PG Basiewicz and CJ Auret*

Feasibility of the Fama and French three factor model in explaining returns on the JSE

ABSTRACT

We test the feasibility of the Fama and French (1993) three factor model on the JSE Limited (JSE) to explain the size and value effects. In time-series tests on grouped data, we show that both the models can capture a substantial amount of time-series variation in most assets, and yield small pricing errors. In tests on ungrouped data, the three factor model can explain the value effect, and goes in the right direction to explain the size effect. Given these results, we propose that our three factor model could be used in expected return estimation for firms listed on the JSE.

1. INTRODUCTION

We test the feasibility of the Fama and French (1993) three factor model on the Johannesburg Stock Exchange to explain the size and value effects. In time-series tests on grouped data, we show that both the models can capture a substantial amount of time-series variation in most assets, and yield small pricing errors. In tests on ungrouped data, the three factor model can explain the value effect, and goes in the right direction to explain the size effect. Given these results, we propose that our three factor model could be used in expected return estimation for firms listed on the JSE.

The derivation of a parsimonious asset pricing model has been a central theme of financial economics for over half a century. While a substantial body of theoretical work has emerged, no model has been accepted by the majority of academics and practitioners. It appears that much of the theory has difficulty capturing the actual behaviour of asset prices, as numerous persistent patterns in stock returns that contradict these rational models have been documented. In particular, two such asset pricing "anomalies" have attracted a considerable amount of attention: the *size effect* and the *value effect*[1].

In recent years the focus of the discipline of asset pricing has shifted away from theoretical modeling towards empirical analysis. Financial practitioners have become reliant on statistical constructs with which they aimed to describe the behaviour of asset prices (*inter alia* Chen, Roll and Ross, 1986; Connor and Korajczyk, 1988). One such empirically derived asset pricing model appears in Fama and French (1993). The authors have incorporated the size and the value effects into an asset pricing equation and they have found the model to be particularly good at explaining returns of many types of stocks.

The three factor model is not a magic bullet for asset pricing. Actually, it constitutes a mild embarrassment to the field of financial economics because it has not been derived theoretically. At the time of its development, there were few, if any, discernable links between the model and formal asset pricing theory. However, its staggering success and relative ease of application led to growth in the model's popularity among academics and eventually practitioners as well (Brealey and Myers, 2000).

Algebraically, it is given by:

$$E_T\left[r_{i,T+1}\right] = r_f + b_i\lambda^{Market} + s_i\lambda^{Size} + h_i\lambda^{Value} \quad \ldots (1)$$

The roman letters in the terms on the right side of Equation 1 represent risk exposures, while the λ's are associated with the premiums on the three types of risk. The familiar empirical specification of the Fama and French three factor model is:

$$r_{i,t} - r_{f,t} = \hat{\alpha}_i + \hat{\beta}_i\left(r_{M,t} - r_{f,t}\right) + \hat{s}_i SMB_t + \hat{h}_i HML_t + \varepsilon_t \quad \ldots (2)$$

Equation 2 represents a regression of realised excess returns of an asset on the market factor and two factor-mimicking portfolios. The SMB (Small minus Big) is the size factor, and is calculated as a return on a zero-cost portfolio that establishes a long position in a portfolio of small firms and finances it with a short position in large firms. Similarly, the value factor, HML (High minus Low), is constructed from a zero-cost portfolio that buys firms with a high book-to-market ratio and shorts firms with a low book-to-market ratio. Because market capitalisation and value ratio indicators are correlated, Fama and French (1993) use a sorting procedure that results in portfolios that do not confound the size and the value effects. In sum, the HML factor captures the

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*Respectively UniCredit CAIBSecurities United Kingdom and School of Economics and Business Sciences, University of the Witwatersrand, Private Bag 3, Wits 2050, South Africa. An earlier version of this paper was presented at the 18th Annual Conference of the South African Finance Association, Cape Town 14 January 2009. This paper has benefitted from comments from a number of colleagues at the conference and from a few points raised by anonymous reviewers.

[1] The ability of a firm's market capitalisation to predict firm level returns appears in Banz (1981) and inter alia Basu (1977, 1983), Chan, Hamao and Lakonishok (1991) and Rosenberg, Reid and Lanstein (1985) document the forecasting power of valuation multiples. For South African evidence see Van Rensburg and Robertson (2003a, 2003b).

value premium that is independent of the effect of size and the SMB factor captures the size premium that is independent of the effect of the book-to-market ratio.

The purpose of this paper is to assess the feasibility of the three factor model proposed in Fama and French (1993) (henceforth, FF3F) for the Johannesburg Stock Exchange (henceforth, the JSE)[2]. However, before we subject the FF3F to the tests, we also show how accurate the CAPM and the APT proposed by Van Rensburg and Slaney (1997) (henceforth, RS-APT) are in explaining the size and value effects on the JSE. The tests of these "traditional" models serve as benchmarks against which the FF3F is then tested.

We perform two types of tests on the FF3F and the two "traditional" models. At first, we perform tests in a time-series format. We regress returns of a series of test assets onto the factors that we *a priori* believe have power to explain asset returns. The resultant intercepts, which are often referred to in the literature as *pricing errors*, are the quantities of interest. Their collective size and statistical significance provide information about the suitability of the asset pricing model being tested. Clearly, pricing errors that are collectively close to zero would suggest that the asset pricing model is adequate in explaining returns of the test assets. Pricing errors that deviate significantly from zero would signal rejection of the asset pricing model being tested. In those time-series tests, the tests assets are portfolios grouped from individual shares.

We also perform tests on ungrouped data. Cochrane (2001) among many argues that risk adjustment with a correctly specified asset pricing model should be complete, meaning that firm characteristics, which have power to forecast returns, should lose their explanatory power when applied to returns that have been adjusted for risk with a correctly specified asset pricing model. We perform such tests, and following Fama and French (1992), we select the firm's market value and its book-to-market ratio as the characteristics which the asset pricing models should price out.

Tests of models akin to the FF3F have been performed on South African data before. Van Rensburg and Robertson (2004) form factors similar to those of Fama and French (1993), and aim to ascertain if loadings on their model can *ex ante* predict returns. Scher and Muller (2005) use the three factor model to test investment performance of professionally managed funds. However, in spite of the fact that Scher and Muller (2005) do provide time-series pricing errors (the intercepts) of various assets, none of the previous tests explicitly test the overall model, and focus solely on risk adjustment.

