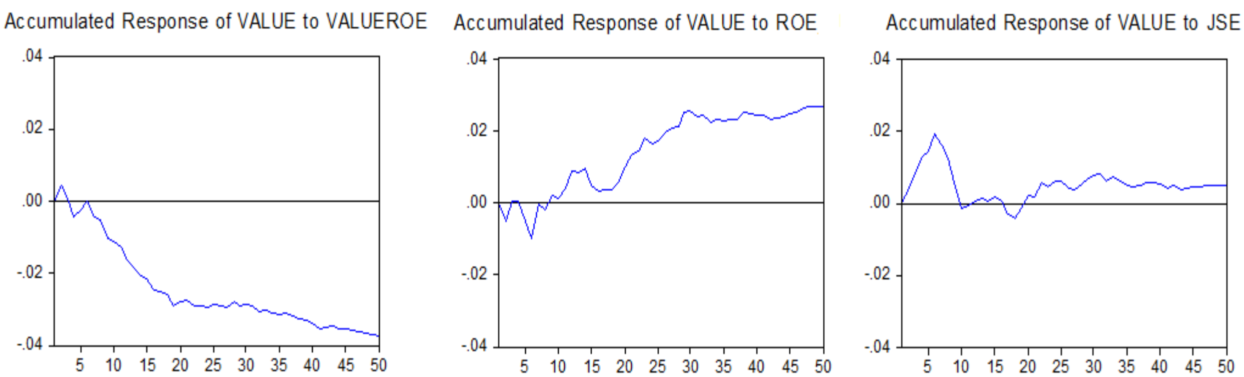
X_t is the clean surplus earnings per share. The same methodology is applied in order to derive a value weighted book value market index, from which the ROE of the market is derived (See Appendix 3 for the full derivation of ROE). Referring to equation 1, A_0 is a vector of intercepts and A_q is a matrix of coefficients for each of the variables within the system lagged q periods. Finally, e_t is a matrix of the reduced form errors where errors are assumed to be uncorrelated and orthogonal. The VAR methodology assumes that each variable within the system is endogenous, consistent with the theoretical underpinnings of efficient markets and the CAPM, the only variables included are the respective returns of the individual portfolios and the returns of the market proxies. The time-series based tests are in effect a preliminary study on the time-series relationship between portfolio returns and their cash flow fundamentals proxied by ROE.

[3] Portfolios are re-sorted every 5 years. For the other results please see Appendix 2

i. *Impulse Response Functions*

Impulse response functions are estimated for the extreme value and small size portfolios in order to determine the relative importance of innovations emanating from other variables within the system. It should be noted that the lag length selected for each of the VARs estimated was set to 12 months as Cohen, Polk and Voulteenaho (2008) found that only after a passage of time; are the first and second moments of share returns affected by cash flow fundamentals[4].

Figure 3: Impulse response function – 5 year value sort (50c restriction)



Impulse response functions were estimated for the value portfolio returns. The value portfolio returns over the entire sample period were set as the dependent or response variable. The VAR further included the time-series return of the JSE ALSI, the market based ROE and the corresponding time-series ROE of the value portfolio, sorted every 60 months. The above graphs indicate the marginal effects of a shock to the ROE of the value portfolio, the JSE ALSI and the ROE of the market on the return on the extreme value portfolio. An interesting result is that a shock to the corresponding ROE return of the value portfolio seems to have a negligible effect on the actual return achieved by the value portfolio. The graph indicates that there is a present initial shock however; the effect of the shock is decreasing over time.

[4] One may take issue with such a methodology as one is generally bound to lag-length criteria tests, yet when utilising the proposed lag lengths, both the IRF's and variance decompositions fail to identify a cash flow effect.

More interestingly, an innovation experienced by the overall ROE of the market has a significantly greater impact on the value portfolios return. The graph indicates that from 10 months post shock, a shock to the overall ROE of the market begins effecting the extreme value portfolio, emphasizing the long run effect of a cash flow shock. A corresponding shock to the JSE ALSI has a negligible effect on the value portfolios returns that only seems to fade 10 months post shock. The above findings imply that the returns of the value portfolio are more sensitive to innovations in the overall cash flow return of the market as opposed to actual price level return of the market proxy, strengthening the case for a cash flow based measure of systematic risk.

Figure 4: Impulse response function – 5 year size sort (50c restriction)

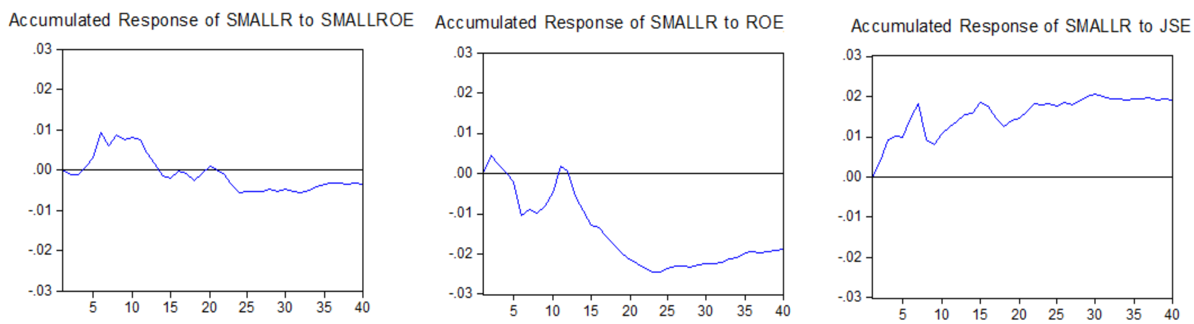
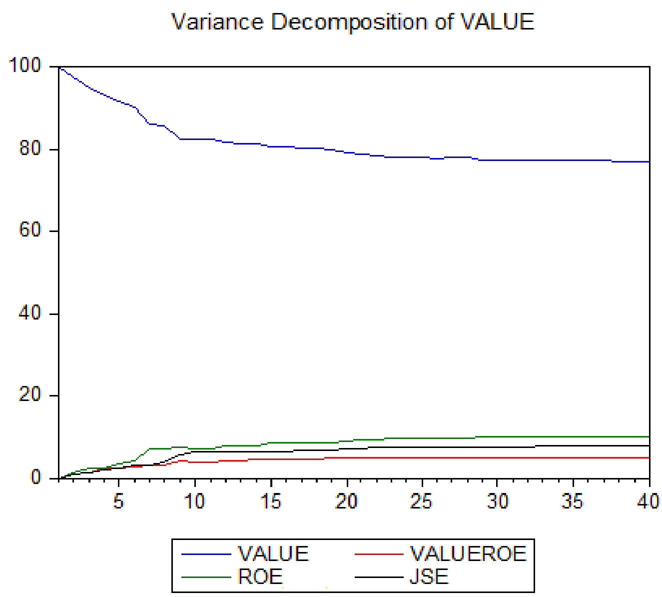


Figure 4 may give some insight as to why the cash flow beta appears less robust when attempting to explain the size effect. In contrast to the findings of Cohen, Polk and Voulteenaho (2008), a shock to the ROE of the market only seems to have an impact 25 months after the shock occurs and begins rising thereafter. A shock to the corresponding ROE of the small portfolio has a large initial impact which seems to die away after 25 months and only begins to increase at around 32 months post shock. Unfortunately, a shock to the JSE seems to have the most significant effect on the small size portfolio returns; implying that the small size portfolio is less sensitive to cash flow shocks of both its corresponding ROE and ROE of the market. The findings thus far indicate that a cash flow based measure of market risk seems more reliable in explaining the value premium and not the size effect.

ii. Variance Decompositions

The forecast error decomposition[5] is the percentage of the variance of the error made in forecasting a variable due to a specific shock at a given horizon. The purpose of variance decomposition is to identify the variation of a variable given a current innovation of another variable. This allows one to identify the effect of an endogenous shock to the evolution of a variable in the system. Using the VARs estimated previously, variance decompositions are run.

Figure 5: Variance Decomposition – 5 year value sort (50c Restriction)

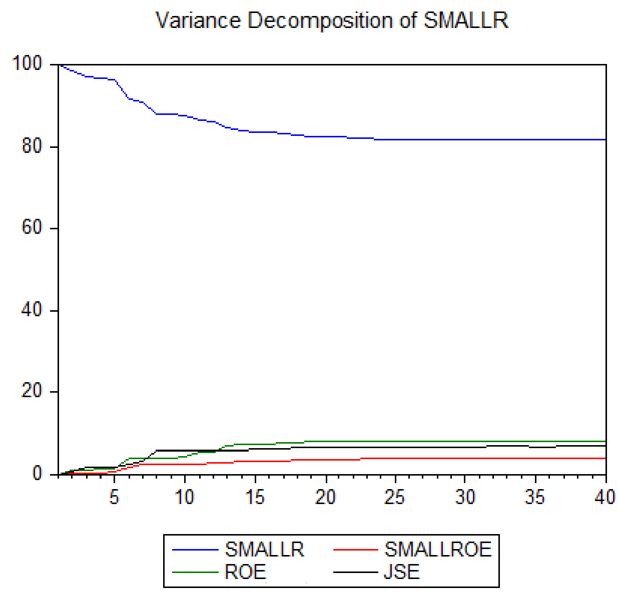


The above variance decomposition of the value portfolio returns is consistent with the impulse response functions. The graph indicates that a shock to the ROE of the market contributes more to the variation in the value portfolio returns than that of a shock to the JSE ALSI return. Once again a shock to corresponding ROE of the value portfolio has a minimal long term effect on the variation in the value portfolio returns. Moreover, the contribution of the value portfolio to its own variance is decreasing over time, consistent with the conclusion of Cohen, Polk and Voulteenaho (2008) that cash flow fundamentals begin dominating the

[5] Used interchangeably with 'variance decomposition'

first and second moments of returns. The findings are interesting as they seem to confirm the evidence presented in the impulse response functions, as over long periods of time the variation in the value portfolios return is dominated by the ROE of the market.

Figure 6: Variance Decomposition – 5 year size sort (50c Restriction)



The results of the variance decomposition conducted on the small size VAR are marginally more promising than the results of the impulse response function conducted on the small size portfolio returns. The above graph indicates that the contribution of a shock to the small size returns contributes less to its own variance over time. Fascinatingly, the market ROE contributes slightly more to the variation in the small size return than that of the JSE. Given the results of the size VAR impulse response function, one would still question as to whether the cash flow beta proposed by Cohen, Polk and Voulteenaho (2008) can adequately explain the small size premium.

The above result should be interpreted with an element of caution, as the size portfolios effect on its own variation does not seem to decreasing with time as a shock at time 1 will still contribute to 80% of the variance of the size portfolio at time 40, and does not seem to be decreasing. Furthermore, a VAR is conducted assuming that the variables included are endogenous to the system; therefore the results do not cater for possible omitted variable bias.

A further caveat is in order as the lag length criteria tests were not employed as they suggested lag lengths of eight to nine months on average. Such a time span would naturally fail to capture the longer term innovations captured when the lag length is set to twelve months (Appendix 2)

c) VECM

Box and Jenkins (1970) described a method for dealing with data that are integrated of order one ("I(1)"). The methodology employs differencing in order to prevent the estimation of spurios relationships between economic variables. Engle and Granger (1987) and Johansen (1988) developed econometric models that use price levels or level data that is typically I(1) in order to estimate long run relationships between variables. The premise of the Engle – Granger and Johansen approach is that important information is lost when differencing time-series data. The purpose of the following estimated vector error correction models (VECMs) is to identify whether there is a consistent long-run relationship between the level returns of the value and size sorted portfolios and the book value[6] of the market represented in levels. The results of the VECM estimations may provide further insight into the relationships between a value, size and cash flow. A further insight will be a comparison between the long-run relationship between the size and value portfolios and the JSE. A positive long-run relationship is expected between the book value based market proxy and the size and value portfolios. In order to strengthen the case for a cash flow based systematic risk measure, further tests are run by placing restriction on variables within both the cointegrating vector and the 'speed of adjustment' matrix. A restriction placed on the cointegrating vector, represented by β, implies the test of equal long-term relationships. The LR test provides insight as to whether two variables have equal long-term relationships with the independent variables. Another restriction test is employed where restrictions are placed on the speed of adjustment vector, represented by α. Such a restriction allows for the testing of whether a variable is weakly exogenous to the system. Similarly, the LR test determines if the restriction of weak exogeniety is binding. The failure to reject such a restriction would imply that the restricted variable does not actually adjust to the long-run equilibrium relationships prescribed by the VECM estimation.

[6] Value-weighted book-value of the market inclusive of gross dividends paid

i. *VECM Methodology*

In order to apply a VECM to the data, the data should be I(1). This presents an issue for the size and value sorted portfolios as value-weighted portfolio levels will be plagued by structural breaks. At each point of re-sorting, specifically over longer holding periods, the price levels of the value-weighted portfolios will fluctuate considerably, possibly resulting in inaccurate relationship measurements. In order to circumvent this issue, it is proposed that the equally-weighted levels be used. This implies that a fictional R100 investment[7] is invested in each of the portfolios sorted on size and value. The resulting level time-series meet all the criteria required by the VECM model, specifically that the size and value portfolios are I(1) in the levels. Cointegration tests are run in order to identify the number cointegrating vectors in the VAR. In total, four VECMs are run where the level of the extreme size and value portfolios are included as well as the JSE level and book value of the market (otherwise referred to as the level ROE). Identification tests for cointegrating vectors are run. The tests utilise two Eigen value tests, namely the trace and rank test statistics that evaluate eigen values in order to determine the number of cointegrating relationships (see appendix 2).

Table 1a: *VECM output for the level ROE, JSE and Value portfolio (50c restriction)*

VECM Estimates		
Cointergrating Vector		Speed of Adjustment Vector
Value	***1***	***-0.00237***
		-0.00127
		[-1.87154]
ROEM	***-21.05864***	***-0.00237***
	-4.71777	*-0.00127*
	[-4.46368]	*[-1.87154]*
JSE	***-19.40451***	***-0.00237***
	-3.85363	*-0.00127*
	[-5.03539]	*[-1.87154]*
C	***444.8325***	

[7] R10 and R1 investments were also tested and the results were consistent

The above VECM indicates that the cointegrating relationship is represented by the following formula:

$$Value = -444.84 + 21.06ROEM + 19.4JSE$$

This implies that, as expected, the value portfolio seems to maintain a positive long-run relationship with the level ROE of the market where the ROE of the market is the monthly change in the value-weighted book value of the entire market inclusive of gross-dividends paid. A test for weak exogeneity is performed by imposing restrictions on the speed of adjustment vector (α vector). In order to test whether the ROE of the market is weakly exogenous to the system, the restriction is imposed setting α_{21} to zero. A rejection of such a test would imply that the ROE of the market is weakly exogenous to the system (refer to Appendix 2 – value VECM with restrictions β(1,1) = 1 and α(2,1) = 0). The LR test produces a p-value of 0.009, resulting in a rejection of weak exogeneity. To strengthen the case of a ROE based risk measure a further restriction is placed, where the cointegrating coefficient of the JSE is set equal to the ROEM (therefore β(1,2) = β(1,3)). The p-value produced by the LR test is 0.86, implying that one fails to reject the null hypothesis of the ROEM and JSE having(at least) an equivalent long run effect on the value portfolio.

Table 1b: *VECM output for the level ROE, JSE and value portfolio with restriction β_{12}=β_{13}*

VECM Estimates		
	Cointergrating Vector	Speed of Adjustment Vector
Value	***1***	***-0.0042***
		-0.00227
		[-1.85077]
ROEM	***-11.80916***	***0.010292***
	-1.99973	*-0.00412*
	[-5.90539]	*[2.49844]*
JSE	***-11.80916***	***0.001761***
	-1.99973	*-0.00316*
	[-5.90539]	*[0.55707]*
C	***255.2584***	
B(1,1)=1, B(1,2)=B(1,3)		
LR test for binding restrictions (rank = 1):		
Chi-square(1)	0.032828	
Probability	0.856221	

A VECM is then estimated with the small size portfolio (in the levels) set as the dependent variable. A caveat should be mentioned about the size VECM. The results of the cointegration tests fail to reject the null hypothesis of no cointegrating relationships. In order to proceed with the testing, we assume that there is at least one cointegrating vector when estimating the VECM.

Table 2: VECM output for the level ROE, JSE and small size portfolio

VECM Estimates		
Cointergrating Vector		Speed of Adjustment Vector
Small	***1***	***-0.01058***
		-0.00709
		[-1.49140]
ROEM	***-2.824973***	***0.032248***
	-0.8084	*-0.01283*
	[-3.49451]	*[2.51361]*
JSE	***-4.306877***	***0.006123***
	-0.71485	*-0.01042*
	[-6.02488]	*[0.58749]*
C	***69.97334***	

The above results imply that both the book value market portfolio and the JSE have positive long run relationships with the small size portfolio. In order to determine whether the book value based market portfolio is weakly exogenous to the estimated system, the restriction of α_{21} equal to zero is set (refer to Appendix 2 – size VECM with restrictions $\beta(1,1) = 1$ and $\alpha(2,1) = 0$). The LR test produces a p-value of 0.23, implying that the book value market proxy (that would be used to estimate cash flow beta and determine systematic risk) may be weakly exogenous to the system. When setting the cointegrating vector coefficients of the JSE equal to the book value market proxy, the LR test fails to reject the null, entailing that over the given sample period, it seems that the book value market proxy has an equivalently significant long run relationship with the size portfolio. This implies that the small size portfolio level returns have an equivalently long run sensitivity to the JSE as they do to the book value market proxy, implying that a cash flow based measure of systematic risk may perform as well as the conventionally measured CAPM beta that uses the JSE ALSI as a market proxy.

Another set of VECM estimations are run where the high minus low (HML) and small minus big (SMB) levels are used as dependent variables. The purpose of the tests is to ascertain whether the book value market proxy has an 'as' significant long-run relationship with the value and size premia (in the levels) when compared with the JSE.

Table 3a: VECM output for the level ROE, JSE and HML level portfolio

VECM Estimates		
Cointergrating Vector		Speed of Adjustment Vector
HML	***1***	***-0.038***
		-0.01773
		[-2.14336]
ROEM	***-5.293752***	***0.026913***
	-0.48803	*-0.01106*
	[-10.8473]	*[2.43237]*
JSE	***-2.77153***	***0.029485***
	-0.57733	*-0.01503*
	[-4.80056]	*[1.96160]*
C	***79.27902***	

As seen previously, both the book value market proxy and the JSE maintain positive long-run relationships. However when placing restrictions on the speed of adjustment vector parameters, the book value market proxy seems to be more weakly exogenous than the JSE.

