Creating efficient portfolio returns applying forecasting techniques and bootstrapping in FTSE 100 and XETRA DAX.

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Abstract

This paper presents forecasting techniques for the British FTSE – 100 and the German XETRA DAX indices that derive from normality tests. We use the Moving Average (MA) approach for 1, 2, and 3 lags, as well as Auto Regressive (AR) for 1, 2, and 3 lags based on daily data. The tests produce satisfactory results and investigate that the movement of the indices can be explained from these statistical techniques. This paper also adopts the traditional Bootstrap test for residuals independence. When using Bootstrap the hypothesis of residual independence cannot be rejected and the power of the forecasting techniques becomes stronger. Hence, we apply the Generalised Method of Moments (GMM) for a non – linear parametric model and we try to identify if it is applicable for optimal portfolio selection criteria. The empirical results show that a portfolio manager can possibly produce a satisfactory return in the long term based on MA, AR, Bootstrap, and GMM techniques.

1. Introduction

The aim of this research is to use the Bootstrap method on the British Index FTSE – 100 and the Xetra DAX indices and to investigate the accuracy of traditional forecasting techniques analysing the market movements. The success of many financial strategies is measured by comparisons against a variety of benchmarks. Equity tracking funds follow a passive strategy in an attempt to produce high returns in conjunction with low risk. Researchers have recently applied extensively the bootstrap method but never relation with forecasting techniques which are widely used by city practitioners, like the MA (3) and AR (3) tests or the Generalised Method of Moments, to the best of our knowledge.

During the last decade, many studies have carried out research based in bootstrapping (see Efron and Tibshirani (1993), which provide a promising tool to practitioners to solve the traditionally unsolvable problems. However, there are cases where standard bootstrap does not perform properly (see Pin – Huang Chou (2004)) and the results do not support the traditional asymptotic theories or simple Markov Chain Monte Carlo Methods. Thus, in this paper, we investigate that using specified probabilistic conditions which are always in line with real market movements and expectations bootstrap produces highly accurate and reliable results in comparison to traditional methods which are either based upon the large number distribution properties of the observations [Pakes (1986), Rust (1987) and Stern (1997)] or the prior beliefs of the authors [Albert and Chib (1993), and Elerian, Chib, and Shephard (2001),], especially for inferences based upon small samples.

Following the research carried out from Pin – Huang Chou (2004) who investigated that the tests were not satisfactory because stock returns are far from iid normally distributed we go investigate normally distributed residuals, obtaining satisfactory results for our tests for both indices. Compared to Chou (2004) we do not create event parameters to introduce special conditions that may lead us to directions that affect the market; and that instead of assuming that there exists normality, we observe it. Moreover, we systematically test for evidence of heteroscedasticity and multi-colinearity. We also perform a non-linear model tested with generalised method of moments.

Furthermore, in cases when standard bootstrap procedures do not produce unbiased or consistent, refinements are suggested to handle this incompatibility. Specifically, Künsch (1989), Politis and Romano (1992), and Freedman (1981) E. Flachaire (2003) and James MacKinnon (2002) proposed different novel bootstrap methods to solve problems in empirical, econometrical and financial analysis.

This paper is organised as follows. Section 2 introduces methodological issues of employing basic Bootstrap methods. Section 3 provides the empirical evidence investigated from the research and provides the results from the applications. Finally, section 4 supplements a short conclusion of this paper and provides suggestions for further research directions.

2. Methodological issues

2.1 The model specification and hypothesis

In our research we use the AR (1), AR (2), AR (3) and MA (1), MA (2), MA (3) forecasting models, we check for the residuals and we apply the bootstrap test on the residuals to determine independence checking for $p < 0.05$.

Standard bootstrap hypothesis test can be explained as follows. Suppose the statistics of interest is θ and the null hypothesis we want to test is $\theta \le \theta$ ($\theta = \theta_0$) for some $\theta_{0,}$ and the alternative hypothesis is $\theta \ge \theta_{0.}$ / $\sqrt{}$ Var (θ) for some θ_0, Then, a pivotal statistics *V* which is a function of θ and θ_0 is constructed (e.g. the *t* statistics usually used in regression model is $(\theta - \theta_0) / \sqrt{\mathrm{Var}(\theta)}$).