2. DATA AND METHODOLOGY

2.1 Data set

One of the key objectives of this research is to perform the tests on a reasonably complete sample of firms in order to minimize survival bias in our test. Our sample period spans from June 1992 to July 2005, yielding 156 monthly observations. However, we include into our dataset each and every firm listed between December 1989 and July 2005. This allows us to collect accounting data which was published before our sample period begins, and gives us ample market data with which to estimate loadings. We collect all the pertinent characteristics for each firm during this period. These include price data, corporate action data and accounting data[3]. Subsequently, we restrict our dataset by focusing only on firms which were listed during our sample period and were not active in the real estate industry. Data limitations force us to cull firms from our sample: we exclude firms where accounting data are missing or stated solely in a foreign currency (loss of 9 firms from our sample)[4], market data are not available (loss of 22 firms)[5] and have been listed for less than 24 months (loss of 83 firms)[6]. These adjustments cause an attrition of 114 firms from the sample, bringing the total to 893 usable companies. These exclusions were distributed evenly throughout our sample period, and thus do not rise sample selection concerns. Cash companies are marked as suspended, and thus implicitly removed from subsequent tests. In sum, the raw number of firm-month observations - where all the firm characteristics are available for a given firm at a given point in time - is about 76 600. This makes our sample possibly the largest dataset that has been used for asset pricing tests on the JSE, and to our knowledge it is the largest dataset used on any African exchange.

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[2] We also tested a version of the three factor model that takes into account the dichotomy of returns on the JSE in that we form a version of the FF3F that replaces the Market factor with a Resi factor and a Findi factor, which are market weighted portfolios of mining shares and financial & industrial shares, respectively. The results were very similar to the tests with the traditional FF3F.

[3] The details pertaining to the construction of firm level variables are available from the authors, or see Basiewicz and Auret (2009).

[4] We excluded firms for which accounting data is not reported in South African Rand. This accounts for six out of the nine firms that were excluded.

[5] Firms were excluded if a credible date of listing, delisting or change of name was not available, or if the price, volume or shares in issue data was not available for a substantial part of the listing.

[6] The rationale for dropping firms with less than 24 months of listing is that this is seen as the minimum number of data points that are necessary to calculate reliable factor loadings.

2.2 Asset pricing tests

Ideally asset pricing tests ought to be performed on individual securities, but statistical considerations force grouping of shares into portfolios (Cochrane, 2001). For one, running asset pricing tests on portfolios severely reduces the impact of firm specific risk on estimation of mean returns and factor loadings. In addition, many formulas used to compute standard errors cannot be applied in situations in which the cross-section of assets is large relative to the length of the sample period. Thus, grouping allows for a decrease in the amount of test assets, while minimising the loss of information.

In asset pricing tests, statistical considerations require the test assets to exhibit wide dispersion in mean returns and factor loadings (Chan, Chen and Hsieh, 1985). Consequently, the choice of test assets used in the empirical analyses follows Fama and French (1993, 1995), who use 25 portfolios formed by an intersecting five size-sorted portfolios and five value indicator-sorted portfolios. In addition, we also follow Lo and MacKinlay (1990), who prove that if the pricing errors of a model are correlated with some characteristic, using portfolios sorted with that characteristic will increase the power of the asset pricing tests.

In our case, the test assets, constructed to capture the size and the value effects, will comprise a set of assets constructed as an intersection of the four size and three value indicator-sorted portfolios, giving a total of twelve assets. Following Basiewicz and Auret (2009), who find that book-to-market (henceforth, BE/ME) is the value indicator which yields the strongest measure of the value premium, we use the BE/ME ratio as a sorting variable. Of course, following Fama and French (1992), we measure size as market capitalisation.

In their seminal article, Fama and French (1993) constructed their factors by initially forming six elementary portfolios, and with a linear combination of these composites they formed their factors. These elementary portfolios were obtained from an independent two-way sort of two size portfolios on three value portfolios. They form the SMB factor by subtracting the average return of three portfolios containing small stocks from the average returns of three large stock portfolios. Similarly, they construct the HML factor by subtracting the average return of the two most-value portfolios from the average return of the most-growth portfolios.

The construction of the Size and Value factors (FF3F factors) in this study follow Fama and French (1993) and are somewhat different from the factors used in prior South African research. The constructed factors are re-balanced annually, not monthly[7]. In addition, only a subset of stocks is used for determination of the breakpoints for the six elementary portfolios. This point merits further explanation. Fama and French (1993) formed their six portfolios using breakpoints of the NYSE listed shares and did not include NASDAQ and AMEX stocks. In other words, they foresaw that the use of the entire cross-section in the determination of the breakpoints would actually result in a portfolio containing "very small" instead of "small" stocks. Simply put, cutting the cross-section of listed shares in half results in one of the portfolios being filled with many tiny capitalisation shares. This problem would be particularly severe for the JSE as there are many "very small" firms listed on the exchange. In order to address this problem, each June, all listed stocks are ranked according to their liquidity. A stock's measure of liquidity is its twelve-month average of its monthly trading volume scaled by the number of shares in issue. Consequently, the breakpoints for the six portfolios of Fama and French (1993) are derived using the 200 most liquid stocks. Stocks included in these elementary portfolios are subject to restrictions on price and liquidity such that in each sort we do not include stocks with price less than 100c and a liquidity measure of less than 0,001.

A possibly more preferable method of factor construction would take into account the segmentation of the JSE into resources as well as financial and industrial shares (i.e. constructing separate HML and SMB factors for each of these two types of stocks). However, such sub-division may induce firm specific variance into the factors. Although Cochrane (2001) provides thorough theoretical reasons why residual risk in factors is a problem, it can be seen intuitively that, if the factor itself is measured with an error, it is difficult to measure exposure to a risk factor. In addition, if FF3F factors are indeed instruments for true innovation in state variables in Merton's (1973) ICAPM (*inter alia* Petkova, 2005; Aretz, Bartram and Pope (2005), unnecessarily large factor variance strongly violates Fama's (1996) argument that the variance of ICAPM factor mimicking must be as small as possible.

As a matter of notation, the SMB factor is referred to as SML factor ("Small minus Large")[8], while HML is referred to as VMG ("Value minus Growth")[9].

[7]We advise against monthly rebalancing, as it may confound the measured premia with the short-term reversal effect of Jegadeesh (1990). Since the effect has been linked to trading costs, it is very likely to be acute on the JSE.

