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ABSTRACT

The finite sample performance of the Wald, GMM and Likelihood Ratio (LR) tests of multivariate asset pricing tests have been investigated in several studies on the US financial markets. This paper extends this analysis in two important ways. Firstly, considering the fact that the Wald test is not invariant to alternative non-linear formulation of the null hypothesis the paper investigates whether alternative forms of the Wald and GMM tests result in considerable difference in size and power. Secondly, the paper extends the analysis to the emerging market data. Emerging markets provide an interesting practical laboratory to test asset pricing models. The characteristics of emerging markets are different from the well developed markets of US, Japan and Europe. It is found that the asymptotic Wald and GMM tests based on Chi-Square critical values result in considerable size distortions. The bootstrap tests yield the correct sizes. Multiplicative from of bootstrap GMM test appears to outperform the LR test when the returns deviate from normality and when the deviations from the asset pricing model are smaller. Application of the bootstrap tests to the data from the Karachi Stock Exchange strongly supports the zero-beta CAPM. However the low power of the multivariate tests warrants a careful interpretation of the results.

Keywords: Zero-beta CAPM, Multivariate Test, Wald, LR, Emerging Markers.

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I. INTRODUCTION

Asset pricing models and their empirical tests constitute a major component of the finance literature. Univariate testing of the Capital Asset Pricing Model (CAPM) introduced by Fama and MacBeth (1973) employed a two-stage test procedure. This two-step procedure has been criticized on two concerns. Firstly the cross section tests involve estimated regressors and therefore are subject to errors-in-variable bias. Secondly asset pricing tests in particular and econometric methods in general that involve estimation or testing in stages are shown to lack efficiency and therefore are less powerful. Affleck-Graves and Bradfield (1993) conclude through simulations that frequent rejection of CAPM tests or equivalently non-rejection of hypothesis that there is no positive linear relationship between beta and returns is due to the low power of the univariate tests associated with smaller sample sizes. According to Shanken (1996) the statistical properties of multi-stage tests are difficult to assess.

Gibbons (1982) developed a multivariate test of the Black's (1972) zero-beta CAPM. In this test the zero-beta CAPM restrictions are directly imposed on the system of multivariate market model equations with each equation corresponding to an asset. The test results in a Likelihood Ratio statistic which is asymptotically Chi-Square distributed. This test does not involve estimated betas as the regressors so the errors-in-variable problem is not of any concern. The test also makes better use of available cross equation information. The multivariate test of Gibbons, Ross and Shaken (1989) is perhaps the most widely used test of the Sharpe-Lintner form of the CAPM. This test provides an exact F-test in the multivariate testing framework. It is valid in small samples if an appropriate risk-free rate of is available. These multivariate tests have been widely used in US and other developed markets data. Both of these multivariate asset pricing tests assume that the returns and the residuals are normally distributed and are cross sectionally dependent but serially uncorrelated and homoskedastic.

Typically a general asset pricing model should satisfactorily describe empirical data under varied market conditions. Unfortunately the multivariate asset pricing studies have not been performed for emerging markets. Emerging markets provide an interesting practical laboratory to test asset pricing models. Several studies have suggested that the characteristics of emerging markets are different from the well developed markets of the US, Japan and Europe. For example, Harvey (1995) found that (i) emerging markets have a higher level of volatility and price changes than developed markets, (ii) a majority of the emerging markets had non-normal returns and (iii) the returns are more predictable than the developed markets. Consequently any multivariate asset pricing test applied to emerging market data need to be robust to these distributional characteristics. Greene (2003, p-110) points out that amongst the three asymptotic tests namely the Wald, LR and LM, only the Wald test is asymptotically valid under non-normality. Its computation requires unconstrained parameters estimates for which OLS (or SUR in system context) can be readily applied. The Wald test assumes the return to be identically and independently distributed (*iid*). The GMM based version of the test allows the test to be conducted with weaker distributional assumptions. Application of asset pricing tests in emerging markets possesses another difficulty. Due to frictions in the money market there are restrictions in unlimited lending and borrowing and so an appropriate risk free-rate is difficult to secure for the emerging capital markets. Fortunately, the Black-CAPM does not require specifying a risk-free rate. This CAPM version is therefore a potential financial model for these markets. Consequently we focus on application and comparison of the performance of several multivariate tests of Black's zero-beta CAPM in the emerging market context.

The finite sample performance of Wald and LR tests of zero-beta CAPM have been investigated in several studies on US markets. The results usually favour the LR test. The Wald test is not invariant to alternative non-linear formulation of the null hypothesis[1]. Therefore it is of interest to study whether a given non-linear form of the Wald test results in considerably different results in finite sample size and power performance of the Black-CAPM especially in comparison to the LR test. Previous studies have not considered this aspect. To be more specific, the null hypothesis that the zero-beta CAPM holds is expressed as

$$H_0 : \alpha_i = \gamma(1-\beta_i), \; i = 1,\ldots,N \tag{1}$$

Here γ represents the zero-beta rate, α_i and β_i are respectively the intercept and slope of *i*th asset in the system of market model equations.

We consider two alternative formulations of this hypothesis:

$$g_{1i} = \frac{\alpha_i}{1-\beta_i} - \frac{\alpha_{i+1}}{1-\beta_{i+1}} = 0, \quad i = 1,\ldots,N-1 \tag{2}$$

and

$$g_{2i} = \alpha_i(1-\beta_{i+1}) - \alpha_{i+1}(1-\beta_i) = 0, \qquad i = 1,\ldots,N-1 \tag{3}$$

The first formulation which we referred to as ratio type is employed by Chou (2000) using the US data and Chou and Lin (2002) for OECD countries data for the Black-CAPM tests. Bealieu et al. (2004) argue that such a formulation suffers from an identification problem due to discontinuity as beta approaches one. As many

[1] This was first demonstrated by Gregory and Veall (1985) via a simulation analysis. They show that the Wald test resulting from two formulations of the same hypothesis e.g. $H_{01} : \beta_1 - 1/\beta_2 = 0$ and $H_{02} : \beta_1\beta_2 - 1 = 0$ are numerically not identical in finite samples.

portfolios betas tend towards one [See Blume (1975)], the sampling distribution of the test statistic with this form may behave poorly in the right tail. Therefore the associated test developed from such a formulation converges poorly to the asymptotic Chi-Square distribution. A formulation similar to that in (2) which we refer to as a multiplicative formulation is considered in Amsler and Schmidt (1985).

This paper addresses the issue of invariance property of the Wald test by considering the non-linear formulations of the Wald and GMM tests and compares them with the LR test. We show that asymptotic Wald and GMM tests result in serious size distortions while the LR test gives more accurate sizes when the returns are allowed to follow certain parametric distribution. For the case when the residuals are non-parametrically resampled from the observed data the performance of the LR test is equally poor. The bootstrap tests rectify the size distortions and render the Wald and GMM tests at par with the LR test. Comparing the alternative formulations of the GMM test it is found that when there are smaller deviations from the asset pricing model the multiplicative form of the GMM test outperform the LR and other tests. As the deviations from the asset pricing tests increase the ability of the LR tests to detect the difference increase rapidly compared to the other tests.

