

**MODELLING THE LONG-AND-SHORT RUN DYNAMICS OF
SHARE PRICE MOVEMENTS IN THE RESOURCE SECTOR**

MSc. Financial Mathematics Dissertation

University of Cape Town

2004-2005

Supervisor: Dr. Paul van Rensburg

Megan Davids

DVDMEG002

The copyright of this thesis vests in the author. No quotation from it or information derived from it is to be published without full acknowledgement of the source. The thesis is to be used for private study or non-commercial research purposes only.

Published by the University of Cape Town (UCT) in terms of the non-exclusive license granted to UCT by the author.

Declaration of Plagiarism

1. I know that plagiarism is wrong. Plagiarism is to use another's work and pretend that it is one's own.
2. This project is my own work.
3. I have not allowed, and will not allow, anyone to copy my work with the intention of passing it off as his or her own work.

Name:

Signature:

Date

Acknowledgements

I wish to express my sincere thanks to the following people and foundations who made this dissertation possible:

Mainly to Dr. Paul van Rensburg for all the assistance he accorded me in supervising this study.

To Professor Cas Troskie, who assisted me with the statistical package EVIEWS.

To the National Research Foundation Council (NRF) who awarded me a very generous scarce skills scholarship.

Lastly to the University of Cape Town's Postgraduate Funding Office for awarding me a generous council bursary.

Abstract

This paper involves the development and estimation of various statistical models that possess significant explanatory power in predicting future returns of resource shares. Models were constructed for IMPLATS, HARMONY, GOLDFIELDS, SASOL and SAPPI. Significant long-term relationships were found between company share price, earnings per share, dividends per share, commodity price and interest rates. The technique of co-integration permits these non-stationary economic variables to be linked by a stable long-term equilibrium relationship. For each co-integrating relationship an error correction model is developed to correct for short-term disequilibrium. The relationship between co-integration and error correction models is further extended to forecast future returns of share prices. A one-month rolling window forecasting method was implemented to forecast future returns of shares over one, two and three months respectively. Findings suggest that these results could be of considerable significance when making bets on a diversified portfolio of investments.

Table of Contents

	Section	Page
1	Introduction	5
2	Description of Data	7
3	Methodology	9
	3.1 Co-integration	9
	3.2 Error Correction Model	13
	3.3 Forecasting using a one-month Rolling Window Approach	15
	3.4 Forecast Evaluation Criteria	19
4	Selection Process	21
	4.1 Identification of Data	21
	4.2 Formulation of Models	26
5	Results	28
6	Summary & Conclusions	50
7	Appendix A: Correlograms of Returns	53
8	Appendix B: Asymptotic Critical Values for Augmented Engle & Granger Test	73
9	Appendix C: Co-integration, Error Correction Models and Rolling Window Forecasting Performance for all Models	74
10	Appendix D: Eviews program, Explanation of Eviews program	95 99
11	References	102

1. Introduction

Predicting future returns of shares on the stock market is an area of considerable interest where much controversy exists. This paper is concerned with building models based on solid theoretical foundations that aim to challenge this uncertainty. The intention was to develop a model for at least one company in each industry sector (mining and non-mining) within the resource sector. Models were successfully constructed for IMPLATS, HARMONY, GOLDFIELDS, SASOL and SAPPI. These models relate company share price, earnings per share, dividends per share, commodity price and long and short term interest rates.

The problem is that most economic time series variables are non-stationary and therefore standard inference procedures are not applicable. A technique called co-integration allows two or more non-stationary economic time series variables to be linked by a stable long term equilibrium relationship without worrying about the dynamics. Economic theory postulates that such variables are allowed to move away from equilibrium in the short term but economic forces are likely to push these variables back toward equilibrium in the long run. An Error Correction Model (ECM) was developed to capture these short run dynamics. At each time period, the ECM corrects the proportion of disequilibrium of the dependent variable (share price) from the previous time period such that the dependent variable frequently and also eventually reaches its long run value.