[8]We prefer the relative "Large" to the absolute "Big", as arguably not all the firms in the "Large" part of the size factor could be considered "Big" by all investors.

[9]This naming convention of the value factor follows the recent view of the factor in the literature

In the time-series tests, we set up a system of regression equations where on the left hand side are the returns of the test assets in excess of the risk free rate while on the right hand side are the factors of an asset pricing model we are testing. In all time-series regression tests it will be assumed that the risk-free asset exists and it is represented by the three-month T-Bill rate, which is obtained from the website of the South African Reserve Bank.

Financial assets do not exist in isolation and there is much correlation between residuals of individual assets, and often can be presented as a Seemingly Unrelated Regression (SURE) system - which Greene (2003) recommends for application in financial markets. The SURE method simultaneously performs a number of OLS regressions, in this way factor loadings for a number of assets can be estimated at the same time. In addition, cross-correlation of returns are taken into account and improves the precision of estimates of $\mathbf{b}_i$;

Formally, in every test of an asset pricing model of N assets, we set up a system with N of the following regressions:

$$r_i - r_f = \alpha_i + f\hat{b}'_i + \varepsilon_t \qquad \ldots (3)$$

The r_i is the realised return series of the ith asset and the r_f is the series of the risk-free rate. The intercept α_i is the pricing error, or Jensen's (1968) alpha, of an ith asset. The vector of the factors is:

$$f = \left[f^M \quad f^{M(lag)} \quad f^R \quad f^{R(lag)} \quad f^I \quad f^{I(lag)} \quad f^{SML} \quad f^{VMG} \right] D$$

The f^M series represents the Market factor, which is the return series on the value-weighted return of all securities in the sample in excess of the risk-free rate. The f^R series represents the Resi factor, which is the value-weighted excess return of all mining shares in the sample. The f^I series represents the Findi factor, which is the value-weighted excess return of all financial and industrial shares in the sample. The series with the *(lag)* superscript are the series of the three factors lagged by a month. The f^{SML} and the f^{VMG} are the size and the value factors. The vector **f** represents the loadings on factors. The matrix **D** is a diagonal matrix of indicator variables that specifies the factors in each regression equation.

Portfolio returns are stationery, but exhibit a non-negligible auto-correlation (Cochrane, 2001). Furthermore, heteroskedasticity may be present in monthly data, meaning standard OLS (and SURE) time-series regressions will not yield efficient estimates, and thus some adjustment to standard errors is often necessary. Consequently, the standard errors are calculated by mapping the system of time-series regressions into a Generalised Method of Moments (GMM) system:

$$g_T\left(\hat{a},\hat{b}\right) = E_T\left(f_t^k \otimes \left(r_t - \iota r_f - \hat{a} - \hat{b}' f_t\right)\right) = 0 \qquad \ldots (4)$$

Where f_t is a vector of cross-section of factor realisations at time t, and superscript k denotes that the first element of the vector is a constant; r_t is the vector of cross-section of returns of all assets; ι is a vector of ones; and a and b are parameters to be estimated, where a is a vector of pricing errors. We use the GMM procedure to calculate standard errors as they are heteroskedasticity and autocorrelation consistent (Cochrane, 2001). MacKinlay and Richardson (1991) formally advocate use of this method.

According to Cochrane (2001), a non-zero asset pricing error of a single asset does not lead to a rejection of the asset pricing model. However, a good model will yield asset pricing errors that are *on average* small. In fact, the time-series test validates a candidate asset pricing model if the estimated intercepts are jointly not statistically different from zero. Gibbons, Ross and Shanken (1989) develop a statistical test (henceforth, the GRS test) for simultaneous significance of a group of intercepts. It assumes that errors are uncorrelated over time, and homoskedastic. Their GRS-statistic follows an F-distribution, and is given by:

$$\frac{T-N-K}{N}\left[1 + E_T\left(f_t\right)' \hat{\Omega}^{-1} E_T\left(f_t\right)\right]^{-1} \hat{a}'\hat{\Sigma}\hat{a} \sim F_{N,T-N-1} \quad \ldots (5)$$

The Σ matrix in the formula often needs to be estimated with:

$$\hat{\Sigma} = E\left(e_t e_t'\right) = \sum_{i=1}^{T} e_t e_t'$$

where $\mathbf{e}_t$ is the vector of cross-section of residuals at time t. The parameter $\hat{\Omega}$ in the equation is the variance-covariance matrix of factor deviations:

$$\hat{\Omega} = \frac{1}{T}\sum_{t=1}^{T}\left[f_t - E_T\left(f_t\right)\right]\left[f_t - E_T\left(f_t\right)\right]'$$

Trivially:

$$E_T = \frac{1}{T}\sum_{t=1}^{T} f_t$$

In order to facilitate comparison with other studies we calculate the value-adjusted size effect after adjustment for risk with a candidate pricing model. We do so by creating an asset which is a linear combination of the original test assets that captures this effect. Specifically, in order to capture the size effect that is independent of the value effect, we form an arbitrage portfolio by taking a long of a portfolio containing small firms in a given value group and a short of a portfolio containing larger firms in the same value group. We create such a portfolio for each value group. Then we form an equal-weighted portfolio of these resultant portfolios. Finally, we run the model shown in Equation 4 on the resultant portfolio. The intercept and the corresponding *t*-value give an indication of the size and significance of the size effect after risk adjustment has been taken into effect. The calculation of the size-adjusted value effect is done in a similar fashion. The value effect is measured within each size group and then aggregated into the final equal-weighted portfolio.

Cochrane (2001), amongst many others, notes that a correctly specified asset pricing model needs to explain all predictable variations in asset returns. Hence, the unexpected part of asset returns (pricing error) should not be predicable with stock characteristics such as size or the BE/ME ratio. Alternatively, in the presence of irrationality in the market, a misspecification of a pricing model, or distortions brought by microstructure effects, the ability of stock characteristics to explain asset prices should still occur. In order to augment the evaluation of an asset pricing model an additional test is required that will pair the predictive power of the model against the assets' characteristics.