Table 3b: VECM Restriction results using SMB and HML as dependent variables

Dependent Variable	**Restriction**	**Chi-Square (1)**	**p-value**
HML	A(2,1)=0	3.222155	0.072648
	A(3,1)=0	4.597747	0.032014
	B(1,2)=B(1,3)	6.725928	0.009502
SMB	A(2,1)=0	1.947768	0.162828
	A(3,1)=0	1.69832	0.192508
	B(1,2)=B(1,3)	6.00849	0.014237

The above table indicates that when using the level excess return earned by the small size and high value portfolios, the test of weak exogeneity of both the book value market proxy and the JSE yields interesting results. When using HML as the dependent variable, the book value market proxy (A(2,1)=0) is weakly exogenous to the system yet, the JSE (A(3,1)=0) is not. Furthermore, the test for equivalent long-run relationships (B(1,2)=B(1,3)) is also rejected. When SMB is used, both the book value market proxy and the JSE are weakly exogenous to the system. When testing the equivalence of their long run relationships with the excess level return earned by the small portfolio, the LR test rejects the null of equivalent long-run relationships.

The above findings seem to be mixed as the book value market proxy seems to be effective as it maintains a significant long run relationship with the small size and value portfolios, however when attempting to explain the level excess returns earned by both the small size and high value portfolios, the book value market proxy seems to lack a significant long-run relationship with either, implying that the cash flow based measure of systematic risk proposed by Cohen, Polk and Vuolteenaho (2008) may not be the saviour of the CAPM.

E. Cross-Sectional Tests

Van Rensburg and Robertson (2003a) found that the CAPM beta fails to explain the size and value premium on the cross-section of average returns on the JSE. Strugnell, Gilbert and Kruger (2011) confirmed the results of Van Rensburg and Robertson (2003a) by testing different beta estimation techniques. The same conclusion was reached, namely that CAPM and beta in its current form, has a negligible (and possibly even an inverse) relationship with returns. Cohen, Polk and Voulteenaho (2008) suggested a method of estimating beta over extended periods of time, using the discounted change in book equity (referred to as ROE) and the overall discounted ROE of the market in order to calculate a cash-flow beta. As mentioned previously, ROE is defined as (See Appendix 3 for the full derivation of ROE):

$$ROE_t = \frac{X_t}{BE_{t-1}} \quad \textbf{(2)}$$

$$X_t = BE_t - BE_{t-1} + Div_t^{gross} \quad \textbf{(3)}$$

The cash flow beta is then estimated by regressing the discounted ROE of the particular share or portfolio on the discounted ROE of the market. The ROE of the market is defined as the change in the value-weighted book-value of the total market. The regression equation employed to estimate cash flow beta is as follows:

$$\rho^j \log(1 + ROE_{i,t}) = \alpha_{i,t} + \beta_{i,t}^{CF} \rho^j \log(1 + ROE_{m,t}) + \varepsilon_{i,t} \quad \textbf{(5)}$$

Cohen, Polk and Voulteenaho (2008) found that when constructing portfolios based on price to book, the cash flow beta estimated using rolling window OLS regressions began to track the returns of the 'value' portfolio and 'growth' portfolio. ρ is calculated as one minus the historical dividend yield of the market proxy. The authors proposed using a discount factor equivalent to scaled by the historical dividend yield of the market proxy and set ρ = 0.975. The historical dividend yield of the ALSI over the study period is 2.71% which equated to a ρ = 0.9736 (An explanation as to why a discount factor is applied can be found in Appendix 3).

i. Methodology and Portfolio Sort

Consistent with the approach of Cohen, Polk and Voulteenaho (2008), portfolios are formed yearly based on size and value criteria and held for a period of 60 months post sort. The reason behind the usage of a 60 month holding period is that although a seven year holding period is more consistent with the methodology of Cohen, Polk and Voulteenaho (2008), constructing overlapping portfolios consisting of 84 months results in only eight overlapping portfolios while a 60 month sort results in 12 overlapping portfolios. The constraint is largely due to the significantly shorter sample period used in this study. At each sorting period, decile break points are inserted and shares are sorted into one of nine portfolios based on book to market and one of ten portfolios based on size. The result is a panel of portfolio returns, betas, median book to markets, average log of size and cash flow betas measured at 11 points over the sample period. The multivariate sort entails a simultaneous sort on both size and value, conducted independently to allow for a variation in one criterion unrelated to the other.

ii. Sample Stats and Overlapping OLS Regressions

The time series averages are calculated for both the size and value sorted portfolios over the sample period.

Table 4a: Sample Statistics – Value Sort

Value -B/M Sort	High B/M	B	C	D	E	F	G	H	Low B/M
Avg 5 year return	**0.042**	**0.041**	**0.024**	**0.024**	**0.024**	**0.022**	**0.019**	**0.018**	**0.019**
	8.44***	4.36**	9.94***	6.70**	6.05**	7.3***	6.86**	7.73***	5.33**
Beta	**0.397**	**0.370**	**0.498**	**0.554**	**0.619**	**0.595**	**0.610**	**0.562**	**0.642**
	11.81**	5.23*	10.55**	11.25**	15.29**	14.469**	19.31***	14.875**	13.35**
Median BM	**4.387**	**1.923**	**1.262**	**0.952**	**0.818**	**0.783**	**0.569**	**0.718**	**0.33**
	25.04***	11.69**	9.76**	7.39**	8.43**	7.26**	10.38**	3.642*	3.36*

(,**,*** indicates 10%,5% and 1% significance)*

Table 4a describes the average returns, average betas and average book to market of portfolios sorted on median book to market. Row 1 represents the average return achieved by each of the 11 overlapping portfolios held for 60 months post sort. As expected, the extreme value portfolio achieves the highest return on average. Average returns seem to decrease monotonically as portfolios move from the high to low book to market classification. Considering the average betas estimated for each of the portfolios, the extreme value portfolio has an average beta of 0.396 on average and is 11.86 standard errors away from zero, while the extreme growth portfolio achieves an average of beta of 0.642 that is 13.35 standard errors away from zero.

Average betas seem to increase as portfolios move from high to low value, implying that beta seems to have an inverse relationship with returns. Interestingly enough, the average book to market of the portfolios 60 months post sort seem to dictate that there is consistency in a firm book to market ratio. The average median book to market ratio for the extreme value portfolio is 4.39 and significant at the 1% level. The persistence is also apparent in the lower book to market portfolio as average median book to market decreases monotonically and the average median book to market of the growth portfolio is 0.33 and significant at the 10% level. The results further confirm that there is a significant value effect on the cross-section of average returns on the JSE, in line with the findings of Van Rensburg and Robertson (2003a), Auret and Sinclaire (2006), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011).

Table 4b: Sample Statistics – Size Sort

Size -Market Cap Sort	Big	B	C	D	E	F	G	H	I	Small
Avg 5 year return	**0.017**	**0.018**	**0.018**	**0.015**	**0.02**	**0.022**	**0.026**	**0.027**	**0.051**	**0.066**
	14.28***	9.97***	7.81**	5.81**	6.38**	6.97**	5.08**	7.02**	5.09**	6.366**
Beta	**0.850**	**0.680**	**0.570**	**0.600**	**0.531**	**0.510**	**0.460**	**0.390**	**0.350**	**0.300**
	70.12***	21.40***	20.44***	29.267***	7.78**	13.96***	13.41***	8.29**	2.87**	3.08**
Average Size	**4.94**	**4.33**	**3.9**	**3.499**	**3.266**	**2.96**	**2.727**	**2.405**	**2.182**	**1.81**
	17.31***	13.54***	12.10***	10.47***	9.82**	8.83**	7.71**	6.43**	5.88**	4.68**

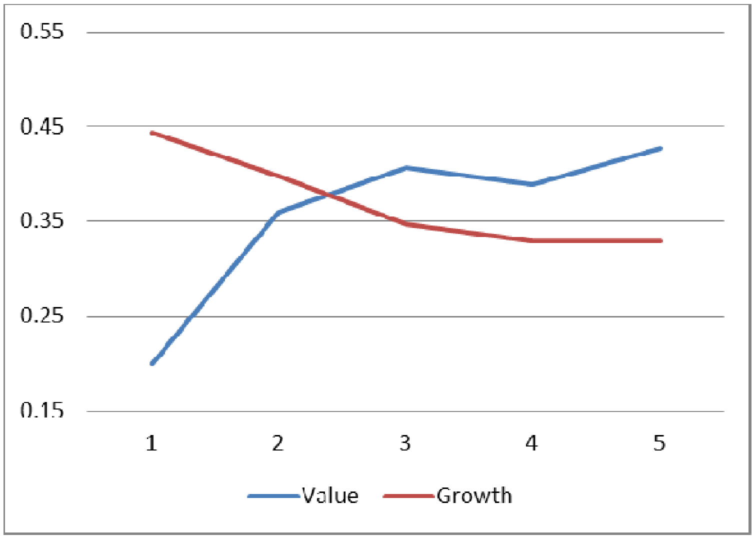
(,**,*** indicates 10%,5% and 1% significance)*

The size sort was conducted in an identical way to the value sort and the results seem to imply a significant size effect that is not explained by the CAPM beta. Considering average returns earned over the 11 five year periods; the extreme small size portfolio achieved an average return of 6.6% (significant at the 5% level) while the large capitalization portfolio achieved a monthly average return of 1.7% over the sample period.

Beta decreases monotonically as size decreases, implying that beta has a negative relationship with average returns. Interestingly, the average size of portfolio constituents remains relatively constant over the various sixty month holding periods. The average log of market capitalization of the large size portfolio is 4.943 and is 17.31 standard errors away from zero (significant at the 1% level) while the small size portfolio has an average log of market capitalization of 1.81 and is 4.68 standard errors away from zero (significant at the 5% level), implying that even sixty months post sort, portfolios maintain their overall size characteristic.

Overlapping OLS regressions allow for the estimation of the evolution of the cash flow based beta over time. In order to estimate the cash flow beta, a cash flow market proxy or ROE of the market is set as the market proxy. Consistent with the methodology employed by Cohen, Polk and Voulteenaho (2008), portfolio cash flow returns, discounted by the historical dividend yield of the JSE, are regressed against the discounted cash flow return or ROE of the cash flow based market proxy. Cash flow betas are then averaged across the cross-sections and then plotted against time.

Figure 7a: Cash flow betas – Five year Value Sort

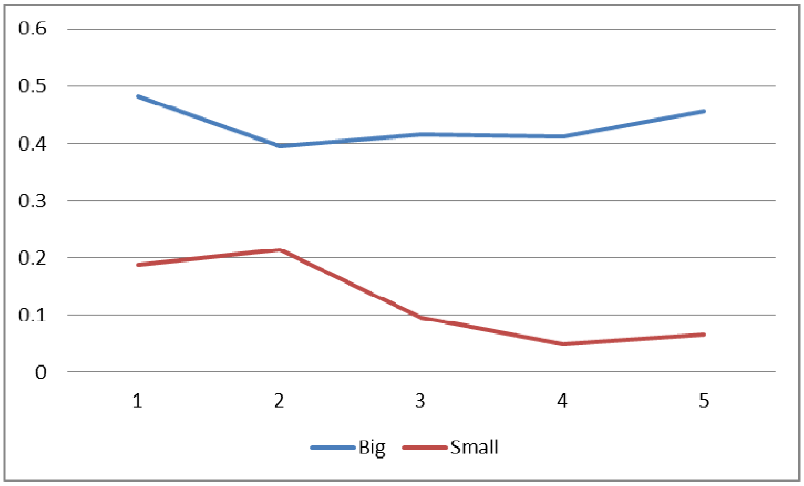


The above figure indicates the evolution of the cash flow betas estimated using rolling window beta estimations. The average cash flow beta of value portfolio at year one is approximately 0.2. The above figure indicates that over the five year holding period, the extreme value portfolios cash flow beta surpasses the growth portfolios cash flow beta around two and a half years post sort and on average is consistently higher than the average cash flow beta of the growth portfolio. The growth portfolios cash flow beta seems to be decreasing through time and flattens out around year five.

The above results are consistent with the findings of Cohen, Polk and Voulteenaho (2008) as the cash flow betas of the extreme value portfolios seem to be positively related with average returns. The conventionally measured CAPM beta has proven ineffective in describing the systematic risk and the evidence indicates that it fails to describe the cross-sectional variation in share returns, specifically when sorting portfolios based on size and value. The implication of such failings entails that the excess returns achieved by extreme small capitalization and value portfolios are not related to systematic risk, resulting in a joint contradiction of CAPM and market efficiency. The above findings seem to imply that the value premium is explained by cash flow risk, entailing that cash flow risk is priced and therefore, the market is somewhat efficient in the long run.

Cohen, Polk and Voulteenaho (2008) focused their study on a value sorted data set and stated that the cash flow beta managed to explain the cross-sectional variation in portfolio returns sorted on size. In order to test this result, rolling window OLS regressions are run on the portfolio ROE's of the size sorted portfolios in order to estimate the evolution of the size portfolios cash flow betas.

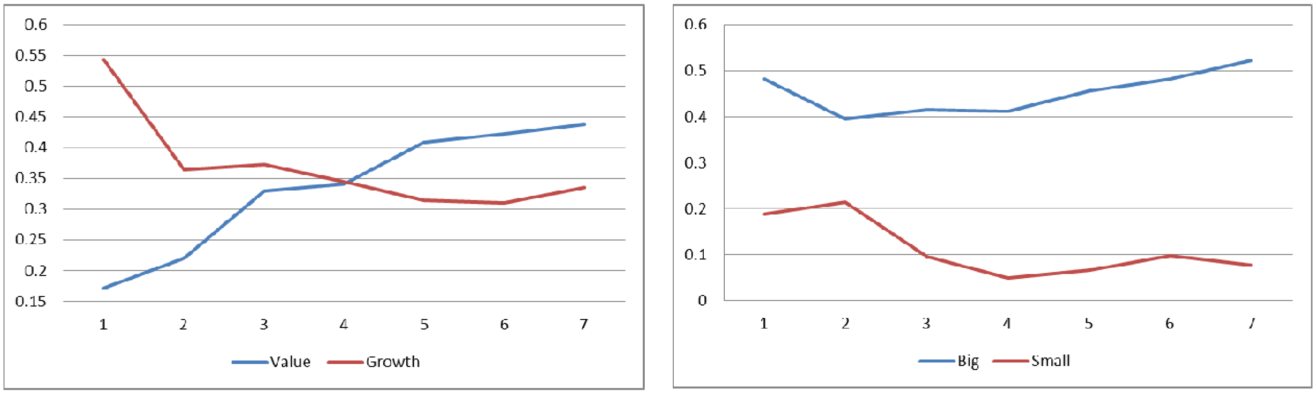
Figure 7b: Cash flow betas – Size Sort



The rolling window cash flow beta estimation seems far less successful when applied to the size sorted portfolios. The large capitalization portfolio has an average cash flow beta that oscillates around 0.5 over five years on average. The small size portfolio cash flow beta is significantly lower on average over a five year period and seems to be decreasing.

The above findings are in contrast to the evidence presented by Cohen, Polk and Vuolteenaho (2008). The above findings indicate that the cash flow beta successfully tracks the returns of the value sorted portfolios over long holding periods, yet the same cannot be said for portfolios sorted on size. It is possible that the holding period of sixty months is too short. Cohen, Polk and Vuolteenaho (2008) constructed portfolios based on price to book and held portfolios for 15 years post sort. Due to the sample period of this study, a 15 year holding period is not plausible but in order to ascertain whether the poor performance of the cash flow beta is a result of a short holding period, the holding period is extended to seven years post sort and overlapping OLS regressions are conducted for both the size and value sorted portfolios.

Figure 8: Cash flow betas – Size and Value sort (7 year holding period)



The above figure displays the evolution of average cash flow betas over seven year holding periods, where portfolios are sorted on the median book to market and average log of market capitalization. The results of the value sorted cash flow betas are consistent with the findings above as the value portfolios average cash flow betas are increasing consistently through time and at year seven are significantly larger than the average cash flow betas of the growth portfolio. Unfortunately, the same cannot be said for the cash flow betas of the size sorted portfolios.

The small size portfolio cash flow betas seem to increase from year one to year two but monotonically decrease thereafter. The large capitalization portfolio cash flow betas are increasing over time. Throughout the holding period, the average cash flow betas of the small size portfolios blot well below those of the large size portfolio. The above findings should be considered with a caveat regarding the rolling window beta estimation. The rolling window beta estimation utilises an “expanding” rolling window that increases with the number of data points included and cuts off at sixty months’ worth of returns. Therefore, the above results should be interpreted with caution.

iii. Cross – Sectional Regressions

The overlapping OLS regression estimations of the cash flow beta presented a quandary as the cash flow beta only seems to explain the value effect and not the small size premium. To corroborate and test the validity of the evidence presented thus far, cross-sectional regressions are employed. As mentioned above, shares have been sorted into nine portfolios based on median book to market and ten portfolios based on average market capitalization, as well as a simultaneous sort on size and value of nine portfolios based on book to market and average size. The regressions are run on portfolios held for 60 months post sort[8]. Hsiao (2007) documented a number of issues faced when dealing with panel data which typically possesses cross-sectional and time series properties. The utilization of various econometric specifications adds both robustness and validity to the study.

The two main regression techniques employed are GMM/dynamic panel estimations and fixed effects regressions with cross-sectional weights. Fixed effects estimation allows for individual and time specific effects to be correlated with independent variables, yet it does not allow for the estimation of coefficients that are time invariant. GMM has the advantage that it is consistent and normally distributed, irrespective of whether alphas are treated as random or fixed. GMM can produce significantly downward biased coefficients specifically in finite samples considered over long time periods.

Table 5a: GMM and Fixed effects regression results – Independent Value Sort

Regression 1: Value Sort

Fixed Effects			*GMM*		
B/M	**Beta**	**CF Beta**	**B/M**	**Beta**	**CF Beta**
0.003			**0.007**		
2.388			*2.640*		
0.019			***0.010***		
	-0.029			**-0.046**	
	-2.810			*-7.780*	
	0.006			***0.000***	
		0.010			**0.004**
		2.033			*2.149*
		0.045			***0.035***
	-0.040	**0.015**		**-0.038**	**0.008**
	-4.283	*3.138*		*-53.000*	*4.320*
	0.000	***0.002***		***0.000***	***0.000***
-0.003		**0.007**	**0.003**		**0.006**
-1.210		*1.466*	*1.644*		*2.004*
0.227		***0.143***	*0.104*		***0.049***

[8] Regressions were also run on portfolio held for seven and the results were basically identical

The above table produces the results of the regressions run on the value sorted portfolios using both fixed effects and GMM/dynamic panel estimators. The regression results confirm the previous findings as there seems to be a significant value effect when using book to market as a value proxy. Both the fixed effects and GMM specifications produce significantly positive coefficients, with the GMM just missing the 1% level. In line with the findings of Van Rensburg and Robertson (2003a) and Strugnell, Gilbert and Kruger (2011), the conventionally measured CAPM beta is significantly negative throughout all the regressions.