Alternatively the ECM can be seen in such a way that short run changes in the dependent variable is either caused by the short run adjustment back to long run equilibrium or by short run changes in other variables that the dependent variable is related to (from co-integrating relationship). An ECM is an extremely flexible model as it allows one to include many lagged difference terms of the dependent and explanatory variables. This model is now also feasible to model the behaviour of share price returns. The only serious difficulty is deciding how many lagged difference terms of the explanatory and / or dependent variables should be added to the model. The validity of the ECM is then tested by investigating the model's ability to forecast over one, two and three months into the future. A one-month rolling window forecasting method was implemented to test the

ECM's forecasting performance. The extrapolative nature of the rolling window approach is distinctive in such a way that it enables the applied model's predictive ability to recover fairly quickly after some economic crisis or rather any unanticipated event. The forecast will clearly not be able to predict unanticipated changes but will take it into account when making the next prediction.

Incidentally this dissertation is also concerned with testing the validity of the Random Walk theory as the ECM developed contains past lagged differences of the dependent variable. This implies that share price changes are also in some way related to past share price changes. The Random Walk theory asserts that future price changes are unpredictable from past price changes and that price changes are therefore completely random. Prices that follow random walk behaviour is said to come from an efficient market thus Random Walk theory is analogous to the Efficient Market Hypothesis (EMH).

I will be using the software package, EVIEWS to conduct all simulations and the method of Ordinary Least Squares (OLS) to perform regressions.

The paper follows the following structure. Section 2 gives a description of the data that will be used in the estimation analysis. Section 3 describes the co-integration, error correction mechanism and rolling window techniques. Model formulation is presented in Section 4. Section 5 presents the results of the methodology applied to the models as well as the forecasting performance for each model. Section 6 summarizes and concludes the paper.

2. Description of Data

The data described below was obtained from Inet-Bridge and was collected monthly for the period 30/04/1971 to 31/07/2004. It is statistically classified as time series data meaning each series is a realization of an underlying random or stochastic process.

Note the variable matching company name corresponds to the closing share price of one company share. Inet provided the corresponding Earnings Yield (EY) and Dividend Yield (DY), which I converted to corresponding Earnings per Share (EPS) and Dividends per Share (DPS). I also converted all the data to one currency; the Rand via the R/\$ exchange rate (USDZAR). A more detailed explanation of the two short and long-term securities also are given below.

SA LONG TERM GOVERNMENT BOND

SA long-term government bond is a long-term bond market instrument, also known as a long term gilt. It is a fixed-interest-bearing security issued by government for the purpose of repaying debt. I will be using the yield on a long-term bond to serve as a proxy for a long term interest rate.

90-DAY BANKERS ACCEPTANCE

A bankers' acceptance is a short-term money market instrument. It is a letter of credit issued by a bank on behalf of a corporation, i.e. a form of secured debt. It trades at a discount rate. I will be using the discount rate of a 90- day bankers' acceptance as a proxy for a short-term interest rate.