We use the approach advocated by Brennan, Chordia and Subrahmanyam (1998) and Van Rensburg and Robertson (2003a). In these tests, we obtain risk-adjusted returns by regressing each stock's excess return onto the factors of the asset pricing model we are testing. The risk-adjusted returns are the sum of the intercept of that regression and the series of residuals. After repeating these regressions for each firm in our sample, we are left with a panel of risk adjusted returns. Subsequently, we perform the Fama-Macbeth (1973) regressions of these risk-adjusted returns onto the lag of firm size and the BE/ME, as these are the variables that were found to have power to forecast returns. The significance of the coefficient on size and BE/ME should be close to zero if the risk-adjustment with the asset pricing model was complete. If these coefficients are larger than zero than firm characteristics continue to have predictive power and the asset pricing model being tested is rejected.

Formally, for each asset *i* in our sample, we regress:

$$r_i - r_f = \hat{\alpha}_i + f\hat{b}'_i + \varepsilon_i \qquad \ldots (6)$$

and calculate, in each period t, a pricing error of asset i by:

$$\hat{\alpha}_i + \varepsilon_{i,t} = r_{i,t} - r_{f,t} - \sum_{j=1}^{K} \hat{b}_{i,j} f_{j,t}$$

where

$f_{j,t}$ is the realisation of factor j at time t and $b_{i,j}$ is the beta on factor j of asset i. Time-series regressions may include lags on the Market, or Resource and Findi, factors, which, according to Dimson (1979) and Ibbotson, Kaplan and Peterson (1997), helps to account for thin trading[10].

Subsequently, Fama-MacBeth regressions are run on the pricing errors of each candidate asset pricing model, where formally the regressions are given by:

$$a + e_{t+1} = c'_t\,\hat{q}_t + \eta_t \qquad \ldots (7)$$

where

the dependant variable, $\mathbf{a} + \mathbf{e}_{t+1}$ is the cross-section of pricing errors of firms in the sample at *t*+1 and the vector of regressors is:

$$c_t = \begin{bmatrix} \iota_N & c^{Size} & c^{BE/ME} \end{bmatrix} D$$

The matrix $\mathbf{c}_t$ represents a cross-section of firm characteristics for firms in our sample at time *t.* Consequently the vector of premia associated with the characterises is:

$$\hat{q}_t = \begin{bmatrix} \hat{\theta}^{Const} & \hat{\theta}^{Size} & \hat{\theta}^{BE/ME} \end{bmatrix} D$$

The matrix **D** is a diagonal matrix of indicator variables that specifies the factors in each regression equation and η_t are the normally identically independently distributed (n.i.i.d.) disturbance terms. Inclusion of individual assets into the Fama-MacBeth tests will be subject to standard restrictions on price and liquidity.

Brennan *et al.* (1998) warn that if the error in the factor loadings is correlated with the characteristics, the Fama-MacBeth estimates of characteristic premia may be biased. If such dependence exists, Brennan *et al.* (1998) note that the time-series of estimated premia is correlated with the factors of the asset pricing model that is used to adjust for risk; and, the coefficient estimate is biased by a proportion of the mean of the factor. The bias is particularly important for the JSE, as

[10]This correction is not applicable to all firms in the sample, as not all firms suffer from the problem of thin trading. Inclusion of unnecessary factor lags in regressions will affect the time-series of estimates of pricing errors ($\alpha_i + \varepsilon_i$); thus the lags of factors are not included in the top 20 percent of largest firms. Also, there is an additional lag (for the total of two) included in the estimation of residuals for the smallest 20 percent of firms.

it is plausible that for small firms, the estimated loading is biased thanks to illiquidity.

Consequently, Brennan *et al.* (1998) propose the estimator that corrects for this mismeasurement. They estimate a premium to characteristic j, $\hat{\xi}_j$, as:

$$\hat{\theta}_j = \hat{\xi}_j + f\hat{k}_j' + u_j \quad \ldots (8)$$

In effect, Equation 8 is a time-series regression of time-series of the characteristic premia computed in each cross-sectional regression in the Fama-MacBeth procedure, $\hat{\theta}_j$, onto factors of a given model, f. The unbiased premium to the characteristic is the intercept term of regression above. Trivially, $\hat{k}_j$ is a vector of arbitrary estimators and u_j is a series of n.i.i.d. disturbance terms. The *t*-statistic associated with the intercept is used for inference, but the variance-covariance matrix of the coefficients computed in regressions of the type shown above is estimated with the Newey and West (1987) method. Thus, the effects of serial correlation of up to four lags are removed.

3. RESULTS

3.1 Time-series test of the CAPM and the RS-APT with the size and value assets.

We begin by looking at two base cases, where assets thought to capture the size and the value effects are subjected to risk adjustment with models that are commonly used among practitioners. At first we look at CAPM-adjusted returns and in the second case we look at returns adjusted by the two-factor APT model proposed by Van Rensburg and Slaney (1997), who provide evidence that their model is more appropriate for explaining returns on the JSE. The philosophy behind the methodology employed in the study stems from arguments in Lo and MacKinlay (1990), as they advocate the use of characteristic-sorted portfolios as tests assets because they note that if the characteristic is correlated with the model's pricing errors then the power of the test is increased.

At first we test the CAPM. In Table 1 we examine the results of the regressions of the twelve test assets onto the standard market factor and its lag. The direction of the mispricing pans out according to the pattern predicted by the size and the value effects. In other words, intercepts of portfolios with small and value firms are generally positive and intercepts of portfolios with large and growth firms are generally negative, and seven (out of the 24) intercepts are different from zero. When we conduct the GRS test which collectively ascertains the statistical significance of the pricing errors we see that the CAPM is rejected at the 10%.

Next we calculate the magnitude of the size effect that is independent of the value effect after risk adjustment with the CAPM. The average spread in intercepts between small and large firms is 0,89% per month on the equal-weighted basis and 1,01% per month on the value-weighted basis. Both of these returns are different from zero at conventional levels, with t-statistics of 2,23 and 2,07 for the equally and value weighted effects, respectively. Risk adjustment with the CAPM brings the spread of intercepts between value and growth firms, on average, to 0,74% per month on the equal-weighted basis and 0,43% on the value-weighted basis. The statistical significance of these effects is low. On the value-weighted basis the size-adjusted value effect yield a t-statistic of 1,02, and thus is not statistically different from zero. On the equal-weighted basis, it yields a t-statistic of 1,67 and is significant at 10%.

Next we turn to the test of the RS-APT model. In Table 2 we show the results of the regressions of the excess returns of the test assets onto the Resi and the Findi factors and their lags. This model too fails in explaining the size and the value effect. In this case, 9 (out of 24) pricing errors are different from zero at conventional levels of statistical significance. The GRS test which tests for joint significance of the asset pricing errors also rejects the model: on the equal-weighted basis the model is rejected at the 10% level, the test rejects the model at the 5% level in the value-weighted case.