The tests are applied to the monthly portfolio returns from the Karachi Stock Exchange[2] which is the largest of the three stock markets in Pakistan. Khawaja and Mian (2005) remarks this market has the typical features of an emerging market. In addition investigating this market might be interesting for investors as for 2002 the market was declared the best performing market in the World in terms of the percent

[2] The Karachi Stock Exchange is the largest of the three stock markets in Pakistan. In mid April, 2006 the market capitalization was a US$ 57 billion which is 46 percent of Pakistan's GDP for the Fiscal Year 2005-06. (Ref: Pakistan Economic Survey 2005-06)

increase in the local market index. See Iqbal and Brooks (2007) for implications of portfolio allocation in this market.

The plan of the paper is as follows. Section II discusses the formulation of the Wald, GMM and LR tests of the Black's CAPM. This section also describes the bootstrap tests. Section III describes the data used in the study and provides some specification tests on the market model residuals. Section IV briefly discusses the result of the empirical tests. In section V the empirical size and power of the tests are evaluated using Monte Carlo simulation experiments. Section VI provides conclusion.

II. MULTIVARIATE TESTS OF THE ZERO-BETA CAPM

A. The Wald test

We assume that the return generating process is the familiar market model:

$$R_t = \alpha + \beta r_{mt} + \varepsilon_t, \quad t = 1,\ldots,T \tag{4}$$

Here $R_t = [r_{1t}\ r_{2t}\ \ldots r_{Nt}]'$ is the $N \times 1$ vector of raw returns on N portfolios, ε_t is the $N \times 1$ vector of disturbances, α and β are $N \times 1$ vector of the intercept and slope parameters respectively. The zero-beta CAPM specifies the following cross sectional relation:

$$E(R_t) - \gamma 1_N = \beta(E(r_{mt}) - \gamma) \tag{5}$$

Here γ is the parameter representing returns on the zero-beta portfolio.

Applying the expectation on (4) yields

$$E(R_t) = \gamma(1 - \beta) + \beta E(r_{mt}), \ i = 1,\ldots,N \tag{6}$$

Comparing (5) and (6) the joint restrictions on the parameter imposed by the zero-beta CAPM are expressed in the following hypothesis.

$$H_0 : \alpha_i = \gamma(1-\beta_i),\ \ i = 1,\ldots,N \tag{7}$$

This is essentially a non-linear constraint on the system of market model equations and the iterative estimation and an LR test for the hypothesis is provided in Gibbons (1982). Chou (2000) developed a Wald test that permits the model to be estimated entirely in terms of alpha and betas by expressing the null hypothesis as:

$$H_0 : \frac{\alpha_i}{1-\beta_i} = \gamma,\ \ i = 1,\ldots,N \tag{8}$$

This is equivalent to $N-1$ joint hypotheses

$$H_0 : \frac{\alpha_1}{1-\beta_1} = \frac{\alpha_2}{1-\beta_2} = \ldots. = \frac{\alpha_N}{1-\beta_N} \tag{9}$$

Let

$$g_i = \frac{\alpha_i}{1-\beta_i} - \frac{\alpha_{i+1}}{1-\beta_{i+1}},\ i = 1,\ldots.N-1 \tag{10}$$

Denote $g(\theta) = [\, g_1 .\ .\ .\ . g_{N-1}\,]'$,where $\theta = [\,\alpha_1 \quad \beta_1 \ .\ .\ .\quad \alpha_N \quad \beta_N\,]'$

The hypothesis to be tested is

$$H_0 : g(\theta) = 0$$

Note that the under normality and *iid* assumption on the error term the OLS estimate $\hat{\theta}$ is asymptotically normally distributed.

$$\hat{\theta} \sim N(0, \Sigma \otimes (X'X)^{-1})$$

Here X is the $T \times 2$ design matrix with a column of 1's and a column containing return of the market portfolio. If the normality assumption is violated then under the *iid* assumption the limiting distribution of $g(\hat{\theta})$ can still be approximated by a normal distribution. Thus the Wald test for the zero-beta CAPM can be formulated as

$$W_1 = g(\hat{\theta})' \left[\left(\frac{\partial g}{\partial \theta'}\Big|_{\theta=\hat{\theta}} \right) \hat{\Sigma} \otimes (X'X)^{-1} \left(\frac{\partial g}{\partial \theta'}\Big|_{\theta=\hat{\theta}} \right)' \right]^{-1} g(\hat{\theta}) \xrightarrow{d} \chi^2_{N-1} \tag{11}$$

Here the partial derivatives $\frac{\partial g}{\partial \theta'}$ are evaluated at the OLS estimates from the unrestricted system.

Keeping in view the concern of Bealieu *et al.* (2004) regarding this form of the Wald test we consider an alternative formulation of the zero-beta CAPM hypothesis with a multiplicative form for the non-linear restriction

$$g_i = \alpha_i(1-\beta_{i+1}) - \alpha_{i+1}(1-\beta_i), \qquad i = 1, \ldots, N-1 \tag{12}$$

In this case the matrix of the partial derivatives is as follows:

$$\frac{\partial g}{\partial \theta'} = \begin{bmatrix} (1-\beta_2) & \alpha_2 & -(1-\beta_1) & -\alpha_1 & 0 & 0 & 0 & . & . & . & 0 \\ 0 & 0 & (1-\beta_3) & \alpha_3 & -(1-\beta_2) & -\alpha_2 & 0 & . & . & . & 0 \\ . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . \\ . & . & . & . & . & . & . & . & . & . & . \\ 0 & 0 & 0 & . & . & . & 0 & (1-\beta_N) & \alpha_N & -(1-\beta_{N-1}) & -\alpha_{N-1} \end{bmatrix} \tag{13}$$

The Wald test can be formulated similar to previous case and is given by (11) with g_i and $\frac{\partial g}{\partial \theta'}$ replaced by (12) and (13) respectively. The test statistic is distributed asymptotically as a Chi-Square distribution with N-1 degrees of freedom.

B. The GMM Test

Although the Wald tests are justified under non-normality they still require the assumption of *iid* disturbances. It is widely reported especially for emerging markets that the residuals may be serially correlated. For example, Harvey (1995) reports such evidence for a group of emerging markets that the returns show greater predicability in these markets than the developed markets. Evidence of serial correlation is also reported in Tables 1 and 2 for our portfolio returns calculated from the Karachi Stock Exchange data.