The cash flow beta is significantly positive when regressed on average returns alone, but only maintains its significance using the GMM specification when regressed with book to market. Interestingly, book to market loses its significance in both the fixed effects and GMM specifications. The findings seem to qualify the notion that the cash flow beta does an adequate job in explaining the value premium, and even maintains a positive coefficient irrespective of the specification used and independent variable included.

Table 5b: GMM and Fixed effects regression results – Independent Size Sort

Regression 2: Size Sort

	Fixed Effects			*GMM*	
Size	**Beta**	**CF Beta**	**Size**	**Beta**	**CF Beta**
-0.007			**-0.002**		
0.001			*-6.283*		
0.000			***0.000***		
	-0.025			**-0.036**	
	-2.278			*-19.536*	
	0.025			***0.000***	
		0.007			**0.002**
		2.118			*2.519*
		0.037			***0.014***
	-0.025	**0.007**		**-0.030**	**-0.003**
	-2.584	*1.838*		*-16.274*	*-1.252*
	0.011	***0.069***		***0.000***	***0.214***
-0.007		**-0.005**	**-0.002**		**0.000**
-4.242		*-1.191*	*-5.673*		*0.031*
0.000		***0.236***	***0.000***		***0.975***

The results of the regressions conducted on the size sorted portfolios seem to confirm the poor ability of the cash flow beta in explaining the size effect. The regression results are consistent between specifications as size maintains a negative and significant coefficient in all regressions. Once again, beta has a significantly negative relationship with returns.

The cash flow beta is significantly positive when regressed alone on average returns, yet when the other independent variables are included, the cash flow beta loses all significance and changes sign in two of the four multivariate regressions. The above evidence contradicts the findings of Cohen, Polk and Vuolteenaho (2008), who found that the cash flow beta succeeds in explaining the size premium. The results presented in table 5b are mixed with regards to the validity of the cash flow beta and its ability to adequately explain the cross-sectional variation in average returns. Once again, the results are consistent with the findings of Van Rensburg and Robertson (2003a), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011) as regression analysis indicates a significant (and independent) size and value effect present on the cross-section of average returns on the JSE. Furthermore, consistent with the findings of Van Rensburg and Robertson (2003a) Strugnell, Gilbert and Kruger (2011), the conventionally measured CAPM beta displays a consistently negative relationship with average returns when using the FTSE-JSE ALSI as a market proxy and conventional OLS regressions as the estimator.

Table 6: GMM and Fixed effects regression results – Simultaneous Size and Value Sort

Regression 3: Size and Value Sort

Fixed Effects				*GMM*			
BM	**Size**	**Beta**	**CF Beta**	**BM**	**Size**	**Beta**	**CF Beta**
0.003	**-0.007**			**0.007**	**-0.003**		
2.070	*-8.037*			*3.332*	*-6.087*		
0.041	***0.000***			***0.001***	***0.000***		
		-0.028				**-0.026**	
		-4.079				*-3.776*	
		0.000				***0.000***	
			0.006				**0.017**
			1.698				*12.819*
			0.093				***0.000***
		-0.028	**0.005**			**-0.038**	**0.007**
		-3.965	*1.496*			*-4.112*	*1.270*
		0.000	***0.138***			***0.000***	***0.208***
-0.008	**0.004**		**0.001**	**0.003**	**-0.005**		**0.017**
-7.439	*2.096*		*0.311*	*0.863*	*-2.854*		*2.610*
0.000	***0.039***		***0.757***	***0.391***	***0.006***		***0.011***

The results presented in table six are mixed with regards to the validity of the cash flow beta and its ability to adequately explain the cross-sectional variation in average returns. Once again, the results are consistent with the findings of Van Rensburg and Robertson (2003a), Basiewicz and Auret (2009) and Strugnell, Gilbert and Kruger (2011) as regression analysis indicates a significant (and independent) size and value effect present on the cross-section of average returns on the JSE. Furthermore, consistent with the findings of Van Rensburg and Robertson (2003a) Strugnell, Gilbert and Kruger (2011), the conventionally measured CAPM beta displays a consistently negative relationship with average returns.

The performance of the cash flow beta proves inconsistent between the regression specifications. Considering the fixed effects regression analysis; the cash flow beta is positive when regressed solely on average returns, yet is only significant at the 10% level. When the cash flow beta is regressed together with the conventionally measured CAPM beta, the CAPM beta remains significantly negative while the cash flow beta has a positive coefficient but is insignificant. The cash flow beta is also insignificant when included in a regression with book to market and size. The cash flow beta retains a positive coefficient yet is only significant in one out of three regressions using the fixed effects specification.

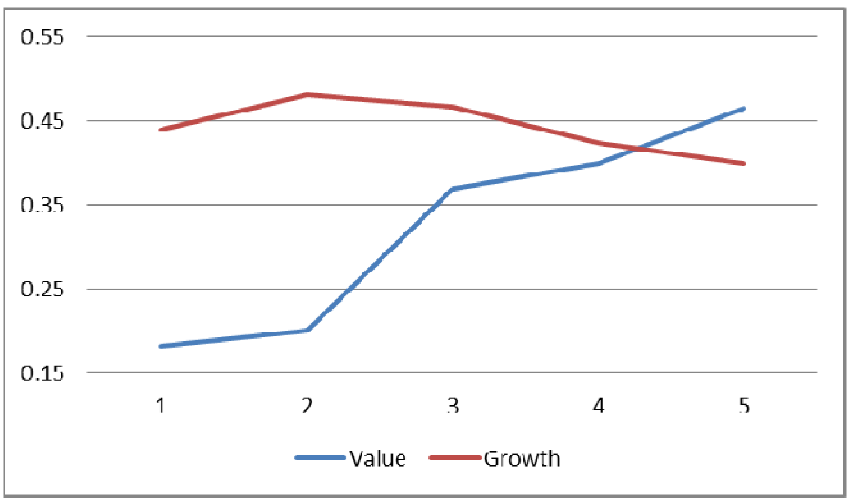
The results of the GMM regressions are more promising. Both book to market and size are significant at the 1% level. Again, the conventionally measured CAPM beta is significantly negative. The cash flow beta, when regressed alone on average returns, is significantly positive at the 1% level. Unfortunately, the only time the cash flow beta loses significance is when combined with the CAPM beta. When both book to market and size are included in the regression with the cash flow beta, the cash flow beta seems to subsume the book to market variable and produces a significantly positive coefficient while the size variable is still significantly negative.

The fixed effects and GMM models used in the regression analysis produce consistent results in the univariate sorts; however, in the multivariate sort the GMM estimations are far more favourable to the cash flow beta. Whenever conducting regression analysis, model misspecification is a concern. In order to alleviate such concerns, multiple econometric specifications are used and ideally, consistent results are produced. Unfortunately, this is not the case. The GMM and fixed effects model are however consistent in identifying a significant and independent value and size effect on the cross-section of average returns over the sample period and maybe more importantly, consistent with the findings of Van Rensburg and Robertson (2003a) and Strugnell, Gilbert and Kruger (2011), the CAPM beta has a significantly negative relationship with average returns.

iv. Robustness Tests

There are two possible explanations behind the cash flow betas inability to explain the small size premium. The first possibility considered is that smaller shares are less liquid and this may negatively affect the estimation of the cash flow beta. By employing a liquidity constraint in the form of a price filter set at 50 cents[9], portfolios are resorted and returns and ROE's are recalculated. The number of size sorted portfolios is reduced to nine to ensure that at all points in time there are shares present in each portfolio. Once again, rolling window cash flow betas are estimated and averaged for each of the portfolios over the sample period.

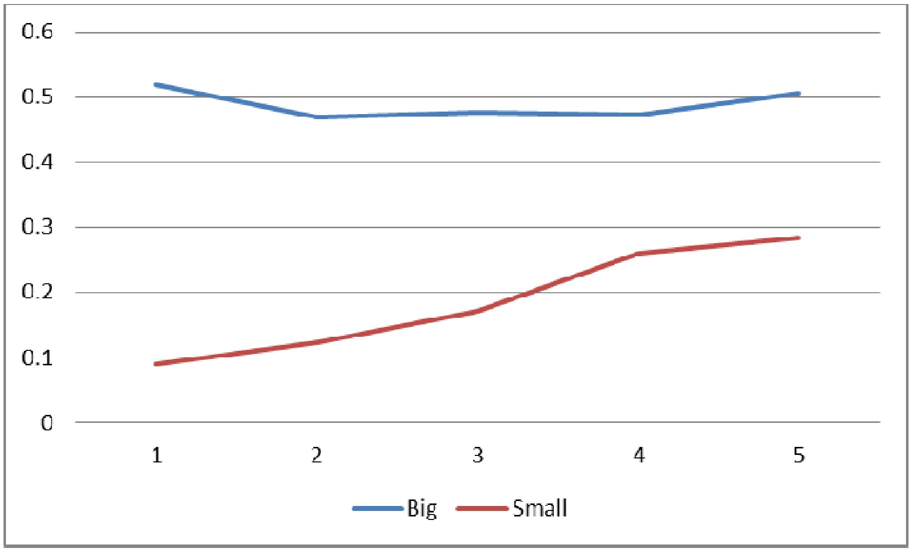
Figure 9a: Cash flow betas – Value Sort (50c restriction)



The application of a price filter to the value sort seems to exacerbate the increase in cash flow betas over a five year period. The above diagram indicates that the point of intersection is around four years post sort and that the cash flow beta of the value portfolio is greater than the cash flow beta of the growth portfolio. Furthermore, when comparing figure 9a to figure 8a, the cash flow betas of the value portfolio increase at a more considerable rate and steeper gradient when a price filter is applied.

[9] Price filters of 75 and 100 cents where used and the results were not significantly different

Figure 9b: Cash flow betas – Size Sort (50c restriction)



The application of a price filter also seems to have a positive effect on the average cash flow betas of the size sorted portfolios. The evolution of the cash flow betas for the large capitalization portfolio is almost identical to the previous estimates in figure 8b. The small size cash flow betas increase monotonically over the 5 year period, implying that there does seem to be a long run increase in cash flow risks of the smaller capitalization shares, yet the cash flow betas fail to overtake those of the large capitalization portfolio.

This seems to imply that liquidity may play a role in the failure of the cash flow betas ability in explaining the cross-sectional variation in returns of portfolios sorted on size. In order to truly test whether liquidity has a part to play in the failure of the cash flow beta, cross-sectional regressions are run using fixed effects, GMM/dynamic panel data and random effects estimation in order strengthen the power of test and produce more concrete evidence regarding the cash flow beta. Once again, the findings can be considered concrete when there is consistency between specification results.

Table 7a: GMM, Fixed and Random effects regression results – Value Sort (50c price filter)

Regression 5: Value Sort
- 50c Restriction

Fixed Effects			*GMM*			*Random Effects*		
BM	**Beta**	**CF Beta**	**BM**	**Beta**	**CF Beta**	**BM**	**Beta**	**CF Beta**
0.001			**0.003**			**0.002**		
1.316			*2.665*			*3.442*		
0.192			***0.009***			***0.001***		
	-0.005			**-0.003**			**-0.015**	
	-0.669			*-2.133*			*-2.323*	
	0.505			***0.036***			***0.022***	
		0.014			**0.012**			**0.001**
		3.796			*1.494*			*0.462*
		0.000			*0.139*			*0.645*
	-0.010	**0.015**		**-0.007**	**0.013**		**-0.019**	**0.016**
	-1.439	*4.016*		*-2.264*	*1.836*		*-3.283*	*4.670*
	0.154	***0.000***		***0.026***	*0.070*		***0.001***	***0.000***
0.001		**0.014**	**0.003**		**0.016**	**0.003**		**0.016**
1.491		*3.851*	*1.473*		*2.091*	*4.710*		*4.632*
0.140		***0.000***	***0.145***		***0.040***	***0.000***		***0.000***

The regression results of the value sorted portfolios with an applied price restriction are presented above. There seem to be some slight differences when comparing results with the previous regression as the CAPM beta is only significantly negative in two of the three univariate regressions when using the GMM and random effects specification, while the fixed effects regressions produce negative CAPM beta coefficients that are not significantly different from zero. Both the fixed effects and GMM models find cash flow beta to be positive yet insignificant when regressed alone on average returns, while the fixed effects specification finds the cash flow beta to be both positive and significant. Surprisingly, the application of the price filter negatively affects book to market as the fixed specification finds book to market to be positive yet insignificant when regressed alone and with cash flow beta. A potential cause of this may be that a price filter combined with the holding period of 60 months may result in a deflating effect of average or median book to market ratio as an explanatory variable, in line with the long term reversal discussed by Lakonishok, Shleifer and Vishny (1994).

When regressing cash flow beta with the CAPM beta on average returns, both the GMM and random effects specifications find the CAPM beta to be significantly negative while all specifications find the cash flow beta to be significantly positive (The GMM only at a 10% level). The results of the regressions of book to market and cash flow beta are semi-consistent across specifications. In the fixed effects and GMM regressions, book to market is subsumed by the cash flow beta. The random effects regressions find both cash flow beta and the book to market ratio to have significantly positive relationships with average returns. The results of the above regression are in line with the original findings that cash flow beta performs very well in explaining the value premium, far better than the conventional CAPM beta and in the long run even book to market. As mentioned previously, the true test of the cash flow beta is whether it can explain the small size premium.

The regression results in table 7b below indicate that when adding a price filter to the size portfolio sort, the CAPM beta is only significantly negative when using the random effects specification. Only the fixed effects specification finds cash flow beta to be a significant explanatory variable when regressed alone on average returns; however the GMM and random effects estimations do not. All estimations are consistent in finding a significant size effect. When including the cash flow beta with the size variable in multivariate regressions, all specifications find that size subsumes the cash flow beta. The application of a price filter seems to have little or no effect on the size coefficients in terms of magnitude. When comparing the regressions presented in table 5b to those presented below, all specifications produce coefficients in the same magnitude, even with the inclusion of a price filter. The value and size regressions seem to produce similar conclusions.

The application of a price filter fails to improve the ability of the cash flow beta in explaining the cross-sectional variation in expected returns. More interestingly, the CAPM beta seems to improve significantly from the price filter. This is consistent with the hypothesis of Cohen, Hawawini, Maier, Schwartz and Whitcomb (1983) and later Liu (2006) who found that liquidity was a significant determinant in the accuracy of beta estimations and the ability of CAPM in explaining the cross-sectional variation in average returns.

Table 7b: GMM and Fixed effects regression results – Size Sort (50c price filter)

Regression 6: Size Sort - 50c Restriction

Fixed Effects			*GMM*			*Random Effects*		
Size	**Beta**	**CF Beta**	**Size**	**Beta**	**CF Beta**	**Size**	**Beta**	**CF Beta**
-0.005			**-0.004**			**-0.004**		
-4.961			*-13.141*			*-8.293*		
0.000			***0.000***			***0.000***		
	-0.011			**-0.016**			**-0.014**	
	-1.643			*-1.397*			*-4.057*	
	0.104			*0.167*			***0.000***	
		0.008			**0.000**			**0.001**
		2.226			*0.001*			*0.462*
		0.029			*0.999*			*0.645*
	-0.012	**0.008**		**-0.016**	**0.004**		**-0.017**	**0.005**
	-2.01	*2.08*		*-1.607*	*0.363*		*-4.533*	*1.768*
	0.048	***0.041***		*0.112*	*0.718*		***0.000***	***0.08***
-0.004		**0.001**	**-0.004**		**0.004**	**-0.004**		**0.002**
-4.852		*0.226*	*-7.152*		*0.551*	*-8.323*		*0.67*
0.000		*0.822*	***0.000***		*0.583*	***0.000***		*0.505*

In all the univariate regressions, the majority of the CAPM beta coefficients are negative, yet insignificant. This is consistent with the findings of Strugnell, Gilbert and Kruger (2011) who found that the CAPM beta no longer has a significantly negative relationship with average returns when using estimation techniques that account for thin trading or illiquidity. A caveat is necessary as price filter is a crude proxy for liquidity, yet the regression results do seem to confirm the time-series test results that there is both a significant value and size effect on the JSE that are impervious to a liquidity filter.

A second potential contributor to the failing of the CAPM, beta and the cash flow beta in explaining the cross sectional variation in average returns on the JSE may be that the JSE ALSI index, which is commonly used as the market proxy, is inefficient. Roll (1977) concluded that the CAPM is untestable due to the immeasurability of the true market portfolio. It was further argued that the usage of proxies will ultimately result in either a type one or type two error. Strugnell, Gilbert and Kruger (2011) implied that a potential source of failure of the CAPM beta is the inefficiency of the JSE ALSI market proxy. The inefficiency of a market proxy may also extend to the value-weighted book value market proxy employed to estimate cash flow betas. In order to test this possibility, both CAPM betas and cash flow betas are recalculated using equally-weighted market proxies. Kruger and Van Rensburg (2008) found that equally weighting benchmarks that suffer from high concentration can result in increased efficiency.[10] By using an equally-weighted market proxy for estimating both the CAPM and cash flow beta, one should better able to explain the small size effect as the returns generated by larger market capitalization firms do not dominate the overall market return.