Variable	Description
AMS	ANGLOPLAT SHARE PRICE
AMS_EPS	ANGLOPLAT EARNINGS PER SHARE
AMS_DPS	ANGLOPLAT DIVIDENDS PER SHARE
IMP	IMPLATS SHARE PRICE
IMP_EPS	IMPLATS EARNINGS PER SHARE
IMP_DPS	IMPLATS DIVIDENDS PER SHARE
PLATPM	PLATINUM PRICE (RANDS per/oz)
ANG	ANGLOGOLD SHARE PRICE
ANG_EPS	ANGLOGOLD EARNINGS PER SHARE
ANG_DPS	ANGLOGOLD DIVIDENDS PER SHARE
HAR	HARMONY SHARE PRICE
HAR_EPS	HARMONY EARNINGS PER SHARE
HAR_DPS	HARMONY DIVIDENDS PER SHARE
GFI	GOLDFIELDS SHARE PRICE
GFI_EPS	GOLDFIELDS EARNINGS PER SHARE
GFI_DPS	GOLDFIELDS DIVIDENDS PER SHARE
GOLR	GOLD PRICE (RANDS per/oz)
SOL	SASOL SHARE PRICE
SOL_EPS	SASOL EARNINGS PER SHARE
SOL_DPS	SASOL DIVIDENDS PER SHARE
BRSPOT	OIL & GAS PRICE (RANDS per/barrel)
SAP	SAPPI SHARE PRICE
SAP_EPS	SAPPI EARNINGS PER SHARE
SAP_DPS	SAPPI DIVIDENDS PER SHARE
PXPULP	PAPER & PULP PRICE (RANDS per/T)
ISC	ISCOR SHARE PRICE
ISC_EPS	ISCOR EARNINGS PER SHARE
ISC_DPS	ISCOR DIVIDENDS PER SHARE
SHRC	STEEL PRICE (RANDS per/T)
J000	FTSE/JSE: RESOURCES PRICE INDEX
J000_EPS	FTSE/JSE: RESOURCES EARNINGS PER SHARE
J000_DPS	FTSE/JSE: RESOURCES DIVIDENDS PER SHARE
J250	FTSE/JSE: ALL SHARE ex RESOURCES PRICE INDEX
J250_EPS	FTSE/JSE: INDUSTRIALS & FINANCIALS EARNINGS PER SHARE
J250_DPS	FTSE/JSE: INDUSTRIALS & FINANCIALS DIVIDENDS PER SHARE
USDZAR	R/\$ EXCHANGE RATE
RLRS	SA LONG TERM GOVERNMENT BOND
RBAS	90-DAY BANKERS ACCEPTANCE (DISCOUNT)

Table 1: INET Data

3. Methodology

3.1. Co-integration

The following multivariate linear regression model will be used to describe relationships among the variables:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_i X_{it} + u_t, \quad [1]$$

where β_i ($i = 0, \dots, I$) are the parameters to be estimated, Y_t are the values of the dependent variable and X_{it} are the values of the independent or explanatory variables, and I denotes the number of explanatory variables in the model. The term u_t is a sequence of errors or disturbances that can be thought of as all the omitted variables that may affect Y but are not included in the model. The main objective of Ordinary Least Squares Regression (OLS) is to estimate the dependent variable Y_t given the fixed or known values of the explanatory variables, X_{it} .

A fundamental importance before conducting any analysis on time series data is to ensure that all the underlying time series is weakly stationary. A stochastic process Y_t is weakly stationary if its mean and variance are constant over time and the covariance between two time periods depends only on the distance between the time periods and not the actual time period at which the covariance is measured. It is therefore also called a covariance stationary process. For the remainder of the paper, the terms stationary, weakly stationary and covariance stationary will be used synonymously. To summarize; a stochastic process Y_t needs to satisfy the following three conditions to be regarded as a weakly stationary process:

- $E(Y_t)$ is constant [2]

- $\text{Var}(Y_t)$ is constant [3]

- for any $t, h \geq 1$, $\text{Cov}(Y_t, Y_{t+h})$ depends only on h and not on t . [4]

A time series which does not fulfill any of the above three conditions is called a non-stationary time series. Most economic time series usually exhibit a consistent upward or downward trend and is therefore non-stationary. Very often when regressing non-stationary series on another one can obtain significant regression results, namely a high R^2 , a low DW and a high significance of coefficients even though there may not be any meaningful economic relationship between the variables. This is known as spurious regression and occurs because the variables exhibit common trends. The concept of spurious regressions amongst variables with stochastic trends was first established by Granger and Newbold¹. Their findings suggest that the regression of non-stationary series on another can only be permitted if the series are co-integrated. Standard asymptotic theory does not apply to regressions involving non-stationary time series.

Before the concept of co-integration was discovered, the classical approach to dealing with non-stationary time series was to difference the variables as many times as needed to make them stationary. This means that a regression involving these differenced variables would then only estimate relationships between the variables in their differenced transformation and not in their level form. Even though standard asymptotic theory would apply to regressions involving the differenced variables, it does not allow one to draw inferences about relationship between the levels of these variables. Co-integration implies that we can estimate relationships between the levels of non-stationary time series without losing any long run information and without the problem of spurious regressions. Co-integration is the process that allows for the regression of non-stationary time series on another provided a linear combination of the series is stationary. When two or more economic time series variables are co-integrated then these variables are linked by a stable long term equilibrium relationship. To see this more clearly; a rearrangement of the regression in [1] can be written as:

$$u_t = Y_t - (\beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \dots + \beta_i X_{it}) \quad [5]$$