One approach to deal with the non-spherical residuals is to employ an estimated robust covariance matrix in the Wald statistics and proceed with the test

$$W_1 = g(\hat{\theta})^{/}\left[\left(\frac{\partial g}{\partial \theta^{/}}\Big|_{\theta=\hat{\theta}}\right)\hat{V}_T\left(\frac{\partial g}{\partial \theta^{/}}\Big|_{\theta=\hat{\theta}}\right)^{/}\right]^{-1} g(\hat{\theta}) \tag{14}$$

Here V_t is the HAC covariance matrix of the parameter estimates. This test is asymptotically distributed as Chi-Square, for details see Ray *et al.* (1998). We can show that the same Wald statistics can be derived using the Hansen's (1982) Generalized Method of Moments. The GMM tests do not require strong distributional assumption regarding normality, heteroskedasticity and serial independence of the residuals. With N assets and T time series observation on each asset the moment conditions vector can be defined as:

$$f_T(\theta) = \begin{bmatrix} \varepsilon_{1t}(\alpha_1, \beta_1) \\ \varepsilon_{1t}(\alpha_1, \beta_1)\mathrm{r_{mt}} \\ \varepsilon_{2t}(\alpha_2, \beta_2) \\ \varepsilon_{2t}(\alpha_2, \beta_2)\mathrm{r_{mt}} \\ . \\ . \\ . \\ \varepsilon_{Nt}(\alpha_N, \beta_N) \\ \varepsilon_{Nt}(\alpha_N, \beta_N)\mathrm{r_{mt}} \end{bmatrix} = \varepsilon_t(\theta) \otimes x_t \quad \text{and} \quad h_T(\theta) = \frac{1}{T}\sum_{t=1}^{T}\varepsilon_t(\theta) \otimes x_t \tag{15}$$

Now we have 2N moment conditions and 2N parameters to be estimated therefore the multivariate system of 2N equations is exactly identified. Here $x_t = [1 \quad r_{mt}]^{/}$

$$\varepsilon_t(\theta) = [\varepsilon_{1t} \;\; \varepsilon_{2t} \;\; \ldots \; \varepsilon_{Nt}]^{/} \text{ and } \varepsilon_{it} = R_{it} - \alpha_i - \beta_i r_{mt}$$

The GMM[3] estimate of the parameter minimizes the quadratic form of the sample moment restriction vector

$$\hat{\theta}_{GMM} = arg\,min \;\; h_T(\theta)' \; W_T \; h_T(\theta) \tag{16}$$

Here W_T is a positive definite weighting matrix whose elements can be functions of parameters and data. Hansen (1982) shows that the optimal weighting matrix is

$$W_T = S^{-1} = \{ Asy\ Var\,[\sqrt{T}\;\, h_T(\theta)]\}^{-1} \tag{17}$$

The asymptotic covariance matrix of the GMM estimator is

$$V = [\,D' S^{-1} D\,]^{-1} \tag{18}$$

Where $D = P\,lim\,[\frac{\partial}{\partial\theta'} h_T(\theta)]$. In practice ' S ' and ' D ' are unknown but the asymptotic results are valid for some consistent estimator ' S_T ' and ' D_T '. For the exactly identified case Mackinlay and Richardson (1991) show that the portfolio efficiency can be tested by first estimating the unrestricted system and then computing the test statistics of the efficiency hypothesis which involve these unrestricted estimates. Moreover in this case the GMM estimator is independent of the weighting matrix and is the same as the OLS estimator; however the covariance matrix must be adjusted to allow for heteroskedasticity and serial correlation. The GMM estimates are asymptotically normally distributed

$$\sqrt{T}\,(\theta - \hat{\theta}) \;\; \sim \;\; N(0, V\;)$$

Here V is as defined above. Any non-linear function g($\hat{\theta}$) of the parameter is also asymptotically normal

$$\sqrt{T}\;[\,g(\theta) - g(\hat{\theta})] \;\; \sim \;\; N\,[\,0, (\frac{\partial g}{\partial\theta'}\,)\,V\;\;(\frac{\partial g}{\partial\theta'}\,)'\;]$$

[3] The just identified system therefore leads to a simple method of moment estimator rather than a generalized method of moment estimator. We continue to use the term 'GMM' following use of the term in literature in this case.

Therefore the GMM based Wald test for the can be formulated as

$$W_2 = g(\hat{\theta})' \left[\left(\frac{\partial g}{\partial \theta'} \Big|_{\theta=\hat{\theta}} \right) \hat{V}_T \left(\frac{\partial g}{\partial \theta'} \Big|_{\theta=\hat{\theta}} \right)' \right]^{-1} g(\hat{\theta}) \qquad (19)$$

Note that GMM procedure arrives at the same Wald test that was developed without resorting to the GMM framework. In this case

$$V_T = [D_T' S_T^{-1} D_T]^{-1} \qquad (20)$$

We estimate these matrices as follows

$$D_T = \frac{1}{T} \sum_{t=1}^{T} I_N \otimes x_t x_t' = I_N \otimes X' X \qquad (21)$$

'S_T' is estimated by Newey-West (1987) HAC covariance matrix, for details see Ray et al (1998).

$$S_T = \frac{1}{T} \sum_{t=1}^{T} \hat{\eta}_t \hat{\eta}_t' + \sum_{v=1}^{p} (1 - \frac{v}{1+p}) \frac{1}{T} \sum_{t=1}^{T} [\hat{\eta}_t \hat{\eta}'_{t-v} + \hat{\eta}_{t-v} \hat{\eta}_t'] \qquad (22)$$

Here $\eta_t = e_t \otimes x_t$ so that $\eta_t \eta_t' = \varepsilon_t \varepsilon_t' \otimes x_t x_t'$. $(1/T) \sum \eta_t \eta'_{t-v}$ and $(1/T) \sum \eta_{t-v} \eta'_t$ are auto covariance matrices of lag v. Here 'p' is the lag length beyond which we are willing to assume that the correlations between η_t and η_{t-v} are essentially zero. We use the Newey-West fixed bandwidth $p = int[4 (\frac{T}{100})^{2/9}]$, where *int[ ]* denotes the integer part of the number. Mackinlay and Richardson (1991) and Chou (2000) employed the White (1980) covariance matrix as 'S_T' which corresponds to p=0 in our case. Thus these authors assume that the disturbances are heteroscedastic but serially independent. The return predicability evidence from the emerging markets calls for a robust covariance matrix such as the Newey-West (1987) covariance matrix.

C. The LR Test

Gibbons (1982) employed the LR test

$$LR = T(\log |\hat{\Sigma}^*| - \log |\hat{\Sigma}|) \xrightarrow{d} \chi^2_{N-1} \qquad (23)$$

Where $\hat{\Sigma}^*$ and $\hat{\Sigma}$ are the restricted and unrestricted covariance matrices of the estimates respectively. The test is derived under the assumption that the returns follow a multivariate normal distribution. Following Gibbons, this test has been widey applied in the multivariate asset pricing studies including Jobson and Korkie (1982), Chou (2000) and Amsler and Schmidt (1985) among others.

D. The Bootstrap Tests of the Zero-Beta CAPM

As discussed in the subsequent analysis, the asymptotic tests especially the Wald and GMM tests of the Black-CAPM have serious size distortions which impede their validity in empirical applications. In this case the residual bootstrap provides an alternative mean of obtaining more reliable p-values of the tests. It is well established that if the test statistic is asymptotically pivotal i.e. the null distribution does not rely on unknown parameters, then the error in size of the bootstrap test is only of the order $O(n^{-j/2})$ compared to the error of the asymptotic test which is of the order $O[^{-n(j+1)/2}]$ for some integer $j \geq 1$[4]. See for example Davidson and MacKinnon (1999). The bootstrap p-values are obtained as follows:

1. The unrestricted system of market model is estimated by the seemingly unrelated regression. The residuals { ε_t } are obtained and the five test statistics are computed. The system is also estimated subject to the zero-beta CAPM restrictions and the

[4] The tests considered in our investigation are all asymptotically pivotal and are asymptotically Chi-Square (N-1).

restricted parameters are estimated. The test statistic for the zero-beta CAPM say W_n is calculated.