Figure 10a: Cash flow betas – Value Sort (Equally weighted market ROE)

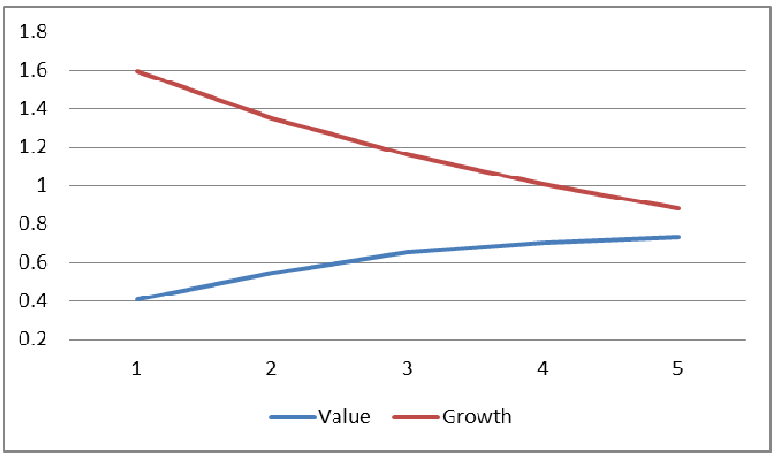
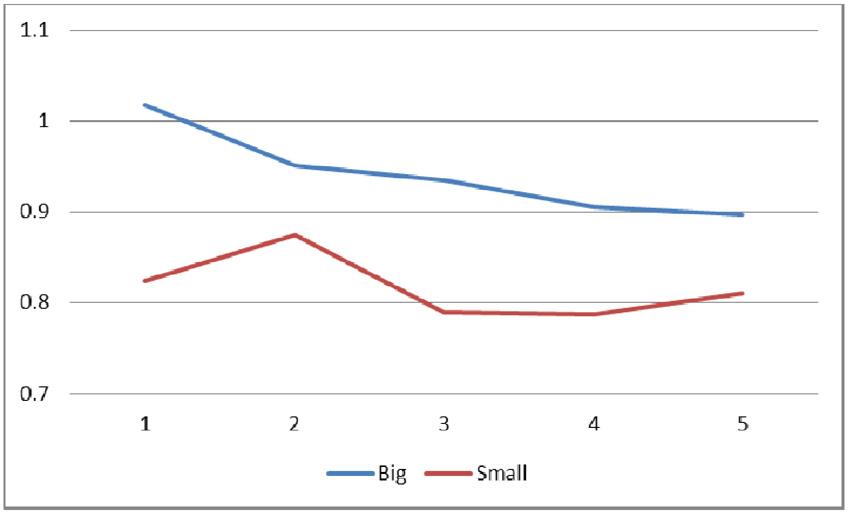


Figure 10a shows the effect of using an equally weighted ROE market proxy on the rolling window cash flow beta estimations. The growth portfolio cash flow betas are decreasing monotonically while the value portfolios are increasing. The value portfolio cash flow betas fail to overtake the growth portfolios cash flow betas over the five years post sort. The effect of an equal-weighted market ROE is detrimental to the cash flow beta estimations of the value portfolio as this is the only scenario where the average cash flow betas of the value portfolio fail to exceed those of the growth portfolio over the five year holding period. Figure 10b below indicates that the results of the cash flow betas of the size sorted portfolios are mixed. An equally-weighted market proxy should enhance beta estimations as there is no bias induced by concentration. Logically, high concentration in market proxies results in the returns that are dominated by the larger capitalization shares.

[10] The authors also noted that the increased efficiency from equal weighting is offset by illiquidity issues. Since the purpose of this exercise is to develop a complete test of the cash flow beta, benchmark liquidity is not a concern.

Figure 10b: Cash flow betas – Size Sort (Equally weighted market ROE)



The average cash flow betas of the large capitalization portfolios seem to decreasing over the five year period, yet the same cannot be said for the small capitalization portfolios as average cash flow betas oscillate around 0.8 over the five year holding period. Interestingly, the difference between average cash flow betas of the small and large portfolios has decreased and cash flow betas of all portfolios are much higher on average. Cross-sectional regressions are once again employed using fixed effects, random effects and GMM/dynamic panel estimations.

Table 8a: GMM and Fixed effects regression results – Value Sort (Equally –weighted market proxies)

Regression 7: Value - Equally Weighted Market Proxies					
Fixed Effects		*GMM*		*Random Effects*	
Beta	**CF Beta**	**Beta**	**CF Beta**	**Beta**	**CF Beta**
0.013		**0.012**		**0.015**	
11.148		*3.004*		*9.271*	
0.000		***0.004***		***0.000***	
	0.002		**-0.011**		**-0.001**
	0.596		-11.609		-0.183
	0.553		***0.000***		*0.855*
0.013	**0.006**	**0.017**	**0.006**	**0.015**	**0.004**
11.760	*1.625*	*2.658*	*1.379*	*9.376*	*0.954*
0.000	***0.108***	***0.010***	*0.172*	***0.000***	*0.342*

The regression results presented above seem to confirm the rolling window cash flow beta estimations of the value sorted portfolios. Estimated CAPM betas are far more accurate as they seem to be significantly powerful in explaining the cross-sectional variation in returns. This is attributable to the equally-weighted market proxy. Unfortunately, one would expect that an equally weighted market proxy should bolster the performance of the cash flow beta, yet cash flow beta only comes up significant in the GMM specification, but with the wrong sign. The CAPM beta is consistent throughout the regressions, implying that a potential cause of CAPM's failing on the JSE may be attributable to the concentration and inherent inefficiency of the FTSE - JSE ALSI. The usage of an equally-weighted market proxy is in contravention with the tenets of portfolio theory and the CAPM. The power of the test is lies in the increased efficiency of equally-weighted market proxies. The effect of using an equally-weighted proxy should have a greater ability in explaining the small-size premium, as the covariance of a small size share or portfolio with the market would naturally be affected by the concentration of large capitalization shares. The JSE is a case in point where the top 40 shares make up more than 80% of the total market value of the index, out of the 450-500 currently listed shares in South Africa.

The cash flow beta has proved quite powerful in explaining the value premium, yet fails in explaining the size premium. By using equally-weighted market proxies, regressions are run in order to determine whether the cash flow beta can successfully explain the size premium.

Table 8b: GMM and Fixed effects regression results – Size Sort (Equally –weighted market proxies)

Regression 8: Size - Equally Weighted Market Proxies					
Fixed Effects		*GMM*		*Random Effects*	
Beta	**CF Beta**	**Beta**	**CF Beta**	**Beta**	**CF Beta**
0.005		**0.008**		**0.016**	
4.190		*1.920*		*6.735*	
0.000		*0.059*		***0.000***	
	0.001		**0.004**		**-0.009**
	0.454		0.770		-2.434
	0.651		*0.444*		*0.017*
0.006	**0.002**	**0.007**	**0.005**	**0.015**	**-0.003**
3.662	*0.893*	*1.568*	*0.821*	*5.670*	*-0.933*
0.000	*0.375*	*0.121*	*0.414*	***0.000***	*0.353*

The results of the beta estimations of the size sorted portfolios using equally-weighted market proxies are presented in Table 8b. The results of the CAPM beta are not surprising as the equally-weighted market proxy removes the effect of concentration, allowing small firm returns to be an equal contributor to the overall market return. The GMM results for the CAPM beta are less convincing than those of the random and fixed effects specifications, yet when regressed alone on average returns, the CAPM beta still is significantly positive at the 10% level. The usage of an equal-weighted market proxy does not benefit the cash flow beta. In both the fixed effects and GMM regressions, cash flow beta maintains a positive coefficient but is not significant in any tests. The cash flow beta is consistently negative per the random effects specification. One would have expected the cash flow beta to have improved when using an equally-weighted market ROE, as the cash flow fundamentals of the small capitalization shares have an equal opportunity to contribute to the overall market ROE. The results seem to imply that the cash flow beta is not a viable catch all proxy or systematic risk factor as it fails in explaining the small size premium. As mentioned previously, the fact that the cash flow beta does well in explaining the value premium is probably due to it being a construct of the book to market ratio.

F. Discussion and Conclusion

The CAPM is still used as a foundational building block to corporate finance and investment theory and expounds the central tenet of finance, the relationship between risk and return. The logical appeal of the CAPM has resulted in many coming to love and cherish a model that continuously fails in the ‘real world’. The general consensus is that there is a relationship between risk and return, yet the CAPM in its pure form fails to describe drivers of risk. There have been numerous attempts to save the CAPM through theoretical and methodological modifications, all the while attempting to maintain the core qualities of the original model. Unfortunately, the successes of such modifications are mixed at best. The same can be said for Cohen, Polk and Vuolteenaho’s (2008) cash flow beta. The evidence presented proves that the cash flow beta does seem to track the returns of value sorted portfolios and, in regression analysis, the cash flow beta did a significantly better job at explaining the cross-sectional variation in returns than the conventional CAPM beta. The fact that the cash flow beta fails to explain the small size premium should not result in a complete disregard of this proposed measure, yet does imply that the cash flow beta is not a “catch-all” risk proxy.

Cohen, Polk and Vuolteenaho (2008) considered the joint hypothesis of validity of the CAPM and efficient markets. The presences of 'stylized' anomalies that are not explained by the CAPM beta are a direct contradiction of both the CAPM and market efficiency. The cash flow beta is a construct of the book to market ratio (See appendix 3) and therefore, the success of the cash flow beta in describing average returns of portfolios sorted on book to market is expected. A true test of the cash flow beta is whether it can successfully explain the size effect. In all of the experiments conducted, the cash flow beta proved far less powerful when faced with portfolios sorted on size. This begs the question of whether the cash flow beta is merely just another failed attempt to salvage the tattered reputation of the CAPM.

A number of robustness checks were considered in order to comprehensively test the cash flow beta. First, a simple price filter of 50 cents was applied to the portfolios in order to act as a crude liquidity filter. The application of the price filter was in effect testing whether illiquidity was preventing the cash flow beta from describing the size premium. The rolling beta estimations showed slightly more positive results as the small size portfolio cash flow betas increased on average over the five year holding periods. The regression results were inconsistent between the specifications with regards to the cash flow beta. The regressions did confirm that the failure of the cash flow beta in explaining the small size premium is probably not attributable to illiquidity. It was also found that when applying the price filter, the CAPM beta was no longer significantly negative and there was still a significant size and value effect.

In order to test whether the cash flow betas failure in explaining the small size premium was attributable to concentration of the ROE market proxy, rolling window cash flow betas were calculated using an equally-weighted ROE market proxy. CAPM betas were also recalculated using an equally weighted market proxy. Concentration reduces the contribution of a small size share or portfolio to the overall market return, which can result in poor beta estimations. Concentration can also negatively affect the efficiency of a market proxy. Both the CAPM and cash flow beta estimations were closer to one, yet the cash flow betas of the value portfolio failed to overtake those of the growth portfolios over the five year period. The small size cash flow betas did not increase monotonically with time, yet they were much closer to the cash flow betas of the large capitalization portfolios. The regression results were unimpressive for the cash flow beta. Focusing on the size sorted portfolio regressions, the cash flow beta was unsuccessful in explaining the cross-sectional variation in size sorted portfolios, and the failure is not attributable to inefficiency of market proxies or concentration. The findings add credence to the results of the VECM estimations as there was little evidence of a significant long run relationship between the excess return earned on a small minus big investment strategy, the ROE of the market and the JSE.

The cash flow beta does however possess a number of positive attributes as it relies on simple methodological modifications that are consistent with asset pricing theory. The foundation of the cash flow beta is that the risk of an asset is dependent on its cash flow sensitivity to the market. The value of a financial asset can be separated into two distinct parts, namely; a discount component (denominator) and a cash flow component (numerator). An increase to the discount factor will result in a lowered present value, yet one is compensated in the future with an increased return. A decrease in the numerator or future cash flow will result in a lower present value that is not compensated in the future. The cash flow fundamentals of an asset are therefore an essential component of an assets overall risk, but not necessarily the only driver of risk. The cash flow beta has an advantage over the conventionally measured CAPM beta as flotation is not a prerequisite for estimation. Capital budgeting, corporate finance and private equity valuations all use some form of the CAPM and an estimation of beta. Hamada (1972) developed a model for manipulating comparison firm beta estimates in order to derive an appropriate cost of capital to be used as a discount rate. The cash flow beta does not require the estimation of a comparison firm's beta and it performs far better than the conventional CAPM.

The results seem to indicate that the cash flow beta captures the cash flow risk present in high value shares but fails to capture the unpriced risk component in small capitalization shares. Fama and French (1992, 1993) hypothesized that risks are multidimensional and that stylized facts that successfully explain the cross-sectional variation in returns, should be utilised in a pricing model. Such an argument presents a fundamental quandary as pricing, returns and risks are then based on factors that are persistent empirical anomalies, lacking theoretical substance. The cash flow beta may not capture all or even most of the cross-sectional variation in share returns, yet it does possess the quality of being logically and fundamentally consistent with asset pricing theory.

In conclusion, the evidence presented is consistent on many fronts with past and current literature. Both the time-series and cross-sectional tests provide evidence of a significant size and value premium present on the cross-section of average returns on the JSE. The CAPM beta, estimated using the JSE ALSI as a market proxy, seems to have a negative relationship with returns. The cash flow beta proposed by Cohen, Polk and Vuolteenaho (2008) does succeed in tracking the returns achieved on the book to market sorted portfolios, however fails to do so with portfolios sorted on size. This is confirmed in cross-sectional regressions, where the cash flow beta successfully explains the value premium yet fails to do the same with the size premium. An advantage of the cash flow beta estimation is the theoretical underpinnings of the model, yet the theoretical attraction is largely undone when faced with portfolios sorted on market capitalization, as it fails to explain the size anomaly. The ideal asset pricing model would be one that succeeds in explaining all pricing anomalies while being based on the theoretical foundations of efficient markets and risk and return. Unfortunately, on a cross-section of average returns on the JSE, the cash flow beta of Cohen, Polk and Voulteenaho (2008) fails to adequately explain the cross-sectional variation in average returns.

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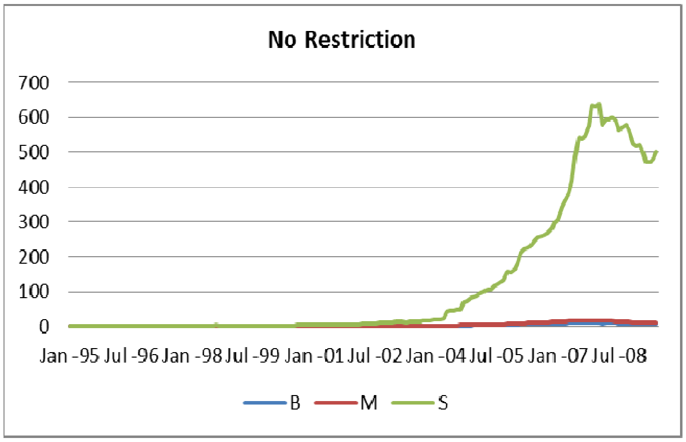
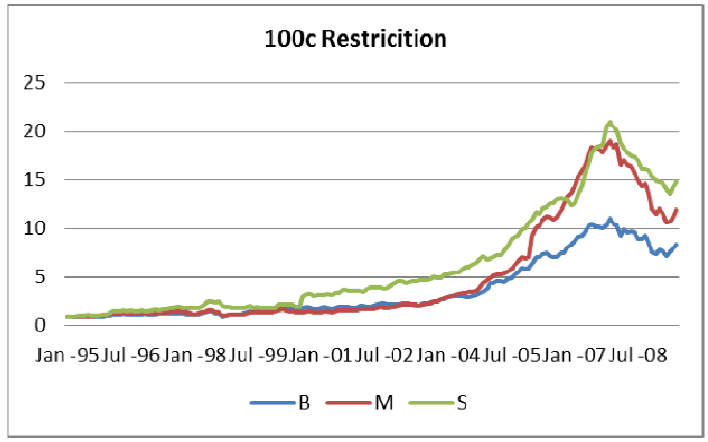
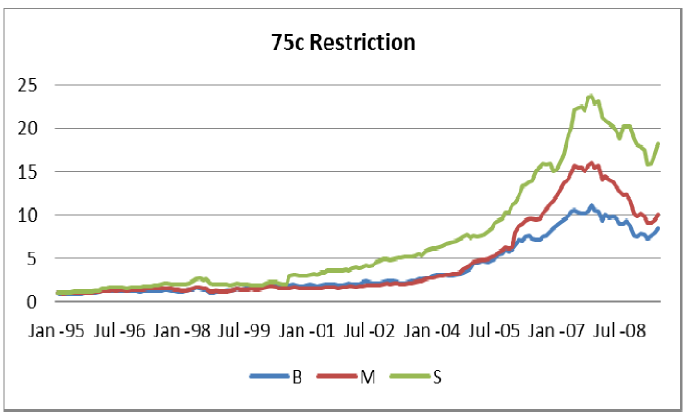
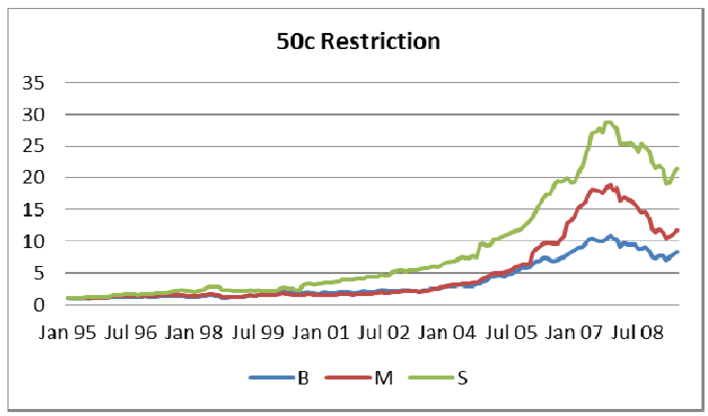
Appendix 1

Size Sort (3 year)