When compared to the CAPM case, if the RS-APT model is used to adjust for risk, the magnitude of the size effect that is independent of the value effect decreases somewhat as the average spread of alphas between large and small firms falls somewhat to 0,95% per month on the value-weighted basis and 0,86% on the equal-weighted basis. Both of these estimates are reliably different from zero at the 5% level, with t-statistics of 2,02 and 2,15 for the value-weighted and equal-weighted estimates respectively. The size-adjusted value effect after adjustment with the RS-APT marginally rises to 0,46% on the value-weighted basis and 0,78% on the equal-weighted basis. However, on the value-weighted basis it is not different from zero at conventional levels (t-statistic is 1,22), but on equal-weighted basis it is different from zero at the 5% level, with a t-statistic of 2,01.

Table 1: The size and value effects after adjustment for risk: The CAPM test

Panel A: The GRS test

Value-Weighted Assets		Equal-Weighted Assets	
F	p-value	F	p-value
1,577	0,097	1,613	0,087

Panel B: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I (Value)	0,32	0,26	0,75**	1,07***	47,3%	57,7%	48,1%	41,6%	0,43	0,48	0,91***	1,32***	59,3%	53,1%	43,8%	27,0%
	0,660	0,730	2,180	2,610					0,820	1,300	2,490	3,560				
II (Middle)	0,20	0,25	0,03	1,04**	45,2%	86,7%	57,5%	49,7%	0,34	0,38	0,01	0,99**	81,1%	45,7%	50,1%	31,0%
	1,080	0,870	0,070	2,180					1,340	1,150	0,030	2,110				
III (Growth)	-0,41**	0,02	0,04	1,02*	35,8%	88,0%	57,0%	52,2%	-0,37	-0,29	0,11	0,76	81,4%	56,2%	50,5%	20,0%
	-2,390	0,050	0,080	1,800					-1,640	-0,610	0,240	1,420				
	Value-Weighted Assets								Equal-Weighted Assets							
	b_M				$b_{M(lag)}$				b_M				$b_{M(lag)}$			
I (Value)	1,15***	0,71***	0,61***	0,51***	0,00	0,21***	0,27***	0,24***	1,16***	0,72***	0,61***	0,40***	0,03	0,21***	0,26***	0,23***
	9,650	12,500	8,750	9,230	-0,040	3,230	3,640	2,440	9,190	10,97	9,680	8,320	0,300	3,090	3,750	2,700
II (Middle)	1,04***	0,62***	0,62***	0,55***	-0,01	0,21***	0,23***	0,17**	0,89***	0,63***	0,62***	0,53***	0,06**	0,23***	0,25***	0,20***
	22,180	15,710	5,260	7,660	-0,410	4,540	4,370	1,990	17,840	9,920	9,040	8,900	2,020	4,660	3,720	2,460
III (Growth)	1,02***	0,69***	0,71***	0,50***	-0,07***	0,13***	0,25**	0,19***	0,97***	0,71***	0,71***	0,55***	-0,01	0,15***	0,27***	0,10
	17,590	7,670	7,060	5,380	-2,220	2,610	3,310	2,590	14,620	8,680	7,510	6,310	-0,400	2,810	3,710	1,350

- significant at 10% level, ** significant at 5% level, *** significant at 1% level

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,M}\left(r_{M,t} - r_{f,t}\right) + b_{i,M(lag)}\left(r_{M,t-1} - r_{f,t-1}\right) + \varepsilon_{i,t}$$ for *t*= 1,2,3…T and *i* = 1,2,3,…N

The regressions are run between July 1992 and July 2005 and t-statistics are calculated with the Newey-West (1987) standard errors using four leads and lags. The r_M is the return on the market factor, which is the value-weighted return of all securities in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The intercept terms are multiplied by 100 for clarity.

Lastly, we emphasize the importance of including the lagged term in the regressions. In the CAPM tests of Table 1, all but three of these loadings are not greater than zero at conventional statistical levels. Actually, a vast majority is different from zero at the 1% level. In addition, the size of the lagged loading is negatively correlated with firm size in that the smaller firms tend to exhibit larger values for the lagged betas. In the RS-APT test, a similar pattern is observed in the Findi factor, as it is reliably different from zero in most 18 (of the 24) regressions, and inversely correlated with firm size. Curiously, the lags on the Resi factor are scantly significant. However, since these loadings ought to be small *a priori*, their low statistical significance may be a consequence of statistical noise.

3.2 Time-series tests of the Fama and French models

Basiewicz and Auret (2009) have shown that on the JSE there is a considerable spread in returns between firms with different size or BE/ME ratios, and we have just shown that the spread does not disappear with an adjustment for risk with the CAPM or the RS-APT. Next, we turn to tests of the Fama and French model of returns on the JSE[11]. The results of time-series tests for the FF3F are shown in Table 3.

Generally, the magnitude and sign of the loadings on the FF3F factors corresponds to the size and value-growth indicator captured by each test asset. In other words, loadings on the SML are larger for portfolios containing smaller firms and loadings on the VMG are greater for portfolios containing firms with high BE/ME ratios. Curiously not all of the assets that contain large firms load negatively on the size factor. In fact, in tests that use equal-weighted assets, these loadings are positive and statistically different from zero. This result is an indication of the skewness in the distribution of market values on the JSE; there are few large firms and the rest of the firms are medium or small. In addition, the same loadings on assets that include growth firms are not reliably negative, but are never significant. Could it be a consequence of there being few truly growth firms listed on the JSE?

[11] We examine in detail only the results of FF3F. We leave out the analysis of the FF3F which replaces the Market factor with the Resi and Findi factors. The results are very similar to the tests of the FF3F. Please contact the authors for the results of these tests.