2. The following steps are repeated 5000 times.

a. A block bootstrap sample { ε_t * } is drawn from { ε_t }. The block length chosen is same as the lag length ' p ' in the HAC covariance matrix. Then the resampled returns are obtained as $R_t{*} = \hat{\gamma}(1-\hat{\beta}) + \hat{\beta} rm_t + \varepsilon_t{*}$

b. The test statistics say W_n * is computed.

3. The bootstrap p-values are computed as the percentage of times W_n * is greater than W_n.

III. DATA AND THE DIAGNOSIS OF THE MARKET MODEL RESIDUALS

A. The Data

The data for this study comprise portfolios formed from a sample of stocks listed on the Karachi Stock Exchange (KSE) and are obtained from the DataStream database. The sample period spans nearly 13 ½ years from October 1992 to March 2006. The data consist of monthly closing prices of 101 stocks and the Karachi Stock Exchange 100 index (KSE-100). The criteria for stocks selection was based on the availability of time series data on continuously listed stocks for which the prices have been adjusted for dividend, stock split, merger and other corporate actions. The KSE-100 is a market capitalization weighted index. It comprises top companies from each sector of KSE in terms of their market capitalization. The rest of the companies are picked on the basis of market capitalization without considering their sectors. We consider the KSE-100 as a proxy for the market portfolio. The 101 stocks in the sample account for approximately eighty per cent of the market in terms of capitalization. Market capitalization data is not routinely available for all firms in the database. However the financial daily, the Business Recorder[5] report information on firms over the recent past[6]. The market capitalization of all selected stocks is collect at the beginning of July 1999 which roughly corresponds to the middle of the sample period considered in the study. We use monthly data and compute the raw returns assuming continuous compounding. To investigate robustness of the empirical results we consider portfolios based on three different formation schemes namely size, beta and industry.[7] Forming portfolios serves two important purposes. Firstly they provide an effective way of handling the curse of dimensionality of the multivariate systems. With large number of parameters working with individual stocks may result in highly imprecise estimates. Secondly forming portfolios with respect to size, beta and industry provides a means of controlling the confounding effects of these characteristics and thus enables unambiguous interpretation of results.

We construct seventeen equally weighted size and beta portfolios. This number was considered keeping in view the desire to include at least five stocks in each portfolio and to avoid over aggregation by forming too few portfolios. First the stocks are ranked on market capitalization in ascending order. The first portfolio consists of the first five stocks while the rest comprise of six stocks each. The beta portfolios are based on ranking of the stocks on the beta estimated via the market model. Portfolio return is calculated as the equally weighted average return of the stocks in the portfolio. For industry portfolios the stocks are classified into sixteen major industrial

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[5] www.businessrecorder.com.pk

[6] Due to the lack of sufficient data on capitalization and relatively short sample period the portfolio re-balancing is not performed.

[7] Some studies, such as Groenewold and Fraser (2001), report that the conclusion of an analysis may be different and even conflicting when different portfolios are employed.

sectors. The sector sizes range from two stocks in the transport sector and thirteen stocks in the communication sector[8]. These sectors serve as natural portfolios.

B. Residual diagnostic tests

All residual diagnostics and the asset pricing tests are performed for two distinct sub-periods: October 1992 to June 1999, July 1999 to March 2006 and the whole period-October 1992 to March 2006. The objective here is to examine the stability of the risk return relationship in the two sub-periods. This is important as the volatile political and macroeconomic scenario in emerging markets might make the return distribution non-stationary and unstable. Each sub-period consists of 81 monthly observations that correspond to 6 ¾ year of monthly data.

Table 1 reports the Mardia (1970) test of multivariate normality of the residuals of the unrestricted market model for the size, beta and industry portfolios. This test is based on multivariate equivalents of skewness and kurtosis measures. The results are reported for the test based on skewness and kurtosis measures separately. Both skewness and kurtosis based statistics are significant indicating and overwhelming rejection of multivariate normality of the residuals. The tests are significant for all cases with size, industry and beta portfolios. Table 2 reports the Hosking (1980) multivariate portmanteau test of no autocorrelation for up to lag 3 in the market model residuals. This test is a multivariate generalization of the univariate test[9] of Box and

[8] The industry sectors employed are Auto and allied, Chemicals, Commercial Banks, Food products, Industrial Engineering, Insurance, Oil and Gas, Investment banks and other financial companies, Paper and board, Pharmacy, Power and utility, Synthetic and Rayon, Textile, Textile Spinning and Weaving, Transport and communication and Other /Miscellaneous firms that include tobacco, metal and building material companies.

[9] The univariate JB tests for normality and the LB test of autocorrelation are also performed which indicate that normality and serial independence is rejected for many individual portfolios regressions. The results are not reported to save space.

Pierce (1970). The results provide evidence of predictability in the residuals for beta and industry portfolios and for the whole sample period for the size portfolios. The residual correlation is however not found for both sample periods with the size portfolios.

IV. THE RESULTS OF EMPIRICAL ANALYSIS

Table 3 presents the results of testing the zero-beta CAPM via the five tests. The tests are reported for the three sets of portfolios and for the two sub-periods: October 1992-June 1999, July 1999-March 2006 and for the whole period. As the asymptotic tests results in considerable size distortions only the bootstrap p-value are reported. All five tests provide strong evidence in support of the Black's zero-beta CAPM. Except for one case of the GMM test with multiplicative formulation with industry portfolios in the first sample period all the bootstrap test results in p-values above 0.9[10]. The tests are also robust across different sets of portfolios. The Wald tests with the two non-linear formulations results in numerically smaller values of the test statistics compared to the LR test which in turn is smaller in value to the GMM tests. Comparison of numerical values of the tests with the two alternative non-linear formulations results in a mixed conclusion but the alternative formulations do not appear to alter the decision to strongly support the financial model. Thus it appears that when the data provide strong support for the asset pricing model as in the present case, forming the test hypothesis in alternative ways is unlikely to change the conclusion drawn from empirical data regarding the test outcome.

[10] Chou and Lin (2002) also report the p-values of GMM and Wald tests in excess of 0.90 for the zero-beta test on the OECD data.

V. SIMULATION EXPERIMENT

To investigate how well the LR test and the Wald and GMM tests with the two formulations of the zero-beta CAPM perform under various distributional specification and to examine their finite sample behaviour we investigate their size and power for the case of size sorted portfolios. Assuming that the null hypothesis is true we evaluate the rejection probabilities that estimate the percent of time of the null hypothesis is rejected in the simulation experiment and compare them with the nominal significance levels. The larger differences between the nominal and empirical rejection rates would indicate that the tests have larger size distortions thereby making the tests statistically unreliable. For power comparison we have chosen the alternative form similar to that employed by Gibbons (1982) i.e.

$$H_1 : \alpha = \gamma(1-\beta) + N(c,1) \quad (24)$$

We chose c = 1 to 3 with an increment of 0.5. That is a normally distributed component is added to intercept vector. According to Gibbons (1982) this type of alternative is compatible with a variety of asset pricing models that are competitors of the CAPM such as the Merton (1973) inter-temporal model with one state variable. This alternative will test the sensitivity of the zero-beta CAPM tests if the average returns are systematically over estimated relative to that predicted by the zero-beta CAPM.