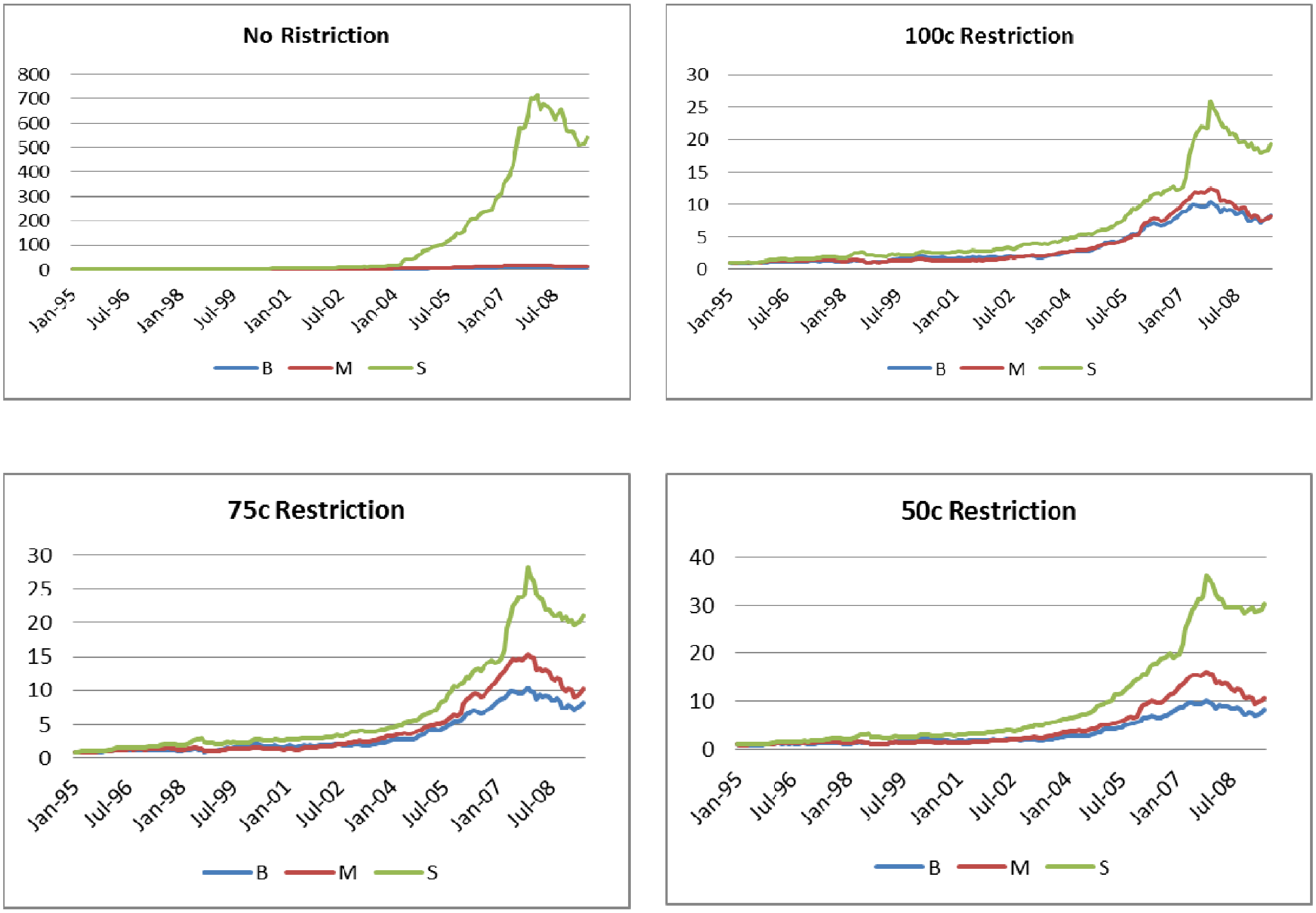






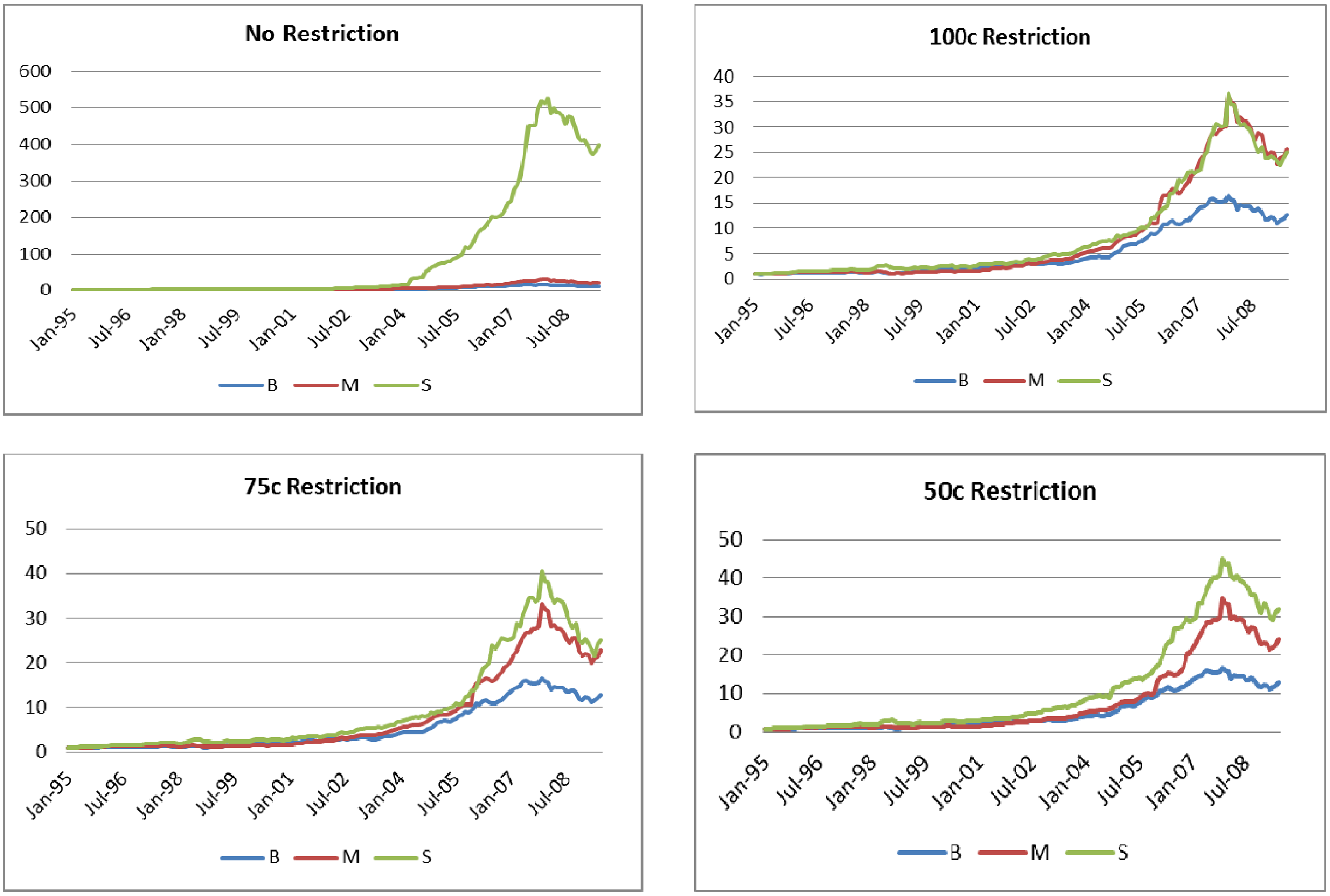
The unrestricted size sort using a three year holding period resulted in a portfolio end value of R511.92 while the large and medium capitalization sorts achieved returns of R8.96 and R12.56 respectively. In the presence of a 50c price filter (entailing the exclusion of any share with an average monthly closing price of less than 50c over the year prior to sort), the small size portfolio achieves a portfolio end value of R21.60. The larger the price restriction, the greater the effect on the small size portfolio as the 100c price filter results in a portfolio end value of R15.00.

Size Sort (5 Year)



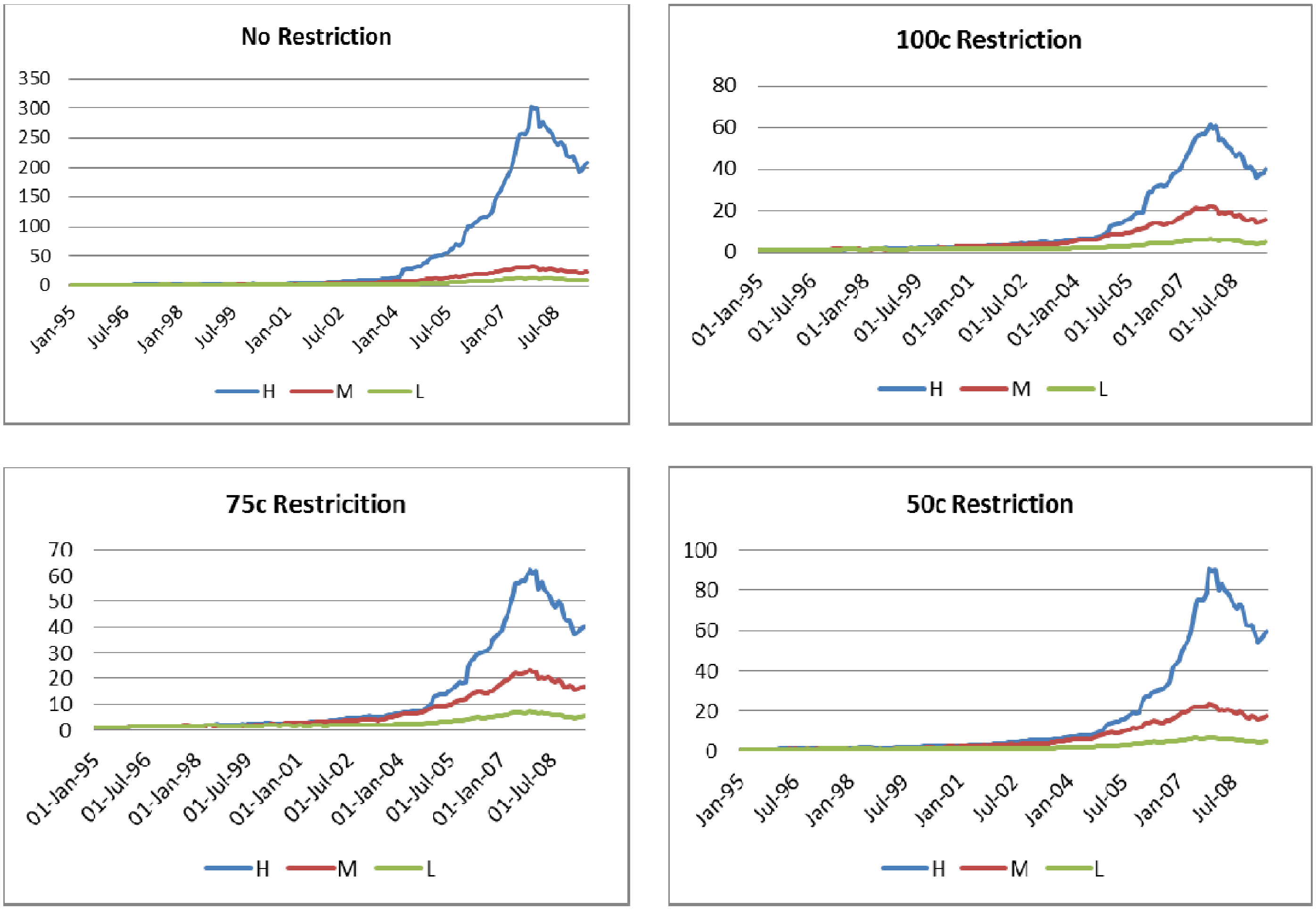
Using a holding period of 5 years post sort, the unrestricted small capitalization portfolio achieves a portfolio end value of R554.99. However, when applying the 50c price filter, the small size portfolio achieves a portfolio end value of R31.10. This seems to indicate that the price filter still has a negative effect on the final portfolio of the small size portfolio but less so than when compared to the holding period of 36 months. The same can be said for the 75c and 100c price restrictions as the small size portfolios achieve final values of R21.86 and R19.87, respectively.

Size Sort (7 Year)



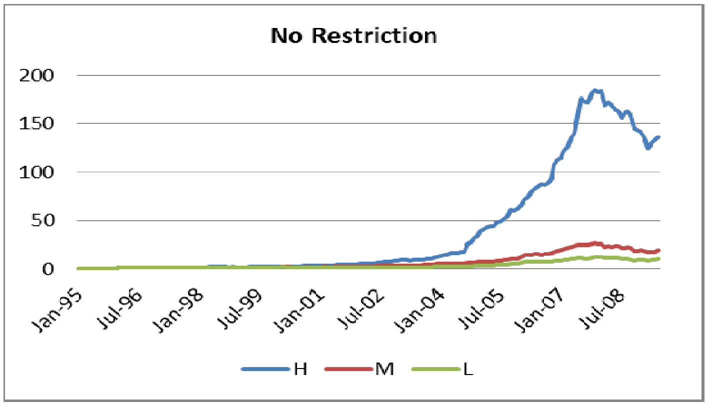
The seven year holding period sort produces interesting results as the small size portfolio at the end of the sample period, with no restriction applied, achieves a final portfolio value of R399.71, which is the lowest 'no restriction' of the three portfolio sorts. However, when applying a price restriction, the small size portfolio end values are the highest out of the three, five and seven year sorts.

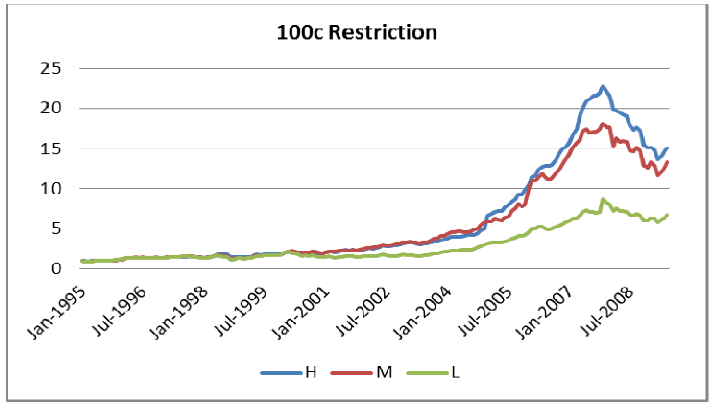
Value Sort (3 Year)

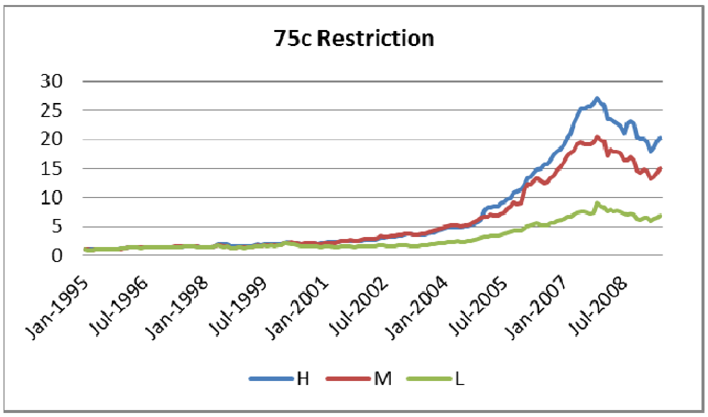


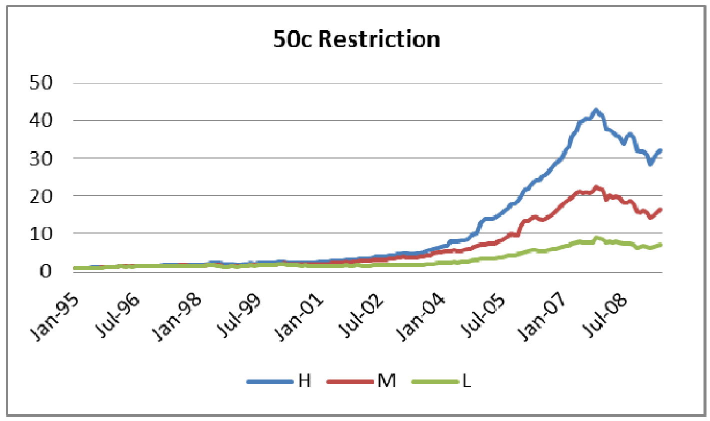
The application of a three year holding period to a value sort, the effect of no price restriction results in the extreme value portfolio achieving a portfolio value of R211.25, which is significantly lower than the corresponding small cap portfolio. Interestingly, the application of a price filter results in significantly higher portfolio values for the extreme value portfolios than any of the corresponding small size portfolios. Considering the case when a 50c price restriction is applied, the extreme value portfolio achieves a portfolio end value of R60.19, entailing that the value effect seems to be less sensitive to the application of a price filter.

Value Sort (5 Year)



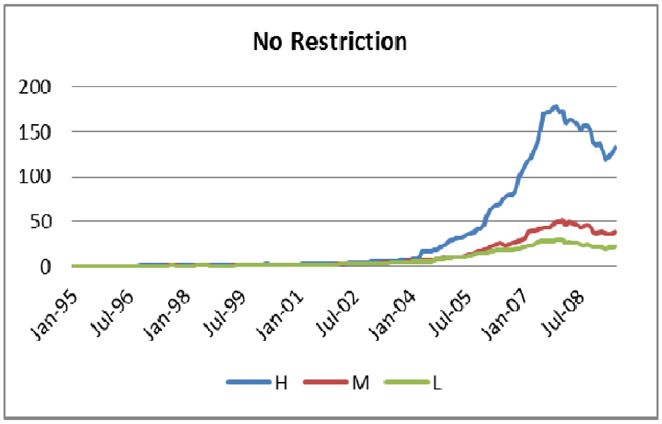


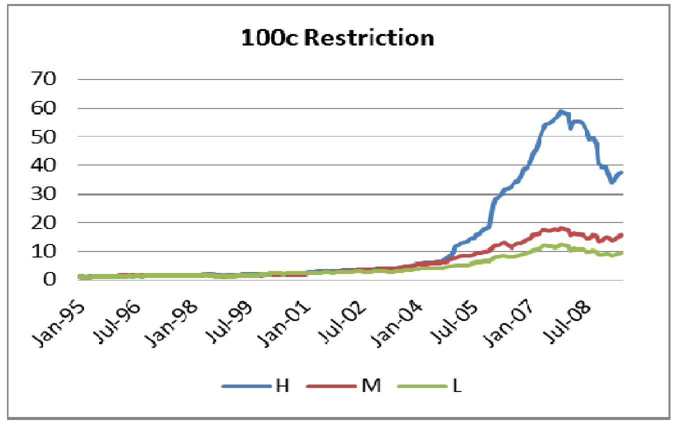


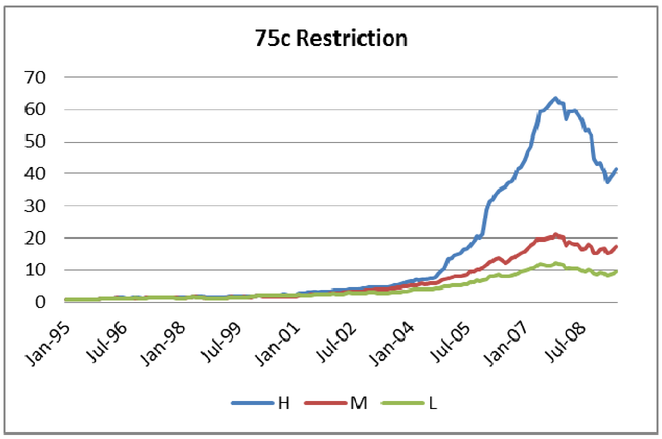


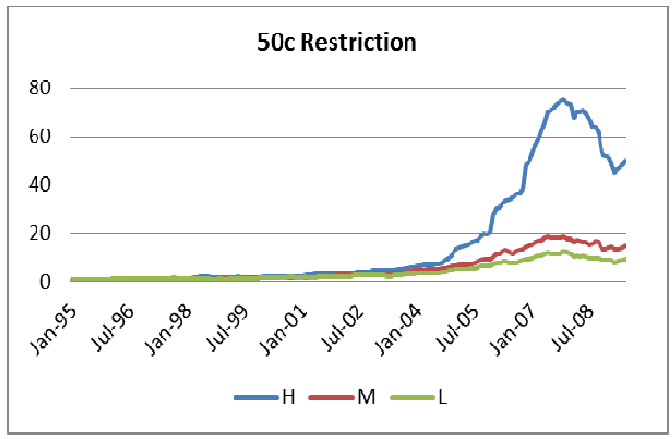
The increasing of the holding period seems to negatively affect the value premium as the unrestricted extreme value portfolio achieves a final portfolio value of R140.38. The same can be said for the extreme value portfolios that are subjected to price filters. The 50c price filter causes the extreme value portfolios final value to drop to R33.18.