¹ C.W.J. Granger and P. Newbold, "Spurious Regressions in Econometrics," *Journal of Econometrics*, vol. 2, 1974, pp. 111-120

The aim is then to find that u_t is stationary or equivalently that a linear combination of X_{it} and Y_t are stationary. It can also be seen from the regression in [5] that the residual series is the difference between the actual and the fitted values of the dependent variable of the regression in [1]. The residual series is also the term that links the short run behaviour of the dependent variable to its long run value. Economic theory postulates that variables that are linked by a stable long term equilibrium relationship may move away from equilibrium in the short term but economic forces are likely to push these variables back to equilibrium in the long term. The residual series is thus the deviation away from equilibrium in the short term and is also called the equilibrium error term. The regression thus seeks to find a co-integrating vector β , which minimizes this error term, where β is the vector of parameter estimates containing the estimated β_i 's from [1].

Before testing for co-integration, it is necessary to establish that all the series involved are integrated of the same order. A stationary series is integrated of order zero, denoted $I(0)$. A time series whose first difference is stationary, is integrated of order one, denoted $I(1)$. Such a series contains one unit root; it is non-stationary in both mean and variance and is known as a random walk. In general if a series has to be differenced d times, it is $I(d)$. Most economic time series are $I(1)$.

Co-integration thus essentially involves checking whether the residual series, u_t , contains a unit root. The most commonly used test for the existence of unit roots is the Augmented Dickey Fuller (ADF) test. The unit root test is based on the regression:

$$u_t = \rho u_{t-1} + \varepsilon_t \quad [6]$$

where the stochastic error term, ε_t , is known as the white noise error term. It has zero mean, constant variance, and are non-autocorrelated. If $\rho = 1$, then u_t contains a unit root and is non-stationary. If $|\rho| < 1$, then u_t is a stable first order autoregressive (AR(1)) process, which means it is a weakly stationary process and is asymptotically uncorrelated. To carry out the ADF test, subtract u_{t-1} from both sides of equation [6] and define $\delta = \rho - 1$ then:

$$\Delta u_t = \delta u_{t-1} + \varepsilon_t \quad [7]$$

The ADF test runs the regression in [7] under the null hypothesis that $\delta = 0$, which is essentially the same as $\rho = 1$. The usual t distribution is inapplicable under this null hypothesis and the t statistic follows the Dickey-Fuller distribution instead. The test statistic is known as the τ (tau) statistic and replaces the conventional t statistic. If the τ statistic exceeds the critical values in absolute value at any of the 1%, 5% or 10% significance levels, then reject the null hypothesis that the series contains a unit root and conclude that the series is stationary. Unfortunately the ADF critical values are not valid for series based on estimated values and since the u_t as illustrated in [5] is based on the estimated parameters β_i 's, it is indeed an estimated value itself. Fortunately the correct critical values were tabulated by Engle and Granger² (EG). A table of the EG critical values can be found in Appendix A. In this context the ADF test is known as the Augmented Engle and Granger (AEG) test and is simply the ADF test conducted with EG critical values. Similarly, if τ is greater than the EG critical values at any of the significance levels then reject the null that the series contains a unit root and conclude that the residual series is stationary and the variables are co-integrated. Davidson & MacKinnon also suggest that it is not necessary to include a constant or a trend term in the test regression [7] if the regression in [1] already includes one or both of these terms as additional regressors. In the analysis only a constant term was included. One would also like to add enough lags of Δu_t as additional regressors to eliminate any evidence of serial correlation.

If the null is not rejected and the AEG test establishes no co-integration then the regression is spurious and one can conclude that there is no long run relationship between the variables. On the other hand, if co-integration was established then one can use the residual series of the co-integrating regression to specify a more general dynamic model, called an error correction model, which may be beneficial in a forecasting application.

² The EG critical values can be found in R. Davidson and J.G. MacKinnon, *Estimation and Inference in Econometrics*, Oxford University Press, New York, 1993, Table 20.2, p. 722.