We first consider the case when the returns are generated by bootstrapping the error terms from the residuals of the market model. As table 2 indicates that the residuals may be serially correlated we performed block bootstrap with block length that is equal to the lag length of the HAC covariance matrix[11]. This choice of block length is consistent with Inoue and Shintani (2006). In this way the finite sample performance

[11] A sensitivity analysis indicates that increasing the block length does not alter the conclusion significantly.

of the tests are investigated when the tests encounter real data. Next we evaluate the size and power of the tests under the assumption that the residuals and returns follow an *iid* normal distribution. To examine the behaviour of the tests when the returns have higher kurtosis and heavier tails relative to normal distribution we also considered the case of errors following a t-distribution with 5 degrees of freedom. To investigate the performance of the tests when the returns data have skewness we considered a mixture normal distribution as an alternative model of the residuals. Finally we examine the non-*iid* distributed data by specifying an autoregressive model of order one for the errors. The sample sizes considered are T = 60 and 162. The first sample size of five years monthly data is considered in most US studies of multivariate asset pricing tests. The second sample size corresponds to entire available sample period which correspond to 13.5 years monthly data.

To generate residual vector from a multivariate normal distribution with zero mean and covariance matrix Σ we set

$$\varepsilon_t = L z_t , \tag{25}$$

Here L is the Cholesky factor of Σ (i.e. $\Sigma = L'L$) and z_t is an $N \times 1$ vector of standard normal random numbers. The residuals from the t-distribution were generated by setting

$$\varepsilon_t = \frac{1}{\sqrt{(\chi_v^2 / v)}} L z_t , \tag{26}$$

Where χ_v^2 denotes a Chi-Square random variate with v degrees of freedom. We set v = 5 to introduce leptokurtosis relative to the normal distribution. We simulated the residual from a mixture normal distribution by setting

$$\varepsilon_t = pN(0,\Sigma) + (1-p)N(\eta,\tau\Sigma) \tag{27}$$

Following Chou (2000) we set the parameter as p=0.7 and τ=5. The negative skewness[12] in the returns was introduced by setting η as the vector of the standard deviation of the observed market model residuals. To ensure zero mean of the disturbances we subtracted $(1-p)\eta$ from the generated residuals. To introduce a non-*iid* distribution for the returns we generated the residuals from a AR (1) model by setting

$$\varepsilon_t = A\varepsilon_{t-1} + e_t \tag{28}$$

The parameters in the diagonal matrix A and the covariance matrix of the residual vector were estimated from the observed data on the market model residuals. As discussed subsequently the Wald and GMM tests with asymptotic Chi-Square critical values result in quite erratic test sizes. The correct sizes were therefore obtained using a computationally intensive bootstrap procedure. The size simulation was carried out as follows:

(1) The null hypothesis is incorporated in the market model and returns are generated from the following equation:

$$R_t{}^* = \hat{\gamma}(1-\hat{\beta}) + \hat{\beta}\, rm_t + \varepsilon_t{}^* \tag{29}$$

The parameters γ, β and Σ are estimated from the observed data in the respective sample. The data on the residuals are drawn from one of the alternative distribution. The observed market portfolio returns is employed in the simulations. The parameters of restricted and unrestricted system of market model are estimated and the test statistic say W_n is computed.

(2) We obtain B = 200 bootstrap runs by resampling the returns from equation (29) again but this time using the parameter estimates from step (1). For each bootstrap

[12] Nine out of 17 observed residuals from the market model regressions have negative skewness. Therefore we have chosen to introduce negative skewness in the returns.

the systems is estimated and the test statistics say W_n* is computed. Bootstrap critical value correspond to a nominal level of ‘a’ as (1-a)th quantile of the bootstrap distribution formed from the 200 W_n * values are obtained.

(3) The above two steps are repeated 5000 times. The size of asymptotic tests is computed as the empirical rejection probability that W_n exceeds the Chi-Square (N-1) critical values in these 5000 simulations. We compute the size of bootstrap tests as empirical rejection probability that W_n exceeds quantile of the bootstrap distribution.

For power simulations the following two step procedure is employed.

(1) The returns from the following equation is generated

$$R_t{*} = \hat{\gamma}(1-\hat{\beta}) + N(c,1) + \hat{\beta}\, rm_t + \varepsilon_t{*} \qquad (30)$$

We estimate γ, β and Σ from the observed data in the respective sample. The data on the residuals are drawn from one of the alternative distribution. The parameters of restricted and unrestricted system of market model are estimated and the test statistic say W_n is computed.

(2) The step (1) is repeated 5000 times for each c from 1 to 3 in the increment of 0.5. The power of the tests is computed as the empirical rejection probability that the computed test exceed the bootstrap critical values obtained in the size simulations. As there are some size distortions even at bootstrap critical values we evaluate only the size corrected power. Our simulations design for size and power evaluation resembles Hall and Horowitz (1996) although we employ a larger number of simulations (5000 instead of 1000) and number of bootstraps (200 instead of 100).

Table 4 presents the rejection probabilities of the five tests of the zero-beta CAPM at the critical values obtained from asymptotic Chi-Square distribution. Except for the case of bootstrap residuals the sizes of the LR test are closer to the nominal values compared to the Wald and GMM tests. Similarly except for the first case of bootstrap distribution both non-linear formulations of the Wald tests results in severe under-rejection. In general no form of the Wald test can be preferred over the other. One the other hand both formulations of the GMM tests over-reject. Increase in sample size from 60 to 162 make the size distortion nearly half but to eliminate the size distortions completely would require much larger sample sizes which are difficult to secure especially for emerging markets. Overall it can be concluded that the LR test results in smaller size distortions for *iid* data. This result is also found to be quite robust to distributional deviation from normality either in the form of higher skewness or excess kurtosis. It appears that when the asymptotic tests face real data (the first case in panel 1) no one of them performs satisfactorily.

As the asymptotic test give quite severe size distortions it is worthwhile to consider the tests with bootstrap critical values. The rejection probabilities of the bootstrap tests are presented in Table 5. The first and very obvious observation from the bootstrap tests is their closer approximation to the nominal sizes. Except for a few cases the error in approximation of the test sizes to the nominal sizes is within 1 % for all the five tests. For example the average percent approximation error for the Wald test with ratio and multiplicative formulation is 0.33, 0.15, 0.31 percent and 0.25, 0.14, 0.42 percent respectively with nominal size of 1%, 5% and 10 %. Generally drawing any conclusion regarding the relative merits of the size of the two formulations is difficult. The two formulations of both the Wald and the GMM tests compare quite favourably with the LR test when the size is evaluated at bootstrap critical values. It is concluded that the asymptotic LR test dominate the other tests especially with the *iid* data but this generalization to bootstrap tests is not extended. In fact bootstrapping the Wald and GMM tests have rendered these tests at par with the LR test despite their poor asymptotic performance.