Table 2 The size and value effect after adjustment for risk: The RS-APT test

Panel A: The GRS test

Value-Weighted Assets		Equal-Weighted Assets	
F	p-value	F	p-value
1,849**	0,041	1,774*	0,052

Panel B: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assetsx							
	α				R^2				α				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I (Value)	0,40	0,32	$0,83^{***}$	$1,12^{***}$	48,9%	56,8%	54,5%	50,3%	0,51	0,54	$0,98^{***}$	$1,37^{***}$	62,8%	58,6%	49,4%	31,9%
	0,850	0,920	2,360	2,870					1,030	1,580	2,620	3,800				
II (Middle)	0,31	0,29	0,07	$1,07^{**}$	50,0%	79,4%	65,1%	57,4%	$0,39^{*}$	0,41	0,05	$1,03^{***}$	85,4%	57,6%	58,7%	31,1%
	1,200	1,060	0,170	2,320					1,800	1,430	0,130	2,230				
III (Growth)	-0,33	0,03	0,08	$1,04^{*}$	42,9%	81,4%	70,8%	62,2%	$-0,32^{*}$	-0,28	0,14	0,76	87,4%	68,0%	60,2%	27,6%
	-1,410	0,090	0,200	1,940					-1,720	-0,650	0,380	1,500				

	Value-Weighted Assets								Equal-Weighted Assets							
	b_R				$b_{R(lag)}$				b_R				$b_{R(lag)}$			
I (Value)	$0,39^{***}$	$0,29^{***}$	$0,31^{***}$	$0,25^{***}$	-0,01	0,00	-0,04	0,00	$0,41^{***}$	$0,35^{***}$	$0,25^{***}$	$0,24^{***}$	-0,05	0,01	0,01	0,01
	5,090	5,040	4,840	3,920	-0,130	0,100	-0,860	0,070	4,600	6,010	3,940	4,550	-0,650	0,400	0,340	0,160
II (Middle)	$0,33^{***}$	$0,08^{**}$	0,07	0,05	-0,03	-0,03	-0,02	-0,02	$0,22^{***}$	$0,08^{**}$	$0,11^{**}$	$0,13^{***}$	0,04	$-0,05^{**}$	-0,04	-0,02
	10,390	2,260	1,510	0,810	-1,200	-1,250	-0,440	-0,380	5,780	1,940	2,200	2,230	1,290	-1,810	-0,780	-0,330
III (Growth)	$0,17^{***}$	0,01	$0,08^{*}$	$0,19^{*}$	-0,01	0,00	$-0,07^{*}$	-0,06	$0,09^{**}$	0,00	0,06	0,12	-0,03	0,01	-0,04	-0,02
	3,100	0,390	1,780	1,750	-0,240	0,040	-1,950	-0,710	2,350	-0,080	1,310	1,260	-1,140	0,180	-0,990	-0,240

	Value-Weighted Assets								Equal-Weighted Assets							
	b_I				$b_{I(lag)}$				b_I				$b_{I(lag)}$			
I (Value)	$0,85^{***}$	$0,54^{***}$	$0,39^{***}$	$0,39^{***}$	0,00	$0,16^{***}$	$0,24^{***}$	$0,19^{***}$	$0,86^{***}$	$0,52^{***}$	$0,45^{***}$	$0,28^{***}$	0,08	$0,14^{***}$	$0,21^{***}$	$0,18^{***}$
	6,880	7,940	5,860	5,780	0,040	3,360	3,640	2,860	7,210	7,220	8,040	4,680	0,790	2,910	3,460	3,020
II (Middle)	$0,73^{***}$	$0,59^{***}$	$0,62^{***}$	$0,55^{***}$	-0,02	$0,24^{***}$	$0,22^{***}$	$0,18^{**}$	$0,78^{***}$	$0,62^{***}$	$0,60^{***}$	$0,46^{***}$	0,00	$0,28^{***}$	$0,25^{***}$	$0,19^{**}$
	17,020	16,160	5,300	6,080	-0,440	5,460	4,590	2,000	19,060	13,15	9,860	6,520	0,060	6,010	5,040	2,090
III (Growth)	$0,87^{***}$	$0,76^{***}$	$0,70^{***}$	$0,41^{***}$	$-0,09^{**}$	$0,14^{***}$	$0,30^{***}$	$0,24^{***}$	$0,95^{***}$	$0,79^{***}$	$0,72^{***}$	$0,54^{***}$	-0,01	$0,16^{***}$	$0,31^{***}$	0,12
	16,170	11,100	7,760	4,870	-1,770	3,450	4,980	2,920	19,270	12,25	8,790	7,160	-0,240	4,200	5,440	1,580

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,R}\left(r_{R,t} - r_{f,t}\right) + b_{i,R(lag)}\left(r_{R,t-1} - r_{f,t-1}\right) + b_{i,I}\left(r_{I,t} - r_{f,t}\right) + b_{i,I(lag)}\left(r_{I,t-1} - r_{f,t-1}\right) + \varepsilon_{i,t}$$

for *t*= 1,2,3…T and *i* = 1,2,3,…N

The regressions are run between July 1992 and July 2005 and t-statistics are calculated with the Newey-West (1987) standard errors using four leads and lags. The r_R is return the Resi factor, which is the value-weighted return of all Resource shares in the dataset. The r_I is the Findi factor, which is the value-weighted return of all Financial and Industrial shares in the dataset, All returns are adjusted for dividends and other payouts. The portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The intercept terms are multiplied by 100 for clarity.

It appears that SML captures a significant amount of variation of the test assets, with value-weighted assets, only one of the 12 estimated loadings on the size factor are not significant; if assets are weighted equally, two of the loadings are not significant. Interestingly, nearly all of the betas that are different from zero are more than three standard deviations from the mean, and some loadings yield *t*-statistics that are as high as those calculated for the market betas.

The VMG is not as robust as the SML. In the value-weighted tests, six out of 12 loadings on the value factor are not significant, while in the equal-weighted tests six are also not significant. However, many of the loadings are different from zero at the 1% level, indicating that the factor is important in capturing variations in returns. Also, not all firms are exclusively value or growth; there are many neutral firms that ought to be uncorrelated with the value factor. In fact, in tests similar to the ones presented here, Fama and French (1996a) do show that about a quarter of the portfolios do not load on their value factor.

The pattern above can be contrasted with the results in Scher and Muller (2005), who also construct a version of the FF3F. Although they do not form portfolios with the same methods used here, they do show 14 assets that are similar to the 12 presented here. In their case, ten assets load significantly on the size factor and only six (less than half) are positive at the 1% level. In contrast, in the tables presented here, all but one or two of the betas on the size factor are not different from zero at the 1% level. In addition, Scher and Muller (2005) find only 4 out of 14 assets (less than a third) load significantly on the value factor, but none of them at the 1% level. In the tests presented here, six (or half) of test assets load positively onto the value factor, and five are different from zero at the 1% level. These findings would suggest that our factors could be more appropriate for asset pricing on the JSE.