From the sample data, we can compute the value of such statistics *d*. Further, we employ the standard bootstrap resampling procedure to calculate the bootstrap sample value of *V* denoted as di^* (i=1 2 … n). Thereafter, we calculate the frequency of the event that di^* is greater than d:

$$P^* d = (1 / n) \sum^{n}_{i=1} I (d_n^* \le d) \qquad (1)$$

this is the bootstrap P-value of the original hypothesis tests. Suppose $P^* d < \alpha$ at a given significant level α, we have sufficient reason to discredit the null hypothesis.

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Our hypothesis is based on the assumption that if $p>0.05$ the hypothesis of residuals independence (= forecasting is accurate) is rejected. As we will see later, the results in Bootstrap investigate the linearity.

To perform the test we follow instruction notes from classical text books. Hence, we first choose a distance, ε. We then consider a pair of points. If the observations of the series truly are iid, then for any pair of points, the probability of the distance between these points being less than or equal to epsilon will be constant. We denote this probability by c_1 (ε).

Then we consider sets consisting of multiple pairs of points. One way we can choose sets of pairs is to move through the consecutive observations of the sample in order. That is, given an observation, and an observation of a series X, we can construct a set of pairs of the form

{[Xs,Xt], [Xs+1,Xt+1], [Xs+2,Xt+2],….,[Xs+m-1, Xt+m-1]} (2)

where m is the number of consecutive points used in the set, or embedding dimension. We denote the joint probability of every pair of points in the set satisfying the epsilon condition by the probability c_m (ε).

The Bootstrap test proceeds by noting that under the assumption of independence, this probability will simply be the product of the individual probabilities for each pair. That is, if the observations are independent then:

$c_m(\varepsilon) = c_1^{m}(\varepsilon)$ (3)

When working with sample data, we do not directly observe $c_1(\varepsilon)$ or $c_m(\varepsilon)$. We can only estimate them from the sample. As a result, we do not expect this relationship to hold exactly, but only with some error. The larger the error, the less likely it is that the error is caused by random sample variation. The Bootstrap test provides a formal basis for judging the size of this error.

To estimate the probability for a particular dimension, we simply go through all the possible sets of that length that can be drawn from the sample and count the number of sets which satisfy the condition. The ratio of the number of sets satisfying the condition divided by the total number of sets provides the estimate of the probability. Given a sample of observations of a series X, we can state this in the following mathematical notation:

$$c_{m,n}(\varepsilon) = [2/(n-m+1)(n-m)] \sum_{s=1}^{n-m+1} \sum_{t=s+1}^{n-m+1} \Pi_{j=0}^{m-1} I_\varepsilon (X_{s+j}, X_{t+j}) \quad (4)$$

where I_ε is the indicator function.

$$I_\epsilon(x, y) = \begin{cases} 1 & \text{if } |x - y| \le \epsilon \\ 0 & \end{cases} \quad (5)$$

Note that the statistics $c_{m,n}$ are often referred to as correlation integrals.

We can then use these sample estimates of the probabilities to construct a test statistic for independence

$$t_{m,n}(\epsilon) = c_{m,n}(\epsilon) - c_{1,n-m+1}(\epsilon)^{m} \quad (6)$$

where the second term discards the last observations from the sample so that it is based on the same number of terms as the first statistic.

Under the assumption of independence, we would expect this statistic to be close to zero. In fact, it is shown in Brock et al. (1996) that

$$(\sqrt{n-m+1})\frac{b_{m,n}(\epsilon)}{\sigma_{m,n}(\epsilon)} \to N(0,1) \tag{7}$$

where

$$\sigma^2_{m,n}(\epsilon) = 4\left(k^m + 2\sum_{j=1}^{m-1} k^{m-j}{c_1}^{2j} + (m-1)^2{c_1}^{2m} - m^2 k {c_1}^{2m-2}\right) \tag{8}$$

and where c_1 can be estimated using $c_{1,n}$. k is the probability of any triplet of points lying within ε of each other, and is estimated by counting the number of sets satisfying the sample condition

$$k_n(\epsilon) = \frac{2}{n(n-1)(n-2)}\sum_{t=1}^{n}\sum_{s=t+1}^{n}\sum_{r=s+1}^{n} (I_\epsilon(X_t, X_s)I_\epsilon(X_s, X_r) + I_\epsilon(X_t, X_r)I_\epsilon(X_r, X_s) + I_\epsilon(X_s, X_t)I_\epsilon(X_t, X_r)) \tag{9}$$

The default is to specify ε as a fraction of pairs, since this method is most invariant to different distributions of the underlying series.