As the asymptotic tests result in quite erratic test sizes we investigate the power only at the bootstrap critical values. Figure 1 present the empirical rejection probabilities of the five tests of the zero-beta CAPM at bootstrap critical values obtained from the size simulations with sample size of 60. The power is computed using the first five years market return data and using the parameter estimates over this period. The LR test clearly dominates the other in the cases of Normal, Mixture Normal and Autoregressive errors. For other two cases GMM test with multiplicative formulation perform better when the test is subject to a smaller deviations from the null hypothesis. At relatively larger deviations LR test dominates the other ones. This result appears to be robust to various type of non-normalities introduced in the simulation experiment as far as the return data remain identically distributed. Also as the distance from the null hypothesis increases the gain in power is more rapid for the LR test. The power of the Wald and GMM tests remain low at the conventional sample size consisting of 5 years monthly data. The power of the Wald and GMM tests do not exceed 0.40 in any of the cases. Figure 2 presents the power when sample size increases to 162 which corresponds to all available sample data. The LR test generally dominates the other tests especially when the returns are subject to larger deviations from the asset pricing model. At relatively smaller deviations the GMM test with multiplicative formulation performs better than the LR tests in cases that represent deviations from non-normality such as the excess kurtosis captured by Student T errors, higher deviation from skewness represented by a Mixture Normal distribution and the case when errors are generated from the real data by bootstrapping. For the normal case the multiplicative form of Wald and GMM test appear to perform better than the ratio formulations. Figure 1 and 2 reveal that power of the Wald and GMM tests appear to increase less rapidly compared to the LR tests as the deviations from the null hypothesis increase. In practice it is difficult to determine the extent of departure from the null hypothesis but it is clear that when the distance between the null and alternative models is smaller it will be extremely difficult for the both asymptotic and the bootstrap tests to detect the difference. Consequently the acceptance of the asset pricing model pose a question of whether the data actually support the model or the results merely reflect the low power of the tests under considerations. This comment applies to the results of empirical tests reported in table 3 for the data from the Karachi Stock market. It is nevertheless expected that bootstrap LR and GMM tests with larger sample sizes will detect the economically and statistically significant differences between the null and alternative models. Thus even the bootstrap based version of these tests requires a careful consideration in practical applications of multivariate asst pricing with finite samples especially in emerging markets.

VI. CONCLUSION

The paper examines the finite sample performance of five multivariate tests of the zero-beta CAPM. The empirical performance of the tests is examined on an emerging market data. It is well established that return characteristics of the emerging markets differ from that of the developed markets. Moreover we account for the fact that money markets in the emerging markets are not perfect so that a reliable risk-free rate is difficult to obtain. The tests considered are Gibbons (1982) LR test and two non-linear formulations of the Wald and an associated GMM test. The formulation of the Wald statistic of the Black-CAPM restriction employed in earlier research [for example, Chou (2000) and Lee *et al.* (1997)] might be associated with identification problems when the parameters of the model (beta of the portfolios) approach one. The paper therefore investigated an alternative formulation of the Wald test and the associated GMM test of the asset pricing model. A Monte Carlo simulation experiment demonstrates that the size distortions of asysmptic tests are considerably higher especially for the Wald and GMM tests. However bootstrap tests rectify the size distortions and render the Wald and GMM tests at par with the LR test. Comparing the alternative formulations of the GMM test it is found that when there are smaller deviations from the asset pricing model the multiplicative form of the GMM test outperform the LR and other tests. As the deviations from the asset pricing tests increase the ability of the LR tests to detect the difference increase rapidly compared to the other tests. While the asymptotic LR test for *iid* data results in correct sizes the Wald and GMM test require computational intensive resampling procedures to recover the correct rejection probabilities. In larger samples the GMM test with the multiplicative formulation generally results in higher power compared to the test with a ratio type formulation. The tests results are based on monthly portfolio data from an emerging market-the Karachi Stock Exchange. The tests strongly support the zero-beta CAPM. However the finite sample properties of the multivariate tests found in the study indicates that non-rejection might be caused by the low power of the tests.

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Table 1: Test of multivariate normality of Market Model residuals

Sample Period	Size Portfolios		Beta Portfolios		Industry Portfolios	
	Skewness	Kurtosis	Skewness	Kurtosis	Skewness	Kurtosis
Oct 92 – Jun 99	95.04 (0.000)	351.05 (0.000)	81.79 (0.002)	345.46 (0.000)	78.62 (0.000)	307.80 (0.000)
Jul 97 – Mar 06	89.89 (0.000)	344.71 (0.000)	84.106 (0.000)	346.28 (0.000)	75.73 (0.000)	308.19 (0.000)
Oct 92 – Mar 06	55.30 (0.000)	372.47 (0.000)	51.07 (0.000)	377.44 (0.000)	47.67 (0.000)	337.32 (0.000)

This table reports the tests of multivariate normality of the residuals of the unrestricted market model. P-values are given in the parenthesis. The Mardia (1970) test of multivariate normality is based on the multivariate skewness and kurtosis measures $D_1 = \frac{1}{T^2}\sum_{t=1}^{T}\sum_{s=1}^{T} r_{ts}{}^3$ and $D_2 = \frac{1}{T}\sum_{t=1}^{T} r_{tt}{}^2$ where $r_{ts} = (X_t - \overline{X})S^{-1}(X_s - \overline{X})$, $\overline{X}$ and S are the sample mean and sample covariance matrix of the residuals respectively. $TD_1/6 \sim \chi^2(f)$ where $f = N(N+1)(N+2)/6$, and $D_2 - \frac{N(N+2)}{\sqrt{8N(N+2)/T}} \sim N(0,1)$

Table 2: Test of serial independence of unrestricted Market Model residuals

Sample Period	Size Portfolios			Beta Portfolios			Industry Portfolios		
	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3	Lag1	Lag2	Lag3
Oct 92 – Jun 99	314.92 (0.141)	626.20 (0.080)	899.47 (0.215)	322.50 (0.085)	628.34 (0.072)	920.50 (0.101)	322.84 (0.002)	594.57 (0.006)	878.34 (0.003)
Jul 97 – Mar 06	312.27 (0.165)	603.84 (0.221)	928.18 (0.073)	339.95 (0.020)	637.04 (0.044)	935.06 (0.053)	286.30 (0.093)	560.00 (0.069)	815.88 (0.112)
Oct 92 – Mar 06	346.26 (0.011)	633.12 (0.055)	922.88 (0.091)	363.82 (0.001)	656.21 (0.013)	943.21 (0.036)	333.35 (0.000)	580.95 (0.018)	855.10 (0.015)

This table reports the tests of serial independence of the residuals of the unrestricted market model. P-values are given in the parenthesis. The Hosking (1980) multivariate portmanteau test is a multivariate generalization of the univariate portmanteau test of Box and Pierce (1970). The test statistic at lag length *s* is

$$Q(s) = T^2\sum_{j=1}^{s}\frac{1}{T-j}tr(C'_{0j}C_{00}{}^{-1}C_{oj}C_{00}{}^{-1}) \sim \chi^2(N^2 s)$$

where $C_{rs} = \frac{1}{T}U'_{-r}U_{-s}$, U_{-i} is the $T \times N$ residual matrix lagged i periods. The test is performed for *s* = 1 2, 3. The initial missing values are filled with zero.

Table 3: The test of Black-CAPM

This table presents the values of the five test statistics resulting from the test of the Black CAPM. Bootstrap p-values based on 5000 simulations are given in parenthesis.

Note: The Wald and GMM tests are adjusted by multiplying (T-N-1)/T and LRT test statistics is adjusted by (T-1.5-N/2)/T to improve their small sample performances. See Gibbons, Ross and Shanken (1989) and Jobson and Korkie (1982) for detail.