Value Sort (7 year)









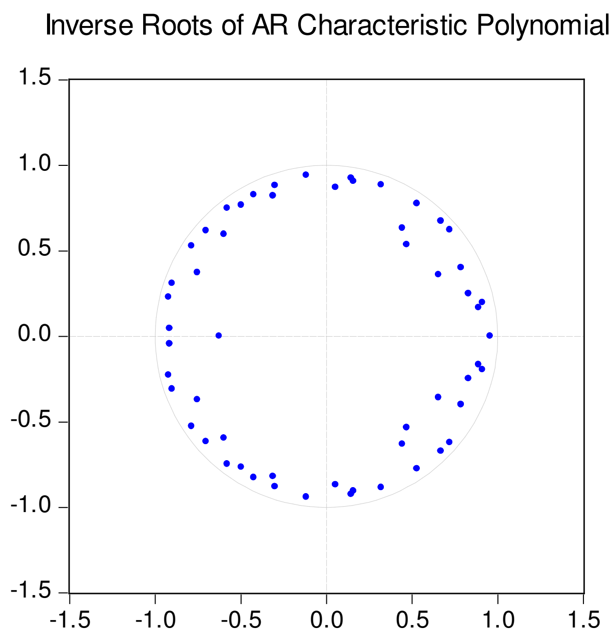
The increasing of the holding period from five to seven years does not seem to have a significant impact on the extreme value portfolios end values. The unrestricted value portfolio achieves an end value of R136.03, which is only around R4 less than the unrestricted extreme value portfolio subjected to a five year holding period. Interestingly, when applying a price filter to the seven year holding period value-growth sorted portfolios, the portfolio end values are higher than those of the five year holding periods. Considering the seven year, 75c restricted extreme value portfolio. It achieved a final portfolio value of R41.78 compared to R20.83 achieved by the same portfolio that was subjected to a five year holding period.

Appendix 2

Vector autoregressions (VAR) and VECM output

1. Value Sort

- Stationarity Test



The above diagram gives the inverse roots of the characteristic polynomial, therefore indicating whether the VAR of value, value ROE, JSE and Market ROE is stable. The diagram indicates that the VAR is stable and therefore each of the constituents is independently stationary.

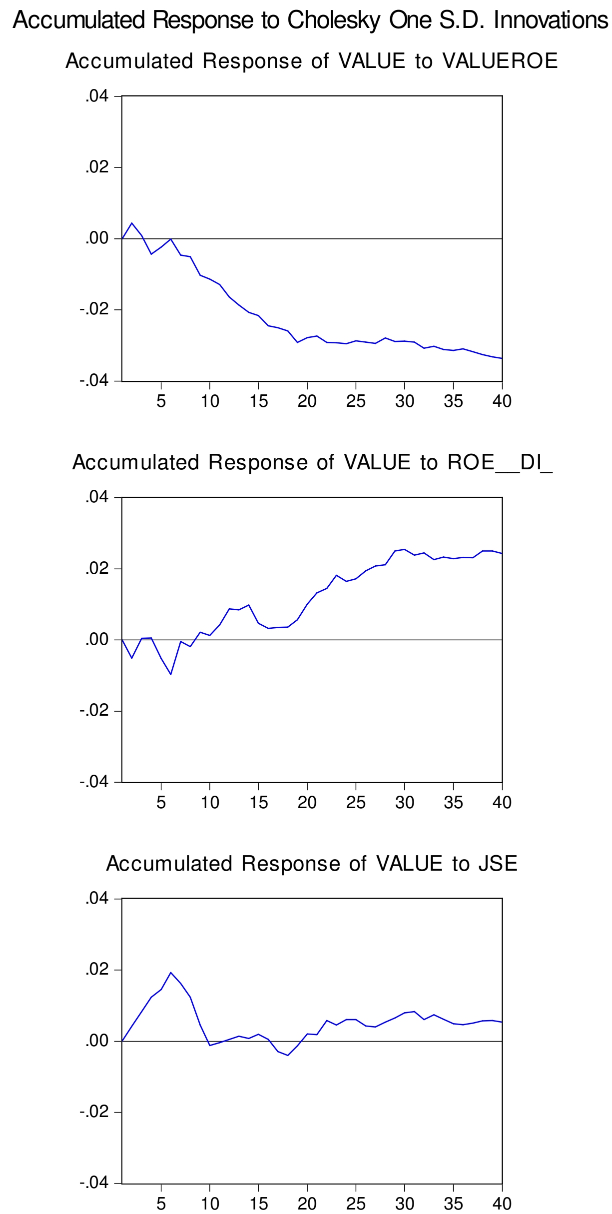
- Lag Length Criteria Test

VAR Lag Order Selection Criteria
Endogenous variables: VALUE VALUEROE ROEM JSE
Exogenous variables: C
Date: 02/06/12 Time: 17:46
Sample: 1995M01 2009M06
Included observations: 156

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1129.866	NA	6.33e-12	-14.43418	-14.35598*	-14.40242*
1	1148.850	36.75089	6.09e-12*	-14.47243*	-14.08143	-14.31362
2	1157.591	16.47291	6.69e-12	-14.37937	-13.67555	-14.09351
3	1175.396	32.64364	6.54e-12	-14.40251	-13.38590	-13.98961
4	1187.426	21.43830	6.90e-12	-14.35162	-13.02219	-13.81166
5	1199.683	21.21371	7.26e-12	-14.30363	-12.66140	-13.63663
6	1213.643	23.44599	7.49e-12	-14.27748	-12.32244	-13.48343
7	1217.897	6.925953	8.76e-12	-14.12688	-11.85904	-13.20579
8	1249.493	49.82489*	7.23e-12	-14.32684	-11.74619	-13.27869
9	1256.564	10.78677	8.20e-12	-14.21235	-11.31890	-13.03716
10	1270.450	20.47296	8.54e-12	-14.18525	-10.97899	-12.88301
11	1281.319	15.46741	9.28e-12	-14.11947	-10.60040	-12.69018
12	1298.090	23.00648	9.38e-12	-14.12936	-10.29748	-12.57302

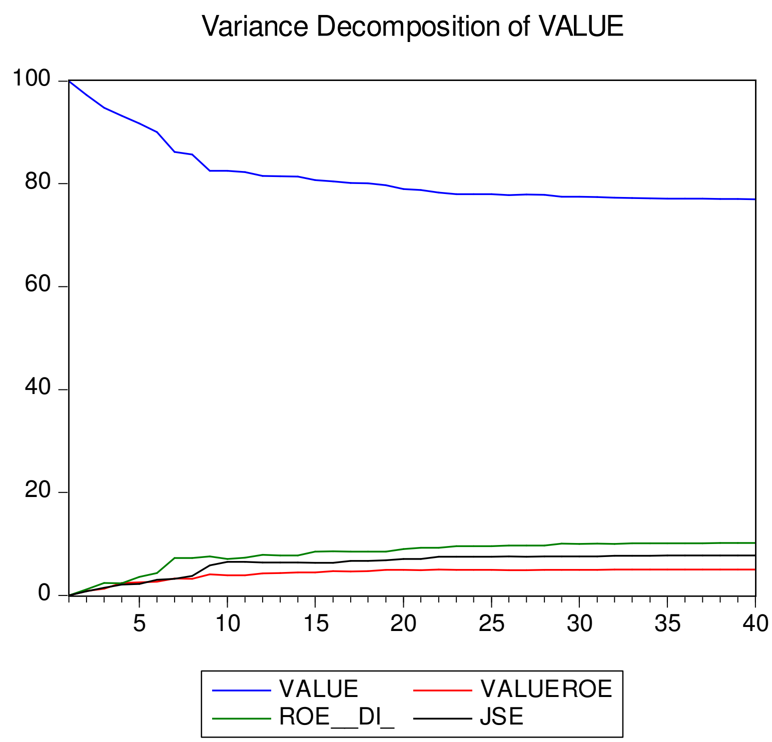
The above table gives the estimated lag length criteria for the estimated VAR. The result indicates that per the LR statistic the ideal number of lags would be 8 on each of the variables. The purpose of such a test is to maintain a balance between goodness of fit and parsimony. Obviously, selecting a VAR with 14 lags on each of the variables is not parsimonious, yet it is necessary to capture the effects of a shock to the ROE of either the market or the relative ROE of the portfolio over the longer-term.

- Impulse Response Functions



The above diagrams indicate the impulse responses of the value portfolio 40 months post shock. The diagrams clearly indicate that a shock to the ROE of the market has the most significant effect on the value portfolios return.

- Variance Decomposition



The above graph represents the effect of a shock of each of the variables in the VAR and its effect on the variance of the value portfolios return. The graph clearly indicates that a shock to the ROE of the market has the greatest effect on the variation in returns of the value portfolio.

- VECM – Value

Trend assumption: Linear deterministic trend
Series: LVALUE LROEM2 LJSE
Lags interval (in first differences): 1 to 12

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None *	0.146370	36.24070	29.79707	0.0079
At most 1	0.060409	11.55256	15.49471	0.1797
At most 2	0.011676	1.832126	3.841466	0.1759

Trace test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None *	0.146370	24.68814	21.13162	0.0151
At most 1	0.060409	9.720437	14.26460	0.2309
At most 2	0.011676	1.832126	3.841466	0.1759

Max-eigenvalue test indicates 1 cointegrating eqn(s) at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The results of the cointegration tests for the value portfolio, level value ROE, level ROE of the market and the JSE are presented above. Both the trace and maximum Eigen value statistics indicate that there is at least one significant cointegrating vector. The VECM is estimated assuming there is at least one cointegrating relationship.

- <u>VECM estimation – No restrictions applied</u>

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
LVALUE(-1)	1.000000		
LROEM2(-1)	-21.05864 (4.71777) [-4.46368]		
LJSE(-1)	-19.40451 (3.85363) [-5.03539]		
C	444.8325		
Error Correction:	**D(LVALUE)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.002369 (0.00127) [-1.87154]	0.005871 (0.00230) [2.55600]	0.000819 (0.00177) [0.46424]

- VECM: Restriction B(1,1) = 1, A(2,1) = 0

Cointegration Restrictions:
B(1,1)=1, A(2,1)=0
Convergence achieved after 150 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	6.788955
Probability	0.009172

Cointegrating Eq:	CointEq1		
LVALUE(-1)	1.000000		
LROEM2(-1)	-3.044395 (0.79501) [-3.82936]		
LJSE(-1)	-4.523374 (0.64939) [-6.96554]		
C	74.79468		
Error Correction:	**D(LVALUE)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.020648 (0.00835) [-2.47230]	0.000000 (0.00000) [NA]	0.008301 (0.01202) [0.69053]

- VECM: Restrictions B(1,1) = 1, B(1,2) = B(1,3)

Vector Error Correction Estimates

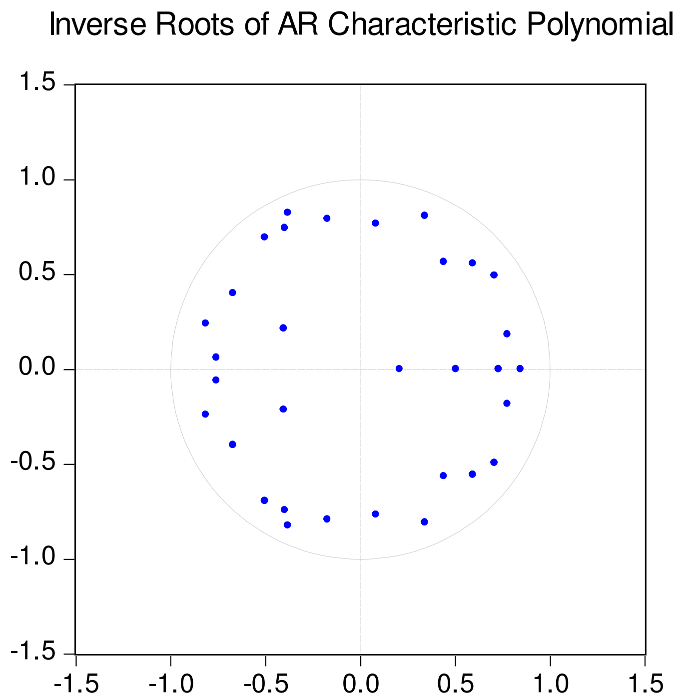
Cointegration Restrictions:
B(1,1)=1, B(1,2)=B(1,3)
Convergence achieved after 12 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	0.032828		
Probability	0.856221		
Cointegrating Eq:	CointEq1		
LVALUE(-1)	1.000000		
LROEM2(-1)	-11.80916 (1.99973) [-5.90539]		
LJSE(-1)	-11.80916 (1.99973) [-5.90539]		
C	255.2584		
Error Correction:	D(LVALUE)	D(LROEM2)	D(LJSE)
CointEq1	-0.004198 (0.00227) [-1.85077]	0.010292 (0.00412) [2.49844]	0.001761 (0.00316) [0.55707]

The above VECM's indicate that the level ROE of the market is not weakly exogenous to the system and is actually equivalent to the levels of the JSE.

2. Size Sort

- <u>Stationarity Test</u>



The above diagram gives the inverse roots of the characteristic polynomial, therefore indicating whether the VAR of size, size ROE, JSE and Market ROE is stable. The diagram indicates that the VAR is stable and therefore each of the constituents is independently stationary.

- Lag-length criteria test

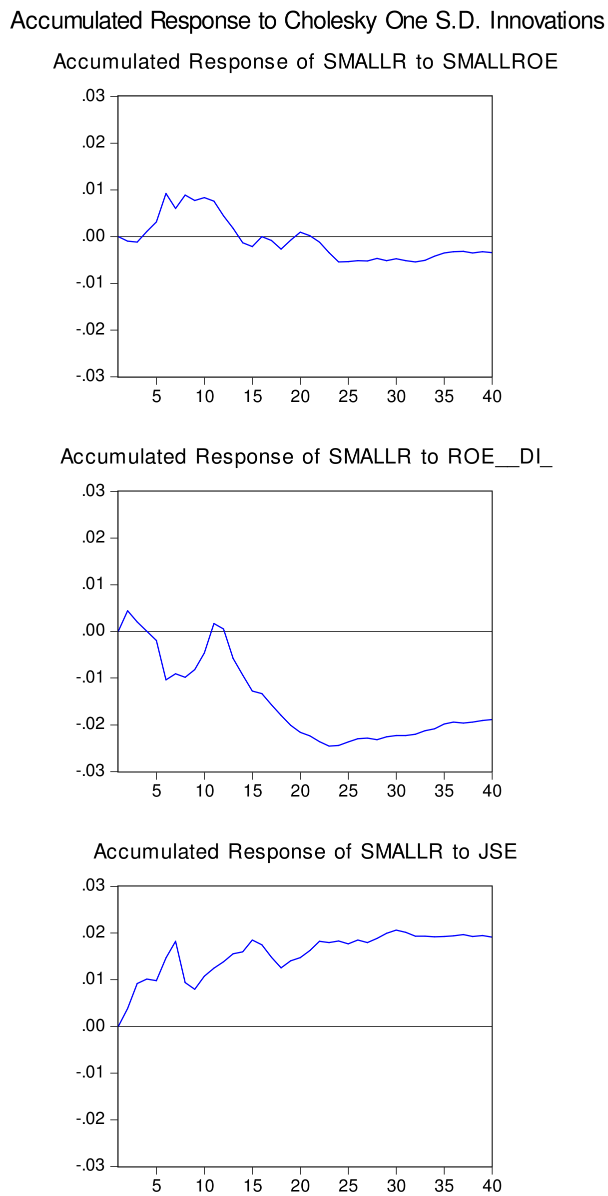
VAR Lag Order Selection Criteria
Endogenous variables: SMALLR SMALLROE ROEM JSE
Exogenous variables: C
Date: 02/06/12 Time: 20:04
Sample: 1995M07 2009M06
Included observations: 156

Lag	LogL	LR	FPE	AIC	SC	HQ
0	1043.927	NA	1.91e-11	-13.33240	-13.25419*	-13.30063*
1	1055.852	23.08572	2.01e-11	-13.28015	-12.88915	-13.12134
2	1071.940	30.31889	2.01e-11	-13.28128	-12.57746	-12.99542
3	1093.599	39.70872	1.87e-11	-13.35383	-12.33721	-12.94092
4	1110.366	29.87950	1.85e-11*	-13.36366*	-12.03424	-12.82371
5	1125.847	26.79511*	1.87e-11	-13.35702	-11.71479	-12.69001
6	1132.579	11.30614	2.12e-11	-13.23820	-11.28316	-12.44414
7	1141.614	14.71016	2.33e-11	-13.14890	-10.88105	-12.22780
8	1150.640	14.23356	2.57e-11	-13.05949	-10.47884	-12.01134
9	1164.528	21.18757	2.67e-11	-13.03241	-10.13895	-11.85721
10	1179.058	21.42322	2.76e-11	-13.01357	-9.807308	-11.71132
11	1185.281	8.856232	3.18e-11	-12.88822	-9.369159	-11.45893
12	1203.199	24.57863	3.16e-11	-12.91280	-9.080932	-11.35646

* indicates lag order selected by the criterion
LR: sequential modified LR test statistic (each test at 5% level)
FPE: Final prediction error
AIC: Akaike information criterion
SC: Schwarz information criterion
HQ: Hannan-Quinn information criterion

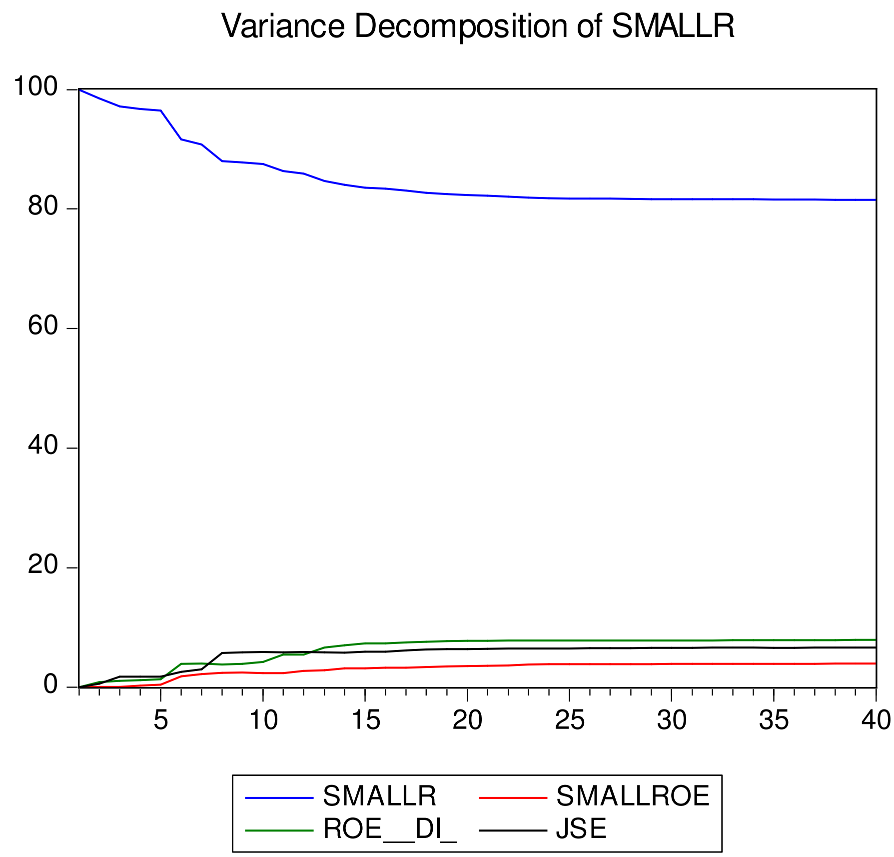
The above test indicates that the most accurate and parsimonious amount of lags is 5 per the LR statistic. Once again 12 lags are used in order to estimate the VAR’s.