Although the pricing errors of the FF3F indicate that the model does not eradicate the size and the value effects because small, and mostly value, firms continue to produce reliably positive intercepts and the portfolios of large growth firms are also mispriced which indicate that the results of the tests seem supportive of the model. The size and the value factors capture a considerable amount of return variation, as the R^2 in all regressions is large - much higher than in the tests of the CAPM. More importantly, the GRS test does not reject the FF3F model as the p-values for both the value-weighted and the equal-weighted specification is well above 90%.

The model's pricing errors can be contrasted to the CAPM and the RS-APT model shown in Tables 1 and 2. In sum, it appears the FF3F has better ability to explain the value effect, but, although it fails to explain the size effect, it reduces its magnitude considerably. Specifically, after adjustment for the value effect, the average spread between intercepts of small and large small stocks is, on average, 0,65% per month on a value-weighted basis and 0,61% per month on an equal-weighted basis. However, both of these effects remain statistically different from zero at conventional levels. The value-weighted and value-adjusted size effect yields a *t*-statistic of 1,9, while on equal-weighted basis it is high at 2,33.

The value effect also seems to be tempered by the FF3F. Risk adjustment brings the average spreads between value and growth firms down to 0,26% per month on the value-weighted basis and 0,60% on the equal-weighted basis. Both estimates are not different from zero at conventional levels: the value-weighted effect yields a t-statistic of 0,77 and the equal-weighted effect yields a t-statistic of 1,62.

3.3 The Fama and French models versus the firm characteristics model

We now turn to our tests on ungrouped data. In these tests we regress pricing errors of individual stocks in our universe onto the firm size and BE/ME ratio, as these characteristics have been shown to have predictive power for stock returns. A coefficient that is close to zero on a given characteristic indicates that the asset pricing model being tested can account for predictability associated with that characteristic. If the coefficient remains significant it implies that risk-adjustment with a given asset pricing error was incomplete and the model is rejected. We first show the results of the two base cases: the adjustment with the CAPM and the adjustment with the APT of van Rensburg and Slaney (1997). The tests use Fama-MacBeth regressions described in Brennan *et al*. (1998), which adjust coefficients for the bias stemming from correlation of individual cross-sectional coefficients and the asset pricing factors. The results are shown in Table 4.

Although both the value and the size effects are marginally reduced after adjustment for risk, it seems that the CAPM and the RS-APT do not "price out" firm characteristics. The RS-APT does a somewhat better job at pricing the effects, as the coefficients on all of the characteristics are smaller. In both specifications, the coefficients on the BE/ME ratio, when tested jointly with the size effect, are no longer different from zero at the 5% level, but are reliably positive at the 10% level.

The three factor model is now tested directly against the characteristics model, as the ability of the model to "price out" characteristics is a direct testimony to its validity. Although the size effect does diminish somewhat after correction with the FF3F, it remains robust. Importantly, it remains significant at the 1% level in most regressions. However, the value effect dissipates after adjustment for risk is made. In particular, even in the univariate regressions, the coefficients on the BE/ME ratio are not significant at the 5% level. Although, the coefficient on the BE/ME ratio is reliably positive at the 10% level, any return predictability associated with the ratio disappears after size is included as the explanatory variable. It has been shown by Basiewicz and Auret (2009) that firm market capitalisation and it's BE/ME ratio are correlated; thus it is plausible that the coefficient on size captures some of the BE/ME premium. Such bias is likely to be small and, given the small coefficients on the BE/ME ratio, certainly not large enough to restore the BE/ME as a valid predictor of returns.

Out findings are somewhat at odds with other South African research. In particular, in results of Van Rensburg and Robertson (2004) firm characteristics keep their power to forecast returns after control for factor loadings. This is true for both loadings on the size and value factor. For our results to fully corroborate their findings we would need to see reliably significant coefficients on the BE/ME and size characteristics. However, in Table 4, we see that after risk-adjustment with the FF3F, BE/ME loses its predictive power, and size effect is attenuated. A possible reason lies in the difference between the methodology used in this study and the Van Rensburg and Robertson (2004) study.

Table 3 The size and the value effect after adjustment for risk: the FF3F test

Panel A: The GRS test

Value-Weighted Assets		Equal-Weighted Assets	
F	p-value	F	p-value
0,610	0,9577	0,552	0,9810

Panel B: Size and BE/ME sorted portfolios

	Value-Weighted Assets								Equal-Weighted Assets							
	A				R^2				*α*				R^2			
	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)	I (Big)	II	III	IV (Small)
I (Value)	$0,15$	$0,11$	$0,37$	$0,65^{**}$	59,5%	58,3%	52,4%	54,6%	$0,25$	$0,31$	$0,54^{*}$	$0,86^{***}$	60,5%	56,5%	60,3%	57,3%
	0,340	0,320	1,340	2,020					0,500	0,840	1,870	3,290				
II (Middle)	$0,24$	$0,02$	$-0,23$	$0,65^{*}$	46,9%	87,6%	71,8%	70,8%	$0,28$	$0,10$	$-0,34$	$0,64^{*}$	81,4%	60,2%	72,0%	47,0%
	1,350	0,090	-0,870	1,890					1,050	0,410	-1,260	1,850				
III (Growth)	$-0,27^{*}$	$-0,12$	$-0,16$	$0,78^{*}$	39,5%	89,0%	65,7%	72,9%	$-0,37^{**}$	$-0,43$	$-0,12$	$0,48$	84,6%	66,6%	71,2%	32,0%
	-1,740	-0,330	-0,600	1,720					-1,970	- 1,000	-0,450	1,050				

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

The table shows results of time-series regressions

$$r_{i,t} = \alpha_i + b_{i,M}\left(r_{M,t} - r_{f,t}\right) + b_{i,M(lag)}\left(r_{M,t-1} - r_{f,t-1}\right) + b_{i,SML}\left(r_{SML,t} - r_{f,t}\right) + b_{i,VMG}\left(r_{VMG,t} - r_{f,t}\right) + \varepsilon_{i,t}$$ for *t*= 1,2,3…T and *i* = 1,2,3,…N

The regressions are run between July 1992 and July 2005 and t-statistics are calculated with the Newey-West (1987) standard errors using four leads and lags. The r_{SML} is a return on a zero-cost portfolio of small capitalization stocks financed with a short position of large capitalization stocks (SML, Small minus Large). Similarly, r_{VMG} is a return on a zero-cost portfolio with a long position in value stocks financed with a short position in growth stocks (VMG, Value minus Growth). SML and VMG are analogous to SMB and HML in Fama and French (1993). The r_M is the return on the Market factor, which is the value-weighted return of all securities in the dataset. All returns are adjusted for dividends and other payouts. The size and BE/ME portfolios are with an intersection of four size-sorted portfolios and three BE/ME-sorted portfolios. The intercept terms are multiplied by 100 for clarity.