3.2. Error Correction Model

Establishing co-integration implies that the variables involved are linked by a stable long term equilibrium relationship. It was explained in the previous section that these variables are allowed to deviate from equilibrium in the short term but economic forces are likely to push them back toward equilibrium in the long run. An error correction model is developed to capture the short run dynamics. The equilibrium error term in [5] serves as the link between the short run behaviour of the dependent variable and its long run value. The simplest ECM is of the form:

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta X_t + \alpha_2 \hat{u}_{t-1} + \varepsilon_t, \quad [8]$$

The regression in [8] essentially relates the change in Y to the change in X and the equilibrium error in the previous period. At each time period, a proportion of the disequilibrium from the previous period is corrected, i.e. Y moves closer toward its equilibrium or long run value through $\alpha_2 \hat{u}_{t-1}$. \hat{u}_{t-1} is called the error correction term and if the coefficient α_2 is statistically significant, it signifies the proportion of the disequilibrium which was corrected. The hat on \hat{u}_{t-1} indicates that it was an estimated value.

Alternatively, short run changes in Y are either caused by short run changes in X explained by ΔX_t , or by the short run adjustment back to long run equilibrium, explained by $\alpha_2 \hat{u}_{t-1}$. The long run value relating Y_t to X_t is essentially the co-integrating parameter estimate found from the initial co-integrating regression.

The simple bivariate model in [8] can further be generalized by adding lagged differences of X_t and Y_t , to capture further dynamics of the ΔY_t . An example would look something like:

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta Y_{t-1} + \varphi_0 \Delta X_t + \varphi_1 \Delta X_{t-1} + \delta u_{t-1} + \varepsilon_t \quad [9]$$

This model relates the change in Y_t to past changes in itself, changes in X_t , past changes in X_t and the error correction term. The ECM in [8] and [9] is an example of a static model as it contains an explanatory variable that is dated contemporaneously with the dependent variable. The use of these models in a forecasting application would not be such a good idea as one would need to forecast the explanatory variable as well.

This study is specifically concerned with developing models that can be used to explain share price behaviour and consequently to predict future returns. Thus the following multivariate dynamic model with no variables dated contemporaneously with the dependent variable is suited for the analysis:

$$\Delta Y_t = \alpha_0 + \alpha_1 \Delta Y_{t-1} + \varphi_0 \Delta X_{1t-1} + \dots + \sigma_0 \Delta X_{it-1} + \delta u_{t-1} + \varepsilon_t \quad [10]$$

Y_t represents the share price, X_{it} represents corresponding EPS, DPS, commodity price and / or interest rate and u_{t-1} the residual error term from the co-integrating relationship. The ECM in [10] relates changes or growth rates of Y_t to past changes in Y_t , as well as to past changes in other variables, X_{it} , that has a long term relationship with Y_t , and also to the error correction term that links the short run behaviour of Y_t to its long run value. This model type is also a representation of a vector autoregressive (VAR) model as it relates changes in Y_t to past changes in Y_t . We seek to find whether this model contains significant predictive power in explaining future share price returns.

Also note how the application of [10] contradicts the efficient market hypothesis (EMH) which states that changes in share price behaviour is uncorrelated to past changes in share price behaviour. This essentially means that past share price returns cannot be used to predict future share price returns. My analysis will therefore also test this version of the EMH.

Since all the variables in [10] are individually stationary, standard asymptotic theory applies and can be used to draw inferences about the model. This study places no emphasis on this aspect but is rather only concerned with the forecasting performance of

each model developed. The dynamic model in [10] can further be generalized by including more lagged differences of X_{it} and Y_t as well as more lags of u_t , if the inclusion of these terms improves the forecasting performance. Deciding which variables and how many lagged difference terms of each of the variables to include can be incomprehensibly challenging. The numbers of permutations that can be constructed are infinite. After much empirical testing, it was decided to estimate three different generalizations of the model in [10] by including one, three and six lagged difference terms of each the dependent and explanatory variables and only one lag of the error correction term. The best model is then selected by evaluating the information criteria used to measure forecasting performance.