- <u>Impulse Response Function</u>



The Impulse response function estimates indicate that a shock to the JSE seems to have the greatest impact on the return of the small portfolio; while a shock to either the ROE of the market or the small portfolios ROE has a negligible effect.

- Variance Decomposition



The results of the variance decomposition are more in favour of the ROE based beta as a change to the ROE of the market seems to contribute the most to the variation in the small portfolios return, surpassing the contribution of the JSE.

- VECM – Size

Sample (adjusted): 1996M07 2009M06
Included observations: 156 after adjustments
Trend assumption: Linear deterministic trend
Series: LSMALL LROEM LJSE
Lags interval (in first differences): 1 to 12

Unrestricted Cointegration Rank Test (Trace)

Hypothesized No. of CE(s)	Eigenvalue	Trace Statistic	0.05 Critical Value	Prob.**
None	0.076899	22.82563	29.79707	0.2547
At most 1	0.056635	10.34298	15.49471	0.2553
At most 2	0.007967	1.247860	3.841466	0.2640

Trace test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

Unrestricted Cointegration Rank Test (Maximum Eigenvalue)

Hypothesized No. of CE(s)	Eigenvalue	Max-Eigen Statistic	0.05 Critical Value	Prob.**
None	0.076899	12.48265	21.13162	0.5008
At most 1	0.056635	9.095120	14.26460	0.2783
At most 2	0.007967	1.247860	3.841466	0.2640

Max-eigenvalue test indicates no cointegration at the 0.05 level
* denotes rejection of the hypothesis at the 0.05 level
**MacKinnon-Haug-Michelis (1999) p-values

The results of the cointegration tests seem to indicate that there is not a single integrating vector as both the Trace and Maximum Eigen value tests fail to reject the null hypothesis of no cointegrating relationships. It is assumed that there is at least a single cointegrating vector.

- VECM – No restrictions applied

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
LSMALL(-1)	1.000000		
LROEM2(-1)	-1.870395 (0.58885) [-3.17636]		
LJSE(-1)	-3.461854 (0.51769) [-6.68715]		
C	49.84006		
Error Correction:	**D(LSMALL)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.019863 (0.01109) [-1.79153]	0.035060 (0.02007) [1.74680]	0.009457 (0.01628) [0.58093]

- VECM estimation: Restriction B(1,1) = 1, A(2,1) = 0

Cointegration Restrictions:
B(1,1)=1, A(2,1)=0
Convergence achieved after 14 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):
Chi-square(1) 1.448391
Probability 0.228786

Cointegrating Eq:	CointEq1		
LSMALL(-1)	1.000000		
LROEM2(-1)	-0.762974 (0.34479) [-2.21286]		
LJSE(-1)	-2.453089 (0.30312) [-8.09273]		
C	26.21682		
Error Correction:	**D(LSMALL)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.028744 (0.02023) [-1.42063]	0.000000 (0.00000) [NA]	0.036223 (0.02900) [1.24917]

- VECM estimation: Restriction B(1,1) = 1, B(1,2) = B(1,3)

Vector Error Correction Estimates

Cointegration Restrictions:
B(1,1)=1, B(1,2)=B(1,3)
Convergence achieved after 98 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	0.698809
Probability	0.403184

Cointegrating Eq:	CointEq1
LSMALL(-1)	1.000000
LROEM2(-1)	-17.43478 (5.09815) [-3.41982]
LJSE(-1)	-17.43478 (5.09815) [-3.41982]
C	379.9471

Error Correction:	D(LSMALL)	D(LROEM2)	D(LJSE)
CointEq1	-0.001958 (0.00116) [-1.69257]	0.004770 (0.00207) [2.30166]	-0.000301 (0.00170) [-0.17693]

The Results of the size VECM are interesting as the ROE of the market seems to be weakly exogenous to the estimated system, but it has an equivalent relationship with the JSE. This seems to imply that both the ROE of the market as well as the JSE ALSI are weakly exogenous, pointing to the possibility that the cash flow beta will probably not succeed in explaining the small size premium and, when using the JSE is an inadequate proxy due to its concentration.

- VECM – HML

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
LHML(-1)	1.000000		
LROEM2(-1)	-2.771530 (0.57733) [-4.80056]		
LJSE(-1)	-5.293752 (0.48803) [-10.8473]		
C	79.27902		
Error Correction:	D(LHML)	D(LROEM2)	D(LJSE)
CointEq1	-0.037997 (0.01773) [-2.14336]	0.029485 (0.01503) [1.96160]	0.026913 (0.01106) [2.43237]

- VECM: Restriction B(1,1) = 1, A(2,1) = 0

Cointegration Restrictions:
B(1,1)=1, A(2,1)=0
Convergence achieved after 8 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):
Chi-square(1) 3.222155
Probability 0.072648

Cointegrating Eq:	CointEq1		
LHML(-1)	1.000000		
LROEM2(-1)	-1.971811 (0.57084) [-3.45425]		
LJSE(-1)	-4.646102 (0.48253) [-9.62855]		
C	62.97328		
Error Correction:	D(LHML)	D(LROEM2)	D(LJSE)
CointEq1	-0.044226 (0.01940) [-2.28023]	0.000000 (0.00000) [NA]	0.032147 (0.01201) [2.67637]

- VECM: Restriction B(1,1) = 1, B(1,2) = B(1,3)

Vector Error Correction Estimates

Cointegration Restrictions:
B(1,1)=1, B(1,2)=B(1,3)
Convergence achieved after 20 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	6.725928
Probability	0.009502

Cointegrating Eq:	CointEq1		
LHML(-1)	1.000000		
LROEM2(-1)	-11.41074 (2.64469) [-4.31458]		
LJSE(-1)	-11.41074 (2.64469) [-4.31458]		
C	247.2369		
Error Correction:	**D(LHML)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.005815 (0.00416) [-1.39846]	0.008525 (0.00346) [2.46542]	0.000244 (0.00263) [0.09290]

- VECM – SMB

Vector Error Correction Estimates

Cointegrating Eq:	CointEq1		
LSMB(-1)	1.000000		
LROEM2(-1)	-1.573528 (0.38522) [-4.08478]		
LJSE(-1)	-3.504518 (0.33564) [-10.4412]		
C	47.10501		
Error Correction:	**D(LSMB)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.059424 (0.02023) [-2.93771]	0.041665 (0.02370) [1.75789]	0.022023 (0.01812) [1.21543]

- VECM: Restriction B(1,1) = 1, A(2,1) = 0

B(1,1)=1, A(2,1)=0
Convergence achieved after 5 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	1.947768
Probability	0.162828

Cointegrating Eq:	CointEq1		
LSMB(-1)	1.000000		
LROEM2(-1)	-1.057587 (0.37411) [-2.82697]		
LJSE(-1)	-3.054636 (0.32596) [-9.37112]		
C	36.28686		
Error Correction:	**D(LSMB)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.068219 (0.02209) [-3.08792]	0.000000 (0.00000) [NA]	0.023928 (0.01951) [1.22672]

- VECM: Restriction B(1,1) = 1, B(1,2) = B(1,3)

Cointegration Restrictions:
B(1,1)=1, B(1,2)=B(1,3)
Convergence achieved after 47 iterations.
Restrictions identify all cointegrating vectors
LR test for binding restrictions (rank = 1):

Chi-square(1)	6.008490
Probability	0.014237

Cointegrating Eq:	CointEq1		
LSMB(-1)	1.000000		
LROEM2(-1)	-13.09051 (3.63212) [-3.60410]		
LJSE(-1)	-13.09051 (3.63212) [-3.60410]		
C	284.3406		
Error Correction:	**D(LSMB)**	**D(LROEM2)**	**D(LJSE)**
CointEq1	-0.001665 (0.00243) [-0.68507]	0.007627 (0.00271) [2.81853]	6.48E-05 (0.00212) [0.03056]

Appendix 3

Derivation of ROE

$$ROE_t = \frac{X_t}{B_{t-1}} \quad where$$

$$X_t \ = \ B_t + D_t - B_{t-1} \quad therefore$$

$$ROE_t = \frac{B_t + D_t - B_{t-1}}{B_{t-1}}$$

$$B_{t-1} + ROE_t(B_{t-1}) = \ B_t + D_t$$

$$\boldsymbol{B_{t-1}(1 + ROE_t) - D_t = \ B_t} \quad (1)$$

The above proves that the book value per share at time *t* is equivalent to the lagged book value per share multiplied by the ROE of the share at time *t*, less the gross dividends paid to the share. When scaling the above equation by the price of the asset at time *t:*

$$\frac{B_{t-1}(1 + ROE_t) - D_t}{P_t} = \ BM_t$$

$$\boldsymbol{\frac{B_{t-1}}{P_t}(1 + ROE_t) - \frac{D_t}{P_t} = \ BM_t} \quad (2)$$

The above equation implies that the book to market of a share at time *t* is equivalent to the lagged book to market per share less multiplied by the ROE of the asset less the dividend yield at time *t*. One can see the definite similarities between the book to market and the usage of ROE in estimating the cash flow beta.

Appendix 4

Cross-sectional Regressions

I. Value Sort – Fixed Effects

Dependent Variable: AVG_RETURN
Periods included: 11
Cross-sections included: 9
Total panel (balanced) observations: 99
Linear estimation after one-step weighting matrix
White cross-section standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MEDIANBM	0.003345	0.001400	2.388321	0.0189
C	0.018996	0.003123	6.082360	0.0000

Weighted Statistics

R-squared	0.071692	Mean dependent var	0.030991
Adjusted R-squared	0.062122	S.D. dependent var	0.015804
S.E. of regression	0.015678	Sum squared resid	0.023842
F-statistic	7.491197	Durbin-Watson stat	1.031994
Prob(F-statistic)	0.007376		

Dependent Variable: AVG_RETURN
Periods included: 11
Cross-sections included: 9
Total panel (balanced) observations: 99
Linear estimation after one-step weighting matrix
White cross-section standard errors & covariance (d.f. corrected)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.029862	0.010628	-2.809638	0.0061
C	0.041934	0.005979	7.013412	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.365476	Mean dependent var	0.028023
Adjusted R-squared	0.301311	S.D. dependent var	0.014818
S.E. of regression	0.012874	Sum squared resid	0.014751
F-statistic	5.695859	Durbin-Watson stat	1.255098
Prob(F-statistic)	0.000003		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFB	0.010052	0.004944	2.033137	0.0450
C	0.021637	0.002312	9.359875	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.248257	Mean dependent var	0.031996
Adjusted R-squared	0.172238	S.D. dependent var	0.016417
S.E. of regression	0.014904	Sum squared resid	0.019769
F-statistic	3.265726	Durbin-Watson stat	1.251442
Prob(F-statistic)	0.001782		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.035046	0.008182	-4.283220	0.0000
CFB	0.015394	0.004903	3.139840	0.0023
C	0.038250	0.003882	9.852340	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.416210	Mean dependent var	0.029008
Adjusted R-squared	0.349870	S.D. dependent var	0.015299
S.E. of regression	0.012542	Sum squared resid	0.013842
F-statistic	6.273918	Durbin-Watson stat	1.441367
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFB	0.007045	0.004805	1.466055	0.1462
MEDIANBM	-0.002572	0.002114	-1.216839	0.2269
C	0.026422	0.004378	6.035785	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.261604	Mean dependent var	0.031250
Adjusted R-squared	0.177695	S.D. dependent var	0.015703
S.E. of regression	0.014669	Sum squared resid	0.018936
F-statistic	3.117723	Durbin-Watson stat	1.246056
Prob(F-statistic)	0.001903		

II. Value Sort - GMM

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments
Transformation: First Differences
White period instrument weighting matrix
White period standard errors & covariance (d.f. corrected)
Instrument list: @DYN(AVG_RETURN,-2)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.765108	0.207976	3.678837	0.0004
MEDIANBM	0.006628	0.002511	2.639003	0.0100

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000841	S.D. dependent var	0.015462
S.E. of regression	0.020736	Sum squared resid	0.033969
J-statistic	5.084999	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.336524	0.132320	2.543265	0.0129
BETA	-0.046231	0.005941	-7.781622	0.0000

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000841	S.D. dependent var	0.015462
S.E. of regression	0.015896	Sum squared resid	0.019962
J-statistic	7.391384	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.432828	0.020769	20.83985	0.0000
CFB	0.004596	0.002138	2.149685	0.0346

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.002356	S.D. dependent var	0.015084
S.E. of regression	0.013476	Sum squared resid	0.014346
J-statistic	33.39449	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.395191	0.030210	13.08142	0.0000
BETA	-0.037946	0.007159	-5.300475	0.0000
CFB	0.008258	0.001909	4.326897	0.0000

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.002356	S.D. dependent var	0.015084
S.E. of regression	0.011769	Sum squared resid	0.010804
J-statistic	40.86864	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.487060	0.067477	7.218109	0.0000
CFB	0.005869	0.002928	2.004031	0.0485
MEDIANBM	0.003074	0.001869	1.644346	0.1041

Effects Specification			
Cross-section fixed (orthogonal deviations)			
Mean dependent var	-0.002356	S.D. dependent var	0.015084
S.E. of regression	0.013699	Sum squared resid	0.014638
J-statistic	31.78121	Instrument rank	45.000000

III. Size Sort – Fixed Effects

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVGS	-0.006842	0.001469	-4.657202	0.0000
C	0.048858	0.005307	9.206844	0.0000

Effects Specification			
Cross-section fixed (dummy variables)			
Weighted Statistics			
R-squared	0.619006	Mean dependent var	0.035502
Adjusted R-squared	0.580522	S.D. dependent var	0.019952
S.E. of regression	0.013211	Sum squared resid	0.017279
F-statistic	16.08467	Durbin-Watson stat	1.038595
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.025470	0.011180	-2.278129	0.0249
C	0.041515	0.006260	6.631850	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.395859	Mean dependent var	0.037442
Adjusted R-squared	0.334835	S.D. dependent var	0.019436
S.E. of regression	0.015888	Sum squared resid	0.024990
F-statistic	6.486916	Durbin-Watson stat	0.892643
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFB	0.007316	0.003454	2.118028	0.0367
C	0.025410	0.001301	19.53720	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.359190	Mean dependent var	0.035227
Adjusted R-squared	0.294462	S.D. dependent var	0.016518
S.E. of regression	0.015984	Sum squared resid	0.025294
F-statistic	5.549200	Durbin-Watson stat	0.703880
Prob(F-statistic)	0.000002		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.025127	0.009722	-2.584478	0.0112
CFB	0.006635	0.003610	1.838254	0.0691
C	0.038834	0.005534	7.017297	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.430242	Mean dependent var	0.035478
Adjusted R-squared	0.366289	S.D. dependent var	0.017481
S.E. of regression	0.015162	Sum squared resid	0.022530
F-statistic	6.727530	Durbin-Watson stat	0.894453
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVGS	-0.006787	0.001600	-4.242108	0.0001
CFB	-0.004541	0.003812	-1.191443	0.2364
C	0.050402	0.006499	7.755517	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.621154	Mean dependent var	0.035164
Adjusted R-squared	0.578631	S.D. dependent var	0.019117
S.E. of regression	0.012956	Sum squared resid	0.016451
F-statistic	14.60731	Durbin-Watson stat	1.061306
Prob(F-statistic)	0.000000		

IV. Size Sort – GMM

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.712638	0.011651	61.16485	0.0000
BETA	-0.035801	0.001833	-19.53643	0.0000

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003920	S.D. dependent var	0.017271
S.E. of regression	0.010662	Sum squared resid	0.010003
J-statistic	43.20847	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.644803	0.014887	43.31319	0.0000
AVGS	-0.002416	0.000384	-6.282886	0.0000

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003920	S.D. dependent var	0.017271
S.E. of regression	0.011577	Sum squared resid	0.011795
J-statistic	34.04256	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.787571	0.005918	133.0873	0.0000
CFB	0.002482	0.000985	2.519269	0.0136

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003920	S.D. dependent var	0.017271
S.E. of regression	0.012459	Sum squared resid	0.013659
J-statistic	35.89028	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.710091	0.012860	55.21795	0.0000
BETA	-0.029659	0.001822	-16.27421	0.0000
CFB	-0.002911	0.002325	-1.252096	0.2139

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003920	S.D. dependent var	0.017271
S.E. of regression	0.010557	Sum squared resid	0.009696
J-statistic	40.93354	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.645898	0.014872	43.43039	0.0000
CFB	4.05E-05	0.001304	0.031073	0.9753
AVGS	-0.002357	0.000415	-5.673374	0.0000

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003920	S.D. dependent var	0.017271
S.E. of regression	0.011658	Sum squared resid	0.011824
J-statistic	34.03784	Instrument rank	45.000000