2.2 Bootstrap

Using the traditional theory, there exist two major methods in Bootstrap: parametric and nonparametric. Using nonparametric bootstrap we can construct confidence intervals and perform hypothesis tests.

Suppose we draw a sample **S** = {X1, X2,…., Xn } from a population **P** = {X1,X2,….,Xn }

We proceed to draw a sample of size n from among the elements of size S sampling with replacement. The result is called bootstrap sample **S*** = {X1*, X2*, ….., Xn *}

The important element here is that the population is to the sample as the sample is to the bootstrap samples.

That is **P** v. s. **S ~ S** v. s. **S***

Following this we use the average of the bootstrapped statistics,

$$\overline{T}^{*} = \widehat{E}^{*}(T^{*}) = \frac{\sum_{b-1}^{R} T_b^{*}}{R} \qquad (10)$$

To estimate the expectation of the bootstrapped statistics. Similarly, the estimated bootstrap variance of T^*

$$\widehat{V}^{*}(T^{*}) = \frac{\sum_{b-1}^{R} (T_b^{*} - \overline{T}^{*})^2}{R-1} \qquad (11)$$

estimates the sampling variance of T, and $SE^*(T^*) = \sqrt{V^*}(T^*)$ is the bootstrap estimate of the standard error of T.

The next step is to derive confidence intervals constructed through the classical theory in text books (first suggested by Efron (1979)).

To construct a 100(1-α) percent confidence interval, following the results in equations (1) and (2), we have

$$\theta = (T - \widehat{B}^{*}) \pm z_{1-\alpha/2} \widehat{SE}^{*}(T^{*}) \quad \text{where } \widehat{SE}^{*}(T^{*}) = \sqrt{\widehat{V}^{*}(T^{*})} \qquad (12)$$

Where $T^*_{[(R+1)\alpha/2]} < \theta < T^*_{[(R+1)(1-\alpha/2)]}$ is the bootstrap estimate of the bias of the statistic *T*.

where $T^*_{(1)}, T^*_{(2)}, \ldots, T^*_{(n)}$ are the ordered bootstrap replicates of the statistic, and the operator $[\bullet]$ indicates rounding to the nearest integer.

However, we shall focus in a more accurate approach which is recommended by many literatures the, so called, bias corrected, accelerated percentile (BCa) intervals. This type of interval can be calculated from observations through the following steps:

1. Let correction factor 1

$$z = \Phi^{-1}\left[\frac{\sum_{b-1}^{R} I(T_b^* \le T)}{R+1}\right] \tag{13}$$

where $\Phi^{-1}(\bullet)$ is the inverse of standard normal cumulative distribution function, is an indicator function satisfying: $I(\bullet)$

$$I(A) = \begin{cases} 1 & \text{if A is true} \\ 0 & \text{if A is false} \end{cases} \tag{5}$$

2. Let $T_{(-i)}$ be the jackknife[1] value of T, and $\overline{T}$ be the average of $T_{(-i)}$. Then correction factor 2

[1] Jackknife value $T_{(-i)}$ refers to the value calculated from the sample when the i-th observation is removed. For reference see Wei Zhen "Bootstrap Methods with application in Econometrics and Finance"

$$a = \frac{\sum_{i=1}^{n}\left(T_{(-i)} - \overline{T}\right)^3}{6\left[\sum_{i=1}^{n}\left(T_{(-i)} - \overline{T}\right)^2\right]^{3/2}} \quad (14)$$

3. Having two correction factors at hand, we compute

$$a_1 = \mathbf{\Phi}\left[z + \frac{z - z_{1-\alpha/2}}{1 - \alpha\left(z - z_{1-\alpha/2}\right)}\right]$$
$$a_2 = \mathbf{\Phi}\left[z + \frac{z + z_{1-\alpha/2}}{1 - \alpha\left(z - z_{1-\alpha/2}\right)}\right] \quad (15)$$

where $\mathbf{\Phi}(\bullet)$ is the standard normal cumulative distribution function.

4. The corrected percentile confidence interval is as follows:

$$T^*_{[Ra_1]} < \theta < T^*_{[Ra_2]} \quad (16)$$

Where the operator $[\bullet]$ indicates rounding to the nearest integer as before. Finally, note that when a=z=0, BCa confidence interval reduces to the percentile interval stated previously.