The next section explains the forecasting method that will be used to test whether the ECM developed is useful in predicting future share price returns.

3.3. Forecasting using a one-month Rolling Window Approach

Split the sample into $n+m$ observations such that the first n observations are used to estimate the parameters of the ECM and the remaining m observations are used to evaluate the forecasting performance of the ECM. The set containing the first n observations is called the in-sample estimation period and the set containing the remaining m observations is called the out-of-sample forecast evaluation period. Let the ECM be the one specified in [10]. Then the parameters are estimated in the in-sample estimation period and the model's forecasting ability is tested in the out-of-sample forecast period. The aim is to obtain forecasts for share price returns over one, two and three months into the future. The forecasts are obtained via a one-month rolling window approach and are executed as follows:

Forecasting one-month future returns:

The first one-step-ahead forecast is made at time n for ΔY_{n+1} and is given by:

$$\hat{f}_{n,1} = E[\Delta Y_{n+1}] = \hat{\alpha}_0 + \hat{\alpha}_1 \Delta Y_n + \hat{\phi}_0 \Delta X_{1n} + \dots + \hat{\phi}_0 \Delta X_{in} + \hat{\delta}u_n \quad [11]$$

where the coefficient estimates are obtained from the regression estimated in the in-sample estimation period. The hat on \hat{f}_n and all the other parameters indicate estimated values. Calculate the one-step-ahead forecast error by subtracting the forecast value from the actual value of ΔY_{n+1} :

$$\hat{e}_{n+1} = \Delta Y_{n+1} - \hat{f}_{n,1} \quad [12]$$

This value will only be known at time $n+1$ when the actual value of ΔY_{n+1} is known. Then to obtain the next one-month-ahead forecast, ΔY_{n+2} , the window of the estimation period is increased by one observation and the parameters in [10] are re-estimated using all $n+1$ observations such that the new parameter estimates obtained at time $n+1$ are used to predict ΔY_{n+2} . The procedure continues until m forecasts are obtained in this way. So for $h = 0, 1, \dots, m-1$, $\hat{f}_{n+h,1}$ is the one-month-ahead forecast of ΔY_{n+h+1} made at time $n+h$, and after each forecast is made the estimation window is expanded by $n+h+1$ observations and the parameters in [10] are re-estimated using all $n+h+1$ observations to forecast the next ΔY_{n+h+1} , hence the name rolling window. Also the m forecast errors (for $h = 0, 1, \dots, m-1$) are

$$\hat{e}_{n+h+1} = \Delta Y_{n+h+1} - \hat{f}_{n+h,1} \quad [13]$$

which is only obtained at time $n+h+1$.

To forecast average share price returns over two-months-ahead, calculate the average of one and two month returns by changing the dependent variable in [10] accordingly:

Let

$$\Delta Z_t = (\Delta Y_t + \Delta Y_{t+1})/2 \quad [14]$$

Then

$$\Delta Z_t = \alpha_0 + \alpha_1 \Delta Y_{t-1} + \varphi_0 \Delta X_{1t-1} + \dots + \sigma_0 \Delta X_{it-1} + \delta u_{t-1} + \varepsilon_t \quad [15]$$

Then the first two-month-ahead forecast is made at time n for ΔZ_{n+1} and is given by:

$$\begin{aligned}\hat{f}_{n,2} &= E[\Delta Z_{n+1}] = E\left[\frac{\Delta Y_{n+1} + \Delta Y_{n+2}}{2}\right] \\ &= \hat{\alpha}_0 + \hat{\alpha}_1 \Delta Y_n + \hat{\phi}_0 \Delta X_{1n} + \dots + \hat{\phi}_0 \Delta X_{in} + \hat{\alpha}_n\end{aligned}\quad [16]$$

where the coefficient estimates are obtained from the regression estimated in the in-sample estimation period and the first forecast is plugged in at $n+2$. Then to obtain the next two-month-ahead forecast, roll window forward by one month (to $n+1$), then

$$\hat{f}_{n+1,2} = E[\Delta Z_{n+2}] = E\left[\frac{\Delta Y_{n+2} + \Delta Y_{n+3}}{2}\right] \quad [17]$$

and the parameters are re-estimated using all $n+2$ observations. Thus for

$h = 0, 1, \dots, m-2$, $\hat{f}_{n+h,2}$ is the two-month-ahead forecast of ΔZ_{n+h+1} , made at the at $n+h$.