Portfolio Method	Wald1	Wald 2	GMM 1	GMM 2	LR
Panel 1: Oct 92 – Jun 99					
Size	6.381	6.504	12.394	15.689	7.445
	(0.978)	(0.981)	(0.983)	(0.941)	(0.996)
Beta	4.885	5.029	5.897	5.815	6.0238
	(0.989)	(0.989)	(0.997)	(0.998)	(0.994)
Industry	10.175	10.113	15.687	19.012	12.295
	(0.944)	(0.973)	(0.992)	(0.896)	(0.983)
Panel 2: Jul 97 – Mar 06					
Size	9.500	8.891	13.134	11.033	10.482
	(0.944)	(0.974)	(0.983)	(0.994)	(0.995)
Beta	10.642	10.648	17.085	19.638	14.551
	(0.985)	(0.976)	(0.981)	(0.943)	(0.987)
Industry	12.583	8.757	24.350	16.613	14.403
	(0.978)	(0.992)	(0.996)	(0.995)	(0.994)
Panel 3: Oct 92 – Mar 06					
Size	8.593	9.748	15.271	13.205	11.709
	(0.982)	(0.976)	(0.962)	(0.982)	(0.977)
Beta	9.775	9.9759	15.147	12.091	11.893
	(0.959)	(0.956)	(0.959)	(0.984)	(0.966)
Industry	11.391	8.762	17.768	10.833	13.927
	(0.960)	(0.985)	(0.999)	(0.998)	(0.974)

Table 4: Size of the Black-CAPM tests with Asymptotic Chi Square Critical Values

This table provides the empirical rejection probabilities of five tests of Black-CAPM model each evaluated with five alternative distribution specifications of the residuals. The result for a nominal size of 'a' % correspond to number of times the test statistic exceeds the (1-a) % quantile of Chi Square Distribution with N-1 degrees of freedom divided by the number of simulation i.e.5000. The market portfolio from observed data is employed in these experiments.

	Wald 1			Wald 2			GMM 1			GMM 2			LR		
	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Panel 1 : Bootstrap Distribution															
T =60	0.023	0.057	0.099	0.010	0.042	0.074	0.500	0.648	0.730	0.475	0.649	0.728	0.259	0.416	0.522
T=162	0.045	0.138	0.230	0.031	0.135	0.220	0.448	0.648	0.751	0.408	0.614	0.726	0.159	0.364	0.507
Panel 2: Normal Distribution															
T =60	0.001	0.001	0.002	0.000	0.001	0.004	0.143	0.249	0.326	0.147	0.260	0.347	0.012	0.052	0.109
T=162	0.002	0.012	0.032	0.002	0.015	0.036	0.056	0.147	0.220	0.056	0.146	0.231	0.008	0.046	0.096
Panel 3. Student t Distribution with 5 degrees of freedom															
T =60	0.001	0.001	0.001	0.000	0.000	0.001	0.120	0.216	0.293	0.116	0.218	0.293	0.010	0.055	0.099
T=162	0.002	0.005	0.016	0.000	0.005	0.013	0.043	0.115	0.181	0.038	0.116	0.186	0.009	0.049	0.097
Panel 4. Mixture Normal Distribution															
T =60	0.002	0.002	0.002	0.000	0.000	0.000	0.093	0.183	0.248	0.106	0.211	0.286	0.010	0.056	0.106
T=162	0.001	0.004	0.012	0.001	0.007	0.014	0.031	0.096	0.161	0.035	0.101	0.160	0.012	0.048	0.098
Panel 5 : AR(1)															
T =60	0.000	0.001	0.003	0.000	0.000	0.001	0.141	0.254	0.333	0.144	0.265	0.349	0.011	0.048	0.096
T=162	0.003	0.012	0.027	0.001	0.011	0.030	0.054	0.130	0.206	0.052	0.141	0.213	0.010	0.042	0.083

Table 5: Size of the Black-CAPM tests with Bootstrap Critical Values

This table provides the empirical rejection probabilities of five tests of Black-CAPM model each evaluated with five alternative distribution specifications of the residuals. The result for a nominal size of 'a' % correspond to number of times the test statistic exceeds the (1-a) % quantile of the bootstrap distribution constructed from bootstrapping the test statistics 200 times. The rejection probabilities are based on 5000 simulations. The market portfolio from observed data is employed in these experiments.

	Wald 1			Wald 2			GMM 1			GMM 2			LR		
	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%	1%	5%	10%
Panel 1: Bootstrap Distribution															
T =60	0.020	0.063	0.119	0.011	0.051	0.096	0.014	0.052	0.099	0.014	0.053	0.106	0.016	0.059	0.110
T=162	0.013	0.048	0.096	0.013	0.049	0.103	0.014	0.059	0.110	0.017	0.059	0.109	0.012	0.051	0.102
Panel 2: Normal Distribution															
T =60	0.010	0.046	0.097	0.012	0.046	0.090	0.017	0.055	0.097	0.029	0.076	0.124	0.013	0.054	0.104
T=162	0.015	0.054	0.099	0.018	0.057	0.106	0.012	0.055	0.106	0.012	0.050	0.096	0.011	0.049	0.098
Panel 3: Student t Distribution with 10 degrees of freedom															
T =60	0.008	0.038	0.080	0.019	0.037	0.078	0.016	0.053	0.099	0.012	0.050	0.094	0.016	0.058	0.103
T=162	0.014	0.050	0.098	0.013	0.051	0.100	0.015	0.058	0.105	0.014	0.046	0.088	0.013	0.053	0.101
Panel 4: Mixture Normal Distribution															
T =60	0.010	0.036	0.078	0.008	0.042	0.085	0.011	0.045	0.087	0.010	0.042	0.087	0.013	0.057	0.106
T=162	0.016	0.052	0.108	0.016	0.053	0.106	0.013	0.050	0.104	0.016	0.056	0.103	0.015	0.054	0.109
Panel 5: AR(1)															
T =60	0.012	0.049	0.101	0.011	0.051	0.100	0.013	0.053	0.099	0.013	0.045	0.085	0.016	0.055	0.105
T=162	0.014	0.049	0.093	0.015	0.049	0.096	0.013	0.054	0.102	0.013	0.051	0.099	0.018	0.055	0.102