2.3 The Generalised Method of Moments

The GMM has initially introduced by Hansen (1982) and Hansen and Singleton (1982) to estimate parameters defined by Euler conditions. Typically in consumption based CAPM (Lucas (1978)) the moment restrictions at date t are:

$P_{i,t} = E_t\ [p_{i,t+1}\ \delta\ (q_t/q_{t+1})\ U'(C_{t+1};\gamma) / U'(C_t;\gamma)]$, i= 1,….,n, (17)

where U is a utility function, $P_{i,t}$ is the observed prices of the n financial assets, q_t the price of the consumption good, C_t the consumption level and E_t denotes the conditional expectation given the available information including the lagged values of prices and income. The parameters of interest are the preference parameter γ and the psychological discount rate δ. The model is semi-parametric. GMM focuses on the estimation of $\theta = (\gamma'\delta')$ and disregards the nuisance parameter, that is the joint conditional distribution of prices $p_{i,t+1}$, $i = 1,\ldots,n$, and consumption C_{t+1}.

Recently different approaches called empirical likelihood, minimum chi – square or information based approach, have been proposed to simplify the derivation of a GMM parameter and to improve its finite sample properties. The basic idea is to estimate jointly the structural parameter θ and the nuisance infinite dimensional parameter under the moment restrictions.

3. Empirical Evidence

3.1 MA, AR and Bootstrap

In this paper we use daily observations for the British index FTSE 100 from April1984 till May 2005 and the German Xetra DAX index from November 1990 until May/2005. In this section we also present tests for Moving Average with 1, 2, 3 lags and for Auto Regression with 1, 2, and 3 lags. Table 1 shows AR and MA term. Each AR term corresponds to the use of a lagged value of the residual in the forecasting equation for the unconditional residual (see table 1). MA represents the moving average term. A moving average forecasting model uses lagged values of the forecast error to improve the current forecast. A first-order moving average term uses the most recent forecast error; a second-order term uses the forecast error from the two most recent periods, and so on. It is worth noting that all autoregressive moving average (ARMA) processes can be written as vector AR(1) processes, although with a possibly higher – dimensional state vector and a possibly singular variance matrix.

Table 1: Test for AR (1) and MA (1) for FTSE 100 and XETRA DAX using 1 Lag.

	Significance level 5% t – test	Probability
Constant	0.058 (0.06)*	0.019 (0.02)*
AR (1)	0.059 (0.062)	0.0001 (0.0000)
MA (1)	0.058 (0.059)	0.0353 (0.0357)
R-squared	0.99933 (0.99935)	

* Note: in parentheses the results for XETRA DAX

In addition, from table 1 and figure 1 we see that the forecasting models explain in a 95% confidence level the movement of both indices.

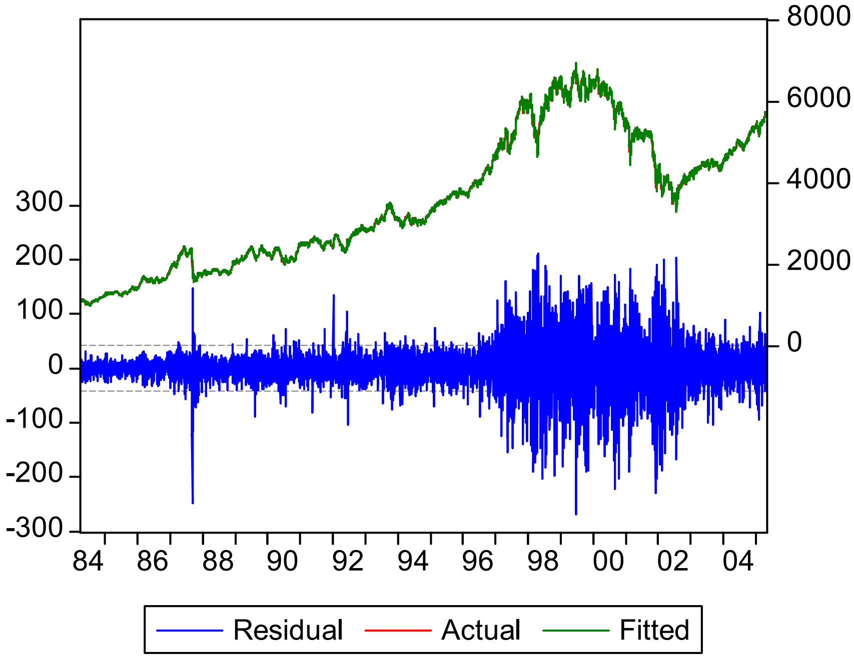
Similarly, the bootstrap test which has been obtained using 1000 repetitions shows (Table 2) that the hypothesis of residual independence cannot be rejected.