At each step the window of estimation is expanded by $n+h+2$ months and the parameters are re-estimated using all $n+h+2$ observations to forecast the next ΔZ_{n+h+1} . Thus $(m-1)$ forecasts are obtained in this way. The $(m-1)$ forecast errors (for $h = 0, 1, \dots, m-2$) are:

$$\hat{e}_{n+h+2} = \Delta Z_{n+h+1} - \hat{f}_{n+h,2} \quad [18]$$

To forecast average share price returns three-months-ahead, we calculate the average of one, two and three month returns by changing the dependent variable in [10] to:

$$\Delta Z_t = (\Delta Y_t + \Delta Y_{t+1} + \Delta Y_{t+2})/3 \quad [19]$$

Then the first three-month-ahead forecast is made at time n for ΔZ_{n+1} and is given by:

$$\hat{f}_{n,3} = E[\Delta Z_{n+1}] = E\left[\frac{\Delta Y_{n+1} + \Delta Y_{n+2} + \Delta Y_{n+3}}{3}\right] \quad [20]$$

where the first forecast is plugged in at $n+3$. Similar to two-month-ahead forecasts, $(m-2)$ forecasts are obtained. Thus for $h = 0, 1, \dots, m-3$, $\hat{f}_{n+h,3}$ is the three-month-ahead forecast of ΔZ_{n+h+1} , made at the at $n+h$. At each step the window of estimation is expanded by $n+h+3$ months and the parameters are re-estimated using all $n+h+3$ observations to forecast the next ΔZ_{n+h+1} . Similarly the $(m-2)$ forecast errors (for $h = 0, 1, \dots, m-3$) are:

$$\hat{e}_{n+h+3} = \Delta Z_{n+h+1} - \hat{f}_{n+h,3} \quad [21]$$

Forecasting average returns over two and three months should be more robust than forecasting over one month as the randomness diversifies away over two months and further away over three months.

To measure the forecast uncertainty, a 95% confidence interval (or forecast interval) is constructed. This implies that we are 95% confident that the forecast interval will contain the true (but unknown) value. To construct this interval, the standard error of the forecast, $se(\hat{f}_n)$, as well as the standard error of the regression, $\hat{\sigma}$, is needed. Eviews tabulates these estimates. Then at each step the standard error of the forecast error is computed via:

$$se(\hat{e}_{n+1}) = \{ [se(\hat{f}_n)]^2 + \hat{\sigma}^2 \}^{1/2} \quad [22]$$

and the 95% forecast interval is

$$\hat{f}_n \pm 1.96 \cdot se(\hat{e}_{n+1}) \quad [23]$$

The advantage of using a rolling window method is that it essentially extrapolates changes from previous changes and under stable conditions can make a fairly accurate prediction. If an unanticipated change does occur, the forecast will not be able to predict the change but will be able to get back on track fairly quickly after the change has occurred, i.e. it will take the change into account when making the next step's prediction.

3.4. Forecast Evaluation Criteria

Recall, three different generalizations of the model in [10] will be created, i.e. by including one, three and six lagged difference terms of each the dependent and explanatory variables and only one lag of the error correction term. The best model is then selected by evaluating the following information criteria used to measure forecasting performance:

- Adjusted R-squared (Adj-R²)
- Akaike Information Criterion (AIC)
- Correlation Coefficient (CC)
- Root Mean Squared Error (RMSE)
- Percentage of correct sign predictions

Adjusted R-squared (Adj-R²)

R² is the most common goodness of fit test which measures the proportion of variation in the dependent variable which is jointly explained by all the explanatory variables. The problem with this statistic is that it never decreases when adding more variables to the model and would therefore be inefficient in deciding how many lags to include in the model. The Adj-R² statistic is a modification of the R² in that it takes into account the loss of degrees of freedom associated with adding extra variables. This statistic is obtained from OLS regression output and the model with the maximum Adj-R² is more efficient.