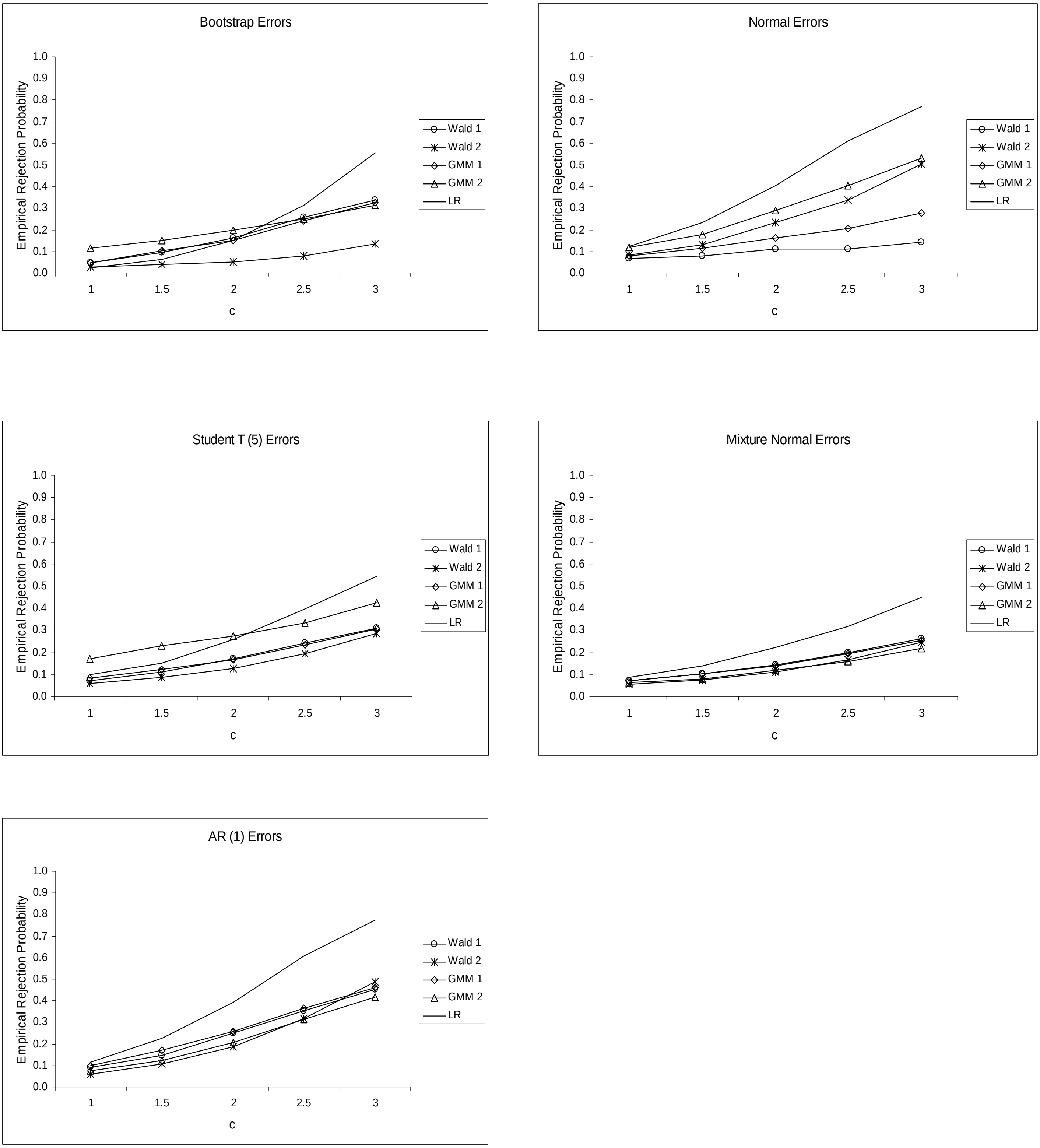

Fig 1: The size corrected power of the bootstrap tests of the zero-beta CAPM under errors generated from alternative distribution at T=60 (at 5% nominal level).

Note: The size corrections are done by employing critical values from size simulations. The rejection probabilities are computed from 5000 simulations. Here ‘c’ measures the deviation from the null hypothesis. The sample size is T=60. This corresponds to 5 years monthly data.

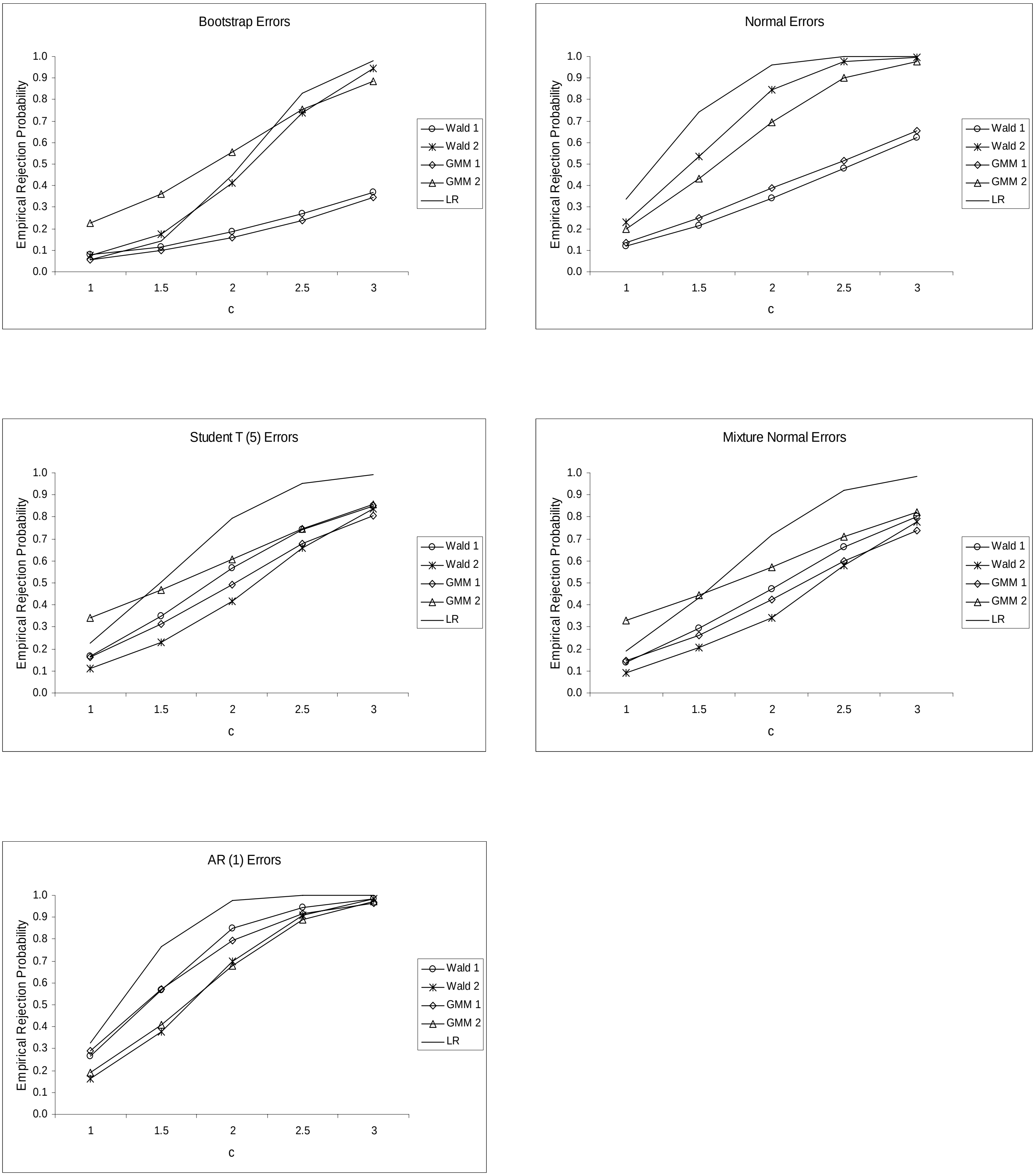

Fig 2: The size corrected power of the bootstrap tests of the zero-beta -CAPM under errors generated from alternative distribution at T =162 (at 5% nominal level).
Note: The size corrections are done by employing critical values from size simulations. The rejection probabilities are computed from 5000 simulations. Here ‘c’ measures the deviation from the null hypothesis. The sample size is T =162. This corresponds to 13.5 years monthly data.

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