Table 2: Bootstrap Test (BDS).

	Dimension	BDS statistic	Std. Error	Normal Prob.	Bootstrp Prob
BDS	2	0.04509	0.00152	0.000	0.000
BDS	3	0.09332	0.002417	0.000	0.000
BDS	4	0.13394	0.00288	0.000	0.000
BDS	5	0.16202	0.00300	0.000	0.000
BDS	6	0.17844	0.00290	0.000	0.000

Note: As we can see $p<0.05$. Hence, the hypothesis of independence in the residuals is not rejected. This implies that there is linearity and that the forecasting is accurate.

Figure 1: the residual distribution pattern for FTSE 100.



The actual model fits in a perfect manner the observations. We can also see the high residuals volatility for period 1999 - 2003.

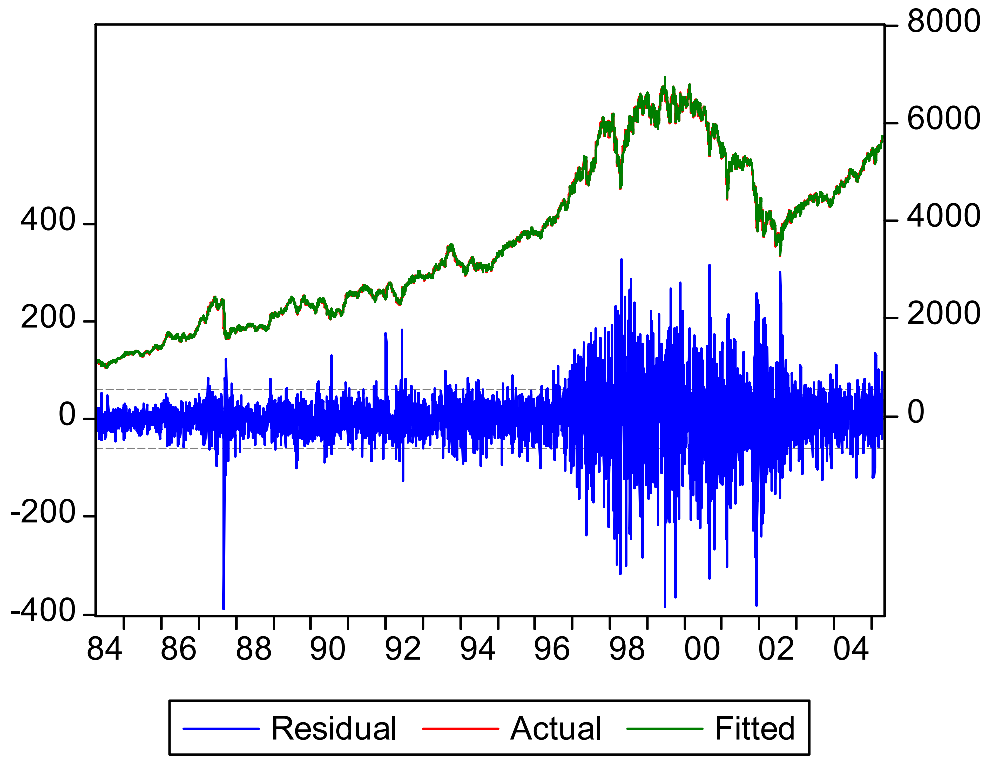
The AR (2) and MA (2) explain in a great proportion the market movements (table 3).

Table 3: Tests of AR (2) and MA (2).

	Significance level 5%	
	t – test	Probability
Constant	0.056 (0.057)	0.0030 (0.0034)
AR (1)	0.055 (0.059)	0.0000 (0.000)
MA (1)	0.054 (0.056)	0.0000 (0.000)
R-squared	0.9986 (0.999)	

Once more we see that the histogram satisfies our criteria (figure 2).

Figure 2: the residual distribution pattern using 2 lags for FTSE 100



In table 4 the hypothesis of iid in the residuals is not rejected

Table 4: Bootstrap Test (BDS).