Table 4 Testing the CAPM and RS-APT against firm characteristics

	Adjusted Coefficients			
	Constant	Size	BE/ME	Average R^2
Panel A: CAPM-adjusted returns				
(1)	$8,37^{***}$	$-5,94^{***}$		0,012
t-stat	2,49	-3,56		
(2)	$6,72^{***}$		$4,82^{***}$	0,010
t-stat	2,49		2,98	
(3)	$8,59^{***}$	$-4,86^{***}$	$3,04^{*}$	0,021
t-stat	2,56	-2,76	1,81	
Panel B: APT-adjusted returns				
(1)	$7,54^{***}$	$-5,69^{***}$		0,013
t-stat	2,50	-3,45		
(2)	$6,01^{***}$		$4,51^{***}$	0,008
t-stat	2,54		3,06	
(3)	$7,83^{***}$	$-4,84^{***}$	$2,75^{*}$	0,020
t-stat	2,55	-2,77	1,80	
Panel C: FF3F-adjusted returns				
(1)	$7,31^{***}$	$-4,12^{***}$		0,007
t-stat	3,54	-2,89		
(2)	$5,11^{***}$		$3,00^{*}$	0,013
t-stat	3,49		1,70	
(3)	$7,22^{***}$	$-3,46^{**}$	1,52	0,012
t-stat	3,58	-2,30	0,82	

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

The adjusted coefficients in the table are calculated with method in Brennan, Chordia and Subrahmanyam (1998), coefficients are the intercepts of time-series regressions the factors on month-by-month coefficients of cross-sectional OLS regressions of model's pricing errors. Model's pricing error of firm *i* in time *t* is a sum of a intercept of a time-series regression of firm's *i* excess return on model's factors and this regression's a residual at time *t*. t-statistics are calculated with the Newey-West (1987) standard errors. Full listing period was used in the time-series regressions. The regressions of top 20% largest firms do not include lagged factors. The regressions of smallest 20% of firms include two lags of the factors on the Market, Resi or Findi factors. The remainder of regressions include one lag of the factor on the Market, Resi or Findi factor. Each month, only stocks with liquidity measure of more than 0,1% or cost more than 100c are included in the regression. Liquidity measure is a twelve-month average of monthly trading volume scaled by end-month shares in issue. Size is the natural logarithm of stock's market capitalization, which is a product of the number of shares outstanding and the share price, BE/ME is the book value of equity scaled by market capitalization. All variables are standardized and winzorised at 2,5% and 97,5%. The reported R^2 is the average of individual R^2 of each cross-sectional regressions. All coefficients are multiplied by 1000, for clarity.

Our findings also contradict one aspect of the results found in Brennan *et al*. (1998), as the authors show that the BE/ME premium persists after control for risk with the FF3F. However, in a longer sample of US stocks, Davis, Fama and French (2000) show evidence that three-factor model may "price out" the explanatory power of characteristics. This finding implies that if the test employed here was to be used in that sample, the BE/ME premium would likely not survive the adjustment for risk with the FF3F.

4. CONCLUSION

In this paper we constructed and tested the three factor model of Fama and French (1993). The tests have provided support for these models for returns on the JSE. The GRS tests have not rejected the model. Specifically, in the time-series test, the spread in pricing errors between small and large firms, as well as value and growth, is reduced when compared with the base case, the risk adjustment with "traditional" models like the CAPM and the RS-APT.

In a time-series test on grouped data, the FF3F have been able to account for the value effect. In the tests on ungrouped data, we found that BE/ME ratio loses its power to predict the pricing errors of these models after size has been included as the explanatory variable. This is a marked success of the three factor model, especially given that these tests have high power. In time-series tests, the size effect has attenuated, but has not been extinguished. In our regressions on ungrouped data, market capitalisation (size) has shown significant power, statistically speaking, to predict the pricing errors left behind by the FF3F.

How does our model compare to the time-series tests of Fama and French (1993)? We see two salient differences. First, our three factor model misprices different types of assets. In the US, it is the return on the portfolios of small and growth firms that is particularly poorly predicted by the model; while it is the small and value firms that the South African model fails to price. Second, the difference is the direction of the mispricing. In the US, the model generally overpredicts the return on small firms and underpredicts the return on large firms an opposite pattern to the one observed here. Curiously, the magnitude of the size and the value premia estimated here are very similar to those in the US, thus the disparity in the results is most probably explained by the much larger spread in the loading on the size and the value loadings that is observed in the US. In fact, a typical spread between the loadings on the size factor is about 1,4, while in the South African data a corresponding spread is about 1. More importantly, the spread between loadings on the value factor is about 1,1 in US data, while the corresponding estimate computed on South African data is about 0,3. We believe there are few truly growth firms listed on the JSE. We believe that persistence of the size effect is not a consequence of irrational mispricing and that market microstructure effects are the main reason for the presence of the size effect. Acharya and Pedersen (2005) and Stoll and Whaley (1983) show that market microstructure effects can explain the size premium and such adjustments (inclusion of a liquidity factor for example) have not been performed here. In addition, the information story of Merton (1987) applies directly to the size effect. The JSE is an illiquid market, where, in comparison to the US, much less time and money is spent on equity research for smaller firms, and thus we are likely to observe more severe mispricing for smaller firms. In fact, on US data, Brennan *et al*. (1998) show that the size effect persists after a control for risk with the FF3F is made, but it dissipates after an adjustment for market microstructure effects. We recommend that this area of research that can be tapped in the future.

Lastly, we would like to address a valid criticism of the three factor model that endogeneity is the sole reason for its successes. In other words, it should not be surprising that returns on a set of assets can be explained by factors computed with a similar method as the test portfolios. Although, it is recognised that endogeneity must have some effect on the results of our asset pricing tests, we can reliably point to a number of properties in our results, which argue against endogeneity being the key driver of the results. For sake of brevity, we would like to omit a thorough discussion on why we believe this to be the case. Correspondence with the authors on this subject will be welcomed as this topic is possibly a fertile area for future research.

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