Akaike Information Criterion (AIC)

The AIC provides a measure of information that strikes a balance between this measure of goodness of fit and parsimonious specification of the model. This statistic is also obtained from OLS regression output and the model with the smallest information criterion should be selected.

Correlation Coefficient (CC)

The CC is the square root of R^2 . This statistic measures the degree of correlation between the dependent variable and the explanatory variables. In $\text{Adj-}R^2$, I mentioned that the R^2 never decreases when adding more variables, so neither will this statistic, thus I will use this measure only to judge whether a significant relationship exists between the variables or not.

Root Mean Squared Error (RMSE)

RMSE is measured by

$$\text{RMSE} = \left(\frac{1}{m} \sum_{h=0}^{m-1} e_{n+h+1}^2 \right)^{1/2} \quad [24]$$

This is essentially the sample standard deviation of the forecast errors. The squared forecast error used to compute the RMSE is also known as the loss associated with the forecast error. This loss function clearly treats positive and negative prediction errors symmetrically and larger forecast errors receive relatively more weight. In reality, the loss function is generally used to calculate the cost associated with the forecast errors. Generally when a forecast is made, the forecaster will make a decision based on the outcome of the forecast and the consequences of the decision may or may not be very expensive, thus care should be taken when choosing a forecast.

Percentage of correct sign predictions

Percentage of correct sign predictions is measured by

$$\% \text{ correct sign predictions} = \frac{1}{m} \sum_{h=0}^{m-1} w_{n+h+1} \quad [25]$$

where

$$w_{n+h+1} = 1 \quad \text{if} \quad (\Delta Y_{n+h+1} \cdot \hat{f}_{n+h,1}) > 0 \quad \text{and}$$
$$w_{n+h+1} = 0 \quad \text{otherwise}$$

This criterion is self-explanatory. Clearly we would like to select the model with the highest % of correct sign predictions.

Achieving the most efficient forecast evaluation criteria results simultaneously is hardly ever the case. Thus it is important to decide which criteria should dominate in selecting the best model. For the purpose of this assignment, RMSE and % correct sign predictions will be the dominant deciding criteria.

4. Selection Process

4.1. Identification of Data

Figures 1 to 9 show graphical illustrations of the time series data presented in Table 1 together with logarithmic transformations and first differences of logarithmic transformations where necessary. Share price, earnings per share and dividends per share are plotted on one graph. Figure 1 plots this information for platinum shares (AMS and IMP), figure 2 for gold shares (ANG, HAR and GFI), figure 3 for oil & gas shares (SOL), figure 4 for paper & pulp shares (SAP) and figure 5 for steel shares (ISC). Figure 6 plots this information for commodity prices (PLATPM, GOLR, BRSPOT, PXPULP and SHRC), figure 7 for the two JSE indices namely Resources (J000) and All Share ex Resources (J250). Figure 8 plots the yields for the interest rate proxies (RLRS and RBAS) and figure 9 plots the exchange rate (USDZAR).

A few variables, namely EPS and DPS of gold, paper and steel shares take on zero and negative values, therefore these variables cannot be transformed to their logarithmic counterparts. The reason for transforming the variables to their logarithmic counterparts is imperative for two main reasons. It linearizes the exponential trend, which has been proven to influence regression results with that of another growing variable, and secondly it allows one to model relative changes rather than actual changes. The graphs clearly show that these variables do not exhibit a specific trend anyway, thus not taking logarithms will do no harm.

The first two plots in each row, namely the levels and logarithmic transformations, clearly show that all these series are non-stationary in both mean and variance. The third plot in each row, namely the first differences confirms that each of the variables are $I(1)$ or rather their first differences are $I(0)$, which is as required by the co-integration method. The beginning dates on the graphs correspond to the time that the data was available from. Data for PXPULP was only available from 1996 onwards as can be seen in Figure 6. Also, it was not necessary to transform the interest rate proxies to their logarithms as these variables are already in proportional terms. These plots will be a little more useful later on when one can actually visualize the long term relationships found.