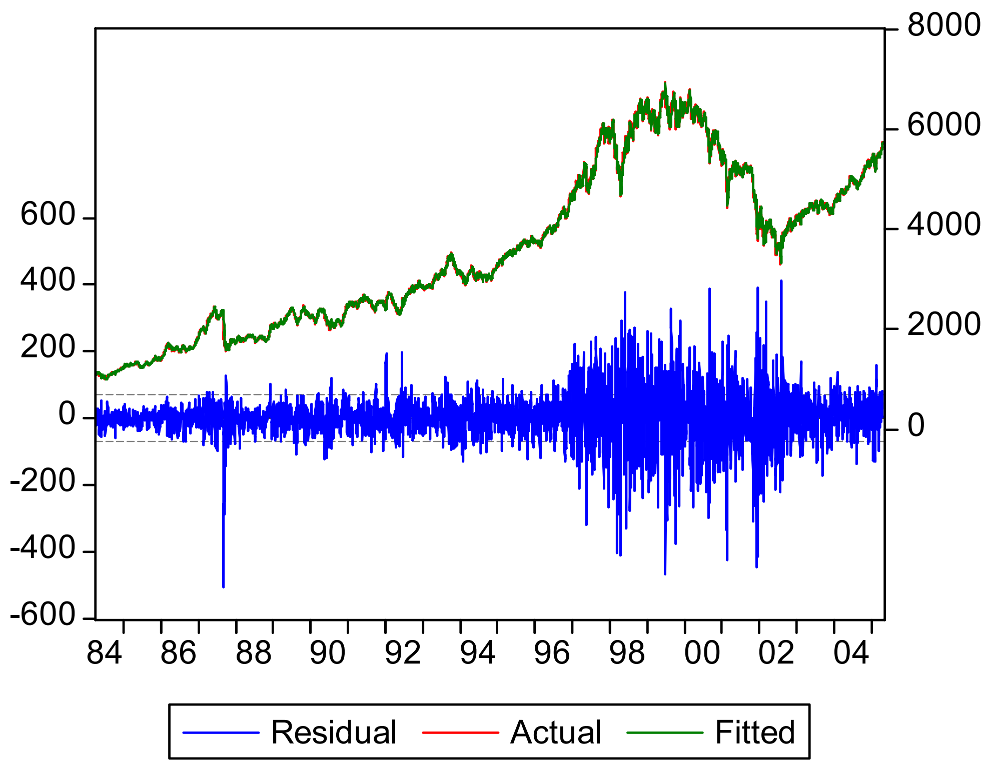
	Dimension	BDS statistic	Std. Error	Normal Prob.	Bootstrp Prob
BDS	2	0.069174	0.001487	0.000	0.000
BDS	3	0.12894	0.002363	0.000	0.000
BDS	4	0.17234	0.002814	0.000	0.000
BDS	5	0.19956	0.00293	0.000	0.000
BDS	6	0.215188	0.002831	0.000	0.000

Furthermore Table 5, 3 lags OLS test produces better probabilistic results when compared to 2 and 1 lags OLS the probabilistic statistic. This means that the movement of both markets is more accurately explained via the Moving Average forecasting technique with 3 lags and the Auto Regressive for 3 lags.

Table 5: AR (3) and MA (3) tests.

	Significance level 5%	
	t – test	Probability
Constant	0.053 (0.054)	0.0005 (0.0005)
AR (1)	0.054 (0.054)	0.0000 (0.0000)
MA (1)	0.051 (0.052)	0.0000 (0.0000)
R-squared	0.9980 (0.9987)	

Figure 3: the residual distribution pattern using 3 lags.



Results from table 6 imply that the hypothesis of independence in the residuals is not rejected.

Table 6: The Bootstrap test for AR (3) and MA (3).

	Dimension	BDS statistic	Std. Error	Normal Prob.	Bootstrap Prob
BDS	2	0.08594	0.00146	0.000	0.000
BDS	3	0.15098	0.002318	0.000	0.000
BDS	4	0.19611	0.002760	0.000	0.000
BDS	5	0.2242	0.002877	0.000	0.000
BDS	6	0.24011	0.002775	0.000	0.000

The tests in the forecasting techniques for AR and MA provide a strong guide to outperform the market in the long term. These forecasting techniques can be characterised as conservative as long as the portfolio manager does not need to trade many times in the market.