V. Size and Value Sort – Fixed Effects

Dependent Variable: AVG_RETURN
Method: Panel EGLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MEDBM	0.002607	0.000686	3.802296	0.0003
AVGS	-0.005549	0.000606	-9.155252	0.0000
C	0.041603	0.002383	17.46003	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.779721	Mean dependent var	2.334532
Adjusted R-squared	0.754690	S.D. dependent var	2.854808
S.E. of regression	1.041590	Sum squared resid	95.47209
F-statistic	31.14939	Durbin-Watson stat	2.109055
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel EGLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.028355	0.006951	-4.079267	0.0001
C	0.042649	0.003813	11.18474	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.459841	Mean dependent var	0.036041
Adjusted R-squared	0.405219	S.D. dependent var	0.020802
S.E. of regression	0.014890	Sum squared resid	0.019732
F-statistic	8.418492	Durbin-Watson stat	1.086557
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel EGLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CFB	0.006403	0.003771	1.697830	0.0930
C	0.024876	0.001729	14.38813	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.391961	Mean dependent var	0.034011
Adjusted R-squared	0.330474	S.D. dependent var	0.017294
S.E. of regression	0.015210	Sum squared resid	0.020590
F-statistic	6.374701	Durbin-Watson stat	0.842118
Prob(F-statistic)	0.000001		

Dependent Variable: AVG_RETURN
Method: Panel EGLS

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.027571	0.006954	-3.964667	0.0001
CFB	0.005057	0.003380	1.496303	0.1382
C	0.040225	0.004182	9.618009	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.472402	Mean dependent var	0.036557
Adjusted R-squared	0.412447	S.D. dependent var	0.021417
S.E. of regression	0.014951	Sum squared resid	0.019672
F-statistic	7.879352	Durbin-Watson stat	1.083746
Prob(F-statistic)	0.000000		

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVGS	-0.008302	0.001116	-7.439396	0.0000
MEDBM	0.003663	0.001747	2.096318	0.0390
CFB	0.001225	0.003936	0.311101	0.7565
C	0.048538	0.005467	8.878960	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.642462	Mean dependent var	0.027412
Adjusted R-squared	0.597257	S.D. dependent var	0.018232
S.E. of regression	0.011570	Akaike info criterion	-5.967532
Sum squared resid	0.011647	Schwarz criterion	-5.652972
Log likelihood	307.3928	Hannan-Quinn criter.	-5.840261
F-statistic	14.21192	Durbin-Watson stat	1.379238
Prob(F-statistic)	0.000000		

VI. Size and Value Sort – GMM

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.377503	0.127308	2.965266	0.0040
MEDBM	0.007214	0.002165	3.331652	0.0013
AVGS	-0.003203	0.000526	-6.087372	0.0000

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.001015	S.D. dependent var	0.013330
S.E. of regression	0.014514	Sum squared resid	0.016431
J-statistic	7.100568	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.493250	0.114586	4.304644	0.0000
BETA	-0.026389	0.006988	-3.776363	0.0003

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.001015	S.D. dependent var	0.013330
S.E. of regression	0.016600	Sum squared resid	0.021770
J-statistic	6.236011	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.047355	0.007556	6.267025	0.0000
CFB	0.016784	0.001309	12.81853	0.0000

Effects Specification

Cross-section fixed (orthogonal deviations)

Mean dependent var	-0.003001	S.D. dependent var	0.015191
S.E. of regression	0.015736	Sum squared resid	0.019561
J-statistic	36.20271	Instrument rank	45.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.355121	0.161873	2.193824	0.0312
BETA	-0.038495	0.009361	-4.112308	0.0001
CFB	0.007260	0.005716	1.270074	0.2078

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.001015	S.D. dependent var	0.013330
S.E. of regression	0.016485	Sum squared resid	0.021196
J-statistic	3.992353	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.130296	0.207479	0.627997	0.5319
CFB	0.017039	0.006529	2.609616	0.0109
MEDIANS	-0.004746	0.001663	-2.853928	0.0055
MEDBM	0.003009	0.003486	0.863190	0.3907

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.001015	S.D. dependent var	0.013330
S.E. of regression	0.013904	Sum squared resid	0.014886
J-statistic	6.278703	Instrument rank	9.000000

VII. Robustness Check – Price Restriction

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.004806	0.007183	-0.669024	0.5052
C	0.024456	0.004044	6.047996	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.246242	Mean dependent var	0.021832
Adjusted R-squared	0.170020	S.D. dependent var	0.010746
S.E. of regression	0.009790	Akaike info criterion	-6.319443
Sum squared resid	0.008530	Schwarz criterion	-6.057310
Log likelihood	322.8124	Hannan-Quinn criter.	-6.213383
F-statistic	3.230564	Durbin-Watson stat	1.133162
Prob(F-statistic)	0.001956		

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
MBM	0.001223	0.000930	1.315612	0.1917
C	0.019937	0.001740	11.45621	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.256903	Mean dependent var	0.021832
Adjusted R-squared	0.181758	S.D. dependent var	0.010746
S.E. of regression	0.009720	Akaike info criterion	-6.333687
Sum squared resid	0.008409	Schwarz criterion	-6.071554
Log likelihood	323.5175	Hannan-Quinn criter.	-6.227628
F-statistic	3.418780	Durbin-Watson stat	1.116346
Prob(F-statistic)	0.001187		

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CF_BETA	0.013728	0.003617	3.795742	0.0003
C	0.014975	0.002025	7.394620	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.348000	Mean dependent var	0.021832
Adjusted R-squared	0.282067	S.D. dependent var	0.010746
S.E. of regression	0.009105	Akaike info criterion	-6.464469
Sum squared resid	0.007378	Schwarz criterion	-6.202336
Log likelihood	329.9912	Hannan-Quinn criter.	-6.358410
F-statistic	5.278115	Durbin-Watson stat	1.255453
Prob(F-statistic)	0.000009		

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.009716	0.006753	-1.438787	0.1538
CF_BETA	0.014680	0.003656	4.015885	0.0001
C	0.019804	0.003914	5.060054	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.362985	Mean dependent var	0.021832
Adjusted R-squared	0.290597	S.D. dependent var	0.010746
S.E. of regression	0.009051	Akaike info criterion	-6.467519
Sum squared resid	0.007208	Schwarz criterion	-6.179172
Log likelihood	331.1422	Hannan-Quinn criter.	-6.350853
F-statistic	5.014430	Durbin-Watson stat	1.452183
Prob(F-statistic)	0.000010		

Dependent Variable: AVG_RETURN
Method: Panel Least Squares

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CF_BETA	0.013835	0.003593	3.850873	0.0002
MBM	0.001290	0.000865	1.491076	0.1395
C	0.012923	0.002437	5.302658	0.0000

Effects Specification

Cross-section fixed (dummy variables)

R-squared	0.364067	Mean dependent var	0.021832
Adjusted R-squared	0.291801	S.D. dependent var	0.010746
S.E. of regression	0.009043	Akaike info criterion	-6.469218
Sum squared resid	0.007196	Schwarz criterion	-6.180871
Log likelihood	331.2263	Hannan-Quinn criter.	-6.352553
F-statistic	5.037927	Durbin-Watson stat	1.371390
Prob(F-statistic)	0.000009		

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.488718	0.016373	29.84898	0.0000
BETA	-0.002564	0.001202	-2.133063	0.0360

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000539	S.D. dependent var	0.010074
S.E. of regression	0.012200	Sum squared resid	0.011758
J-statistic	7.273275	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.571647	0.044580	12.82298	0.0000
MBM	0.002631	0.000987	2.665467	0.0093

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000539	S.D. dependent var	0.010074
S.E. of regression	0.012839	Sum squared resid	0.013022
J-statistic	8.650565	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.439640	0.097090	4.528170	0.0000
CF_BETA	0.011745	0.007862	1.493855	0.1392

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000539	S.D. dependent var	0.010074
S.E. of regression	0.011605	Sum squared resid	0.010640
J-statistic	6.496130	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.369058	0.119505	3.088217	0.0028
BETA	-0.007087	0.003131	-2.263675	0.0264
CF_BETA	0.012696	0.006916	1.835707	0.0702

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000539	S.D. dependent var	0.010074
S.E. of regression	0.011913	Sum squared resid	0.011071
J-statistic	6.041339	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.519232	0.129755	4.001628	0.0001
CF_BETA	0.016055	0.007677	2.091255	0.0398
MBM	0.003227	0.002190	1.473188	0.1447

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000539	S.D. dependent var	0.010074
S.E. of regression	0.013174	Sum squared resid	0.013537
J-statistic	6.518832	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.014675	0.006318	-2.322858	0.0223
C	0.029845	0.003642	8.194189	0.0000

Effects Specification			S.D.	Rho
Cross-section random			0.001893	0.0360
Idiosyncratic random			0.009790	0.9640

Weighted Statistics			
R-squared	0.049172	Mean dependent var	0.018377
Adjusted R-squared	0.039369	S.D. dependent var	0.010359
S.E. of regression	0.010153	Sum squared resid	0.009999
F-statistic	5.016324	Durbin-Watson stat	1.144958
Prob(F-statistic)	0.027393		

Unweighted Statistics			
R-squared	0.069513	Mean dependent var	0.021832
Sum squared resid	0.010529	Durbin-Watson stat	1.087308

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.019159	0.005836	-3.283126	0.0014
CF_BETA	0.016134	0.003455	4.670394	0.0000
C	0.024234	0.003560	6.807413	0.0000

Effects Specification			S.D.	Rho
Cross-section random			0.001468	0.0256
Idiosyncratic random			0.009051	0.9744

Weighted Statistics			
R-squared	0.221217	Mean dependent var	0.019227
Adjusted R-squared	0.204992	S.D. dependent var	0.010449
S.E. of regression	0.009317	Sum squared resid	0.008333
F-statistic	13.63462	Durbin-Watson stat	1.462878
Prob(F-statistic)	0.000006		

Unweighted Statistics			
R-squared	0.238975	Mean dependent var	0.021832
Sum squared resid	0.008612	Durbin-Watson stat	1.415551

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
CF_BETA	0.015644	0.003378	4.631732	0.0000
MBM	0.002650	0.000563	4.710433	0.0000
C	0.009914	0.002143	4.626632	0.0000

Effects Specification		S.D.	Rho
Cross-section random		0.000000	0.0000
Idiosyncratic random		0.009043	1.0000

Weighted Statistics			
R-squared	0.299047	Mean dependent var	0.021832
Adjusted R-squared	0.284444	S.D. dependent var	0.010746
S.E. of regression	0.009090	Sum squared resid	0.007932
F-statistic	20.47824	Durbin-Watson stat	1.431795
Prob(F-statistic)	0.000000		

Unweighted Statistics			
R-squared	0.299047	Mean dependent var	0.021832
Sum squared resid	0.007932	Durbin-Watson stat	1.431795

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.012162	0.006051	-2.009835	0.0475
CF_BETA	0.008017	0.003855	2.079550	0.0405
C	0.023342	0.002788	8.372311	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics			
R-squared	0.309239	Mean dependent var	0.023648
Adjusted R-squared	0.230743	S.D. dependent var	0.011791
S.E. of regression	0.008245	Sum squared resid	0.005983
F-statistic	3.939565	Durbin-Watson stat	1.149232
Prob(F-statistic)	0.000187		

Unweighted Statistics			
R-squared	0.246090	Mean dependent var	0.020585
Sum squared resid	0.006001	Durbin-Watson stat	1.103875

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVSIZE	-0.004506	0.000908	-4.961011	0.0000
C	0.035625	0.003475	10.25252	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.503585	Mean dependent var	0.022416
Adjusted R-squared	0.453386	S.D. dependent var	0.010563
S.E. of regression	0.006874	Sum squared resid	0.004205
F-statistic	10.03172	Durbin-Watson stat	1.233946
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.470508	Mean dependent var	0.020585
Sum squared resid	0.004215	Durbin-Watson stat	1.254897

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.010870	0.006616	-1.642931	0.1039
C	0.026232	0.003243	8.088348	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.239733	Mean dependent var	0.023108
Adjusted R-squared	0.162852	S.D. dependent var	0.011008
S.E. of regression	0.008493	Sum squared resid	0.006419
F-statistic	3.118230	Durbin-Watson stat	1.028023
Prob(F-statistic)	0.002635		

Unweighted Statistics

R-squared	0.193220	Mean dependent var	0.020585
Sum squared resid	0.006422	Durbin-Watson stat	0.961567

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.461385	0.216657	2.129559	0.0363
BETA	-0.015556	0.011139	-1.396564	0.1665

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000840	S.D. dependent var	0.007640
S.E. of regression	0.009644	Sum squared resid	0.007348
J-statistic	8.632651	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.186478	0.164670	1.132437	0.2609
AVSIZE	-0.004483	0.000627	-7.151899	0.0000
CF_BETA	0.003843	0.006978	0.550755	0.5834

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000840	S.D. dependent var	0.007640
S.E. of regression	0.008011	Sum squared resid	0.005005
J-statistic	4.796381	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.439289	0.160700	2.733590	0.0077
BETA	-0.015956	0.009929	-1.606953	0.1121
CF_BETA	0.003822	0.010532	0.362895	0.7177

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000840	S.D. dependent var	0.007640
S.E. of regression	0.009724	Sum squared resid	0.007375
J-statistic	8.565987	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	-0.017241	0.003804	-4.532553	0.0000
CF_BETA	0.005215	0.002950	1.767720	0.0803
C	0.027225	0.002045	13.31475	0.0000

Effects Specification

	S.D.	Rho
Cross-section random	0.000000	0.0000
Idiosyncratic random	0.008254	1.0000

Weighted Statistics

R-squared	0.175923	Mean dependent var	0.020585
Adjusted R-squared	0.158755	S.D. dependent var	0.009012
S.E. of regression	0.008266	Sum squared resid	0.006559
F-statistic	10.24700	Durbin-Watson stat	1.079444
Prob(F-statistic)	0.000093		

Unweighted Statistics

R-squared	0.175923	Mean dependent var	0.020585
Sum squared resid	0.006559	Durbin-Watson stat	1.079444

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVSIZE	-0.004201	0.000505	-8.322831	0.0000
CF_BETA	0.001527	0.002280	0.669618	0.5047
C	0.033930	0.002026	16.74952	0.0000

Effects Specification

	S.D.	Rho
Cross-section random	0.000531	0.0059
Idiosyncratic random	0.006882	0.9941

Weighted Statistics

R-squared	0.416176	Mean dependent var	0.019942
Adjusted R-squared	0.404013	S.D. dependent var	0.008969
S.E. of regression	0.006924	Sum squared resid	0.004603
F-statistic	34.21662	Durbin-Watson stat	1.151392
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.418386	Mean dependent var	0.020585
Sum squared resid	0.004629	Durbin-Watson stat	1.144785

VIII. Robustness Checks: Equally-weighted Market Proxies

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	0.012789	0.001147	11.14813	0.0000
C	0.015691	0.003580	4.383260	0.0000

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.504908	Mean dependent var	0.028356
Adjusted R-squared	0.454842	S.D. dependent var	0.017723
S.E. of regression	0.013272	Sum squared resid	0.015677
F-statistic	10.08494	Durbin-Watson stat	0.619247
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.565109	Mean dependent var	0.027908
Sum squared resid	0.016011	Durbin-Watson stat	0.592533

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	0.013077	0.001112	11.75982	0.0000
CF_BETA	0.006325	0.003891	1.625380	0.1077
C	0.009531	0.003995	2.385780	0.0192

Effects Specification

Cross-section fixed (dummy variables)

Weighted Statistics

R-squared	0.523787	Mean dependent var	0.028314
Adjusted R-squared	0.469672	S.D. dependent var	0.017723
S.E. of regression	0.013206	Sum squared resid	0.015348
F-statistic	9.679133	Durbin-Watson stat	0.653339
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.572663	Mean dependent var	0.027908
Sum squared resid	0.015733	Durbin-Watson stat	0.624862

Dependent Variable: AVG_RETURN
Method: Panel Generalized Method of Moments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.533523	0.137581	3.877873	0.0002
BETA	0.017394	0.006543	2.658432	0.0095
CF_BETA	0.005947	0.004314	1.378578	0.1720

Effects Specification

Cross-section fixed (first differences)

Mean dependent var	0.000934	S.D. dependent var	0.020120
S.E. of regression	0.012358	Sum squared resid	0.011913
J-statistic	6.343671	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	0.014914	0.001591	9.375618	0.0000
CF_BETA	0.003693	0.003871	0.954142	0.3424
C	0.010225	0.004602	2.221945	0.0286

Effects Specification

	S.D.	Rho
Cross-section random	0.004938	0.1214
Idiosyncratic random	0.013283	0.8786

Weighted Statistics

R-squared	0.476024	Mean dependent var	0.017579
Adjusted R-squared	0.465108	S.D. dependent var	0.018240
S.E. of regression	0.013340	Sum squared resid	0.017084
F-statistic	43.60727	Durbin-Watson stat	0.597150
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.472939	Mean dependent var	0.027908
Sum squared resid	0.019404	Durbin-Watson stat	0.525747

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section weights)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	0.006485	0.001771	3.662199	0.0004
CF_BETA	0.001901	0.002129	0.892606	0.3745
C	0.017161	0.003757	4.567901	0.0000

Effects Specification			
Cross-section fixed (dummy variables)			
Weighted Statistics			
R-squared	0.461191	Mean dependent var	0.025308
Adjusted R-squared	0.399963	S.D. dependent var	0.014065
S.E. of regression	0.012237	Sum squared resid	0.013178
F-statistic	7.532332	Durbin-Watson stat	0.565157
Prob(F-statistic)	0.000000		
Unweighted Statistics			
R-squared	0.529220	Mean dependent var	0.024732
Sum squared resid	0.015663	Durbin-Watson stat	0.489504

Dependent Variable: AVG_RETURN

Variable	Coefficient	Std. Error	t-Statistic	Prob.
AVG_RETURN(-1)	0.788152	0.106633	7.391250	0.0000
BETA	0.016016	0.003924	4.081051	0.0001
CF_BETA	0.007465	0.002630	2.838904	0.0058

Effects Specification			
Cross-section fixed (orthogonal deviations)			
Mean dependent var	-0.002967	S.D. dependent var	0.013886
S.E. of regression	0.009845	Sum squared resid	0.007560
J-statistic	3.268619	Instrument rank	9.000000

Dependent Variable: AVG_RETURN
Method: Panel EGLS (Cross-section random effects)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
BETA	0.015187	0.002678	5.670198	0.0000
CF_BETA	-0.003279	0.003515	-0.932786	0.3533
C	0.014435	0.005245	2.752017	0.0071

Effects Specification

	S.D.	Rho
Cross-section random	0.005042	0.1338
Idiosyncratic random	0.012828	0.8662

Weighted Statistics

R-squared	0.299348	Mean dependent var	0.015052
Adjusted R-squared	0.284751	S.D. dependent var	0.015520
S.E. of regression	0.013125	Sum squared resid	0.016538
F-statistic	20.50766	Durbin-Watson stat	0.428928
Prob(F-statistic)	0.000000		

Unweighted Statistics

R-squared	0.410011	Mean dependent var	0.024732
Sum squared resid	0.019629	Durbin-Watson stat	0.361387