Following the MA forecasting technique in conjunction with the bootstrap test for linearity, which secures our forecasting accuracy, we examine (figure 3) that for a portfolio manager the 6,000 level in FTSE 100 is a good starting point to close long positions and to open short positions.

However, the MA technique can not give us enough information for the period of depression between 2000 and 2003. Indeed, the MA implies that we were in a bubble area since 1996. As a result, the exact period of the rapid decline in the stock markets is not accurately observed. Consequently, following the MA forecasting technique someone should focus on a passive way of investing in the FTSE 100 index. This means that a portfolio manager should carry a long position from 1984 until 1996 and from 2003 until today.

As a result, there are several limitations using the MA and AR forecasting techniques. Even with satisfactory results from the tests in bootstrap, a portfolio manager should have opportunity costs following the above forecasting techniques. This occurs mainly due to the absent of momentum driven factors in the techniques which create opportunistic trading and need a more dynamic and flexible approach in asset allocation.

3.2 Optimal Portfolio Selection and GMM

Based on data for FTSE 100 and XETRA DAX we consider a mean - variance framework for given $\alpha \in [0,\infty]$

$$\min_{s} \{J_\alpha (s) / s \in S\}$$

Where J_α (s) is the quadratic objection function which ensures the simultaneous maximisation of expected return and minimisation of expected risk.

$$J_\alpha (s) = - <\varepsilon(r),s> + \log \alpha <s - \bar{s}, \Lambda(s - \bar{s})> + \log (u^2), \qquad (19)$$

$\varepsilon(r) \in R^n$ is the expected return vector of the set of assets being considered with

$$r = \varepsilon(r) + \varepsilon, \qquad (20)$$

$\varepsilon \sim N(0,\Lambda)$ is the random error, $\Lambda \in R^{nXn}$ is the covariance matrix of the returns, $s \in R^n$ is the portfolio weights to be optimally determined, $\bar{s}$ denotes the benchmark weights which s should follow closely, and S is the feasible set of these weights, including the restrictions specified by the investor. This formulation enables the tracking of benchmark $\bar{s}$ and has to be tested M times to obtain the optimal portfolio. The error ε can be viewed either as the error between the actual retrun and its forecast, ε (r) or the error of the return of its historical mean, when ε (r) is equivalent to this mean. The parameter u^2 describes the overreaction that investors tend to follow and we use it in the square root because we want our model to be tested in maximum conditions of inefficient market behaviour. Consequently, Λ can be the covariance of the return forecast errors or the historical covariance of the return. The parameter log α is the price of risk, interpreted as the shadow price of an associated optimisation constrained by the quadratic risk in (18). Accordingly, as log α increases from zero, so does the emphasis on caution, or risk aversion. Similarly, a high value of u^2 implies that investors act irrational. Our objective includes the following components: a chi – square distance is used for the optimisation with respect to the conditional distributions associated with the sample values of the conditioning variable, whereas an information criterion is used for the conditioning value of J_α (s).

Table 7: Optimal portfolio selection

Moment	α	β	u
E (logu)	0.0408	0.0864	0.0726*
E(logu^2)	0.0613	0.0937	0.0703*

Note: *95% confidence interval

In table 7 we see that the GMM estimator is less than 1, producing an efficient estimator of β. Also, we do not reject the hypothesis that a portfolio choice may be created using the GMM method in our sample.

4. Conclusions

In this paper forecasting tests for the British Index FTSE 100 and the German XETRA DAX index have been made based on iid normality. In our research the Moving Average forecasting method with 3 lags is seen to be the most appropriate to forecast the future market movements as long as it explains past movement with a high degree of accuracy and the actual model fits the observations.

As it has also been documented the bootstrap method investigates that there is independence in the residuals. As a result, the bootstrap method is also appropriate for both indices. The performances of these tests are satisfactory because the observations satisfy the iid condition of normally distributed residuals. Moreover, the application of GMM shows the usefulness of this technique to construct an optimal portfolio.

The forecasting techniques are used to analyse the position that a portfolio manager should acquire in the market. The empirical evidence shows that past performance determines the most important constituents of the market. Some limitations have been observed to demonstrate the disadvantages of the forecasting techniques used in this research.

Further research may be needed at this issue to observe more information that this method may provide to portfolio selection strategies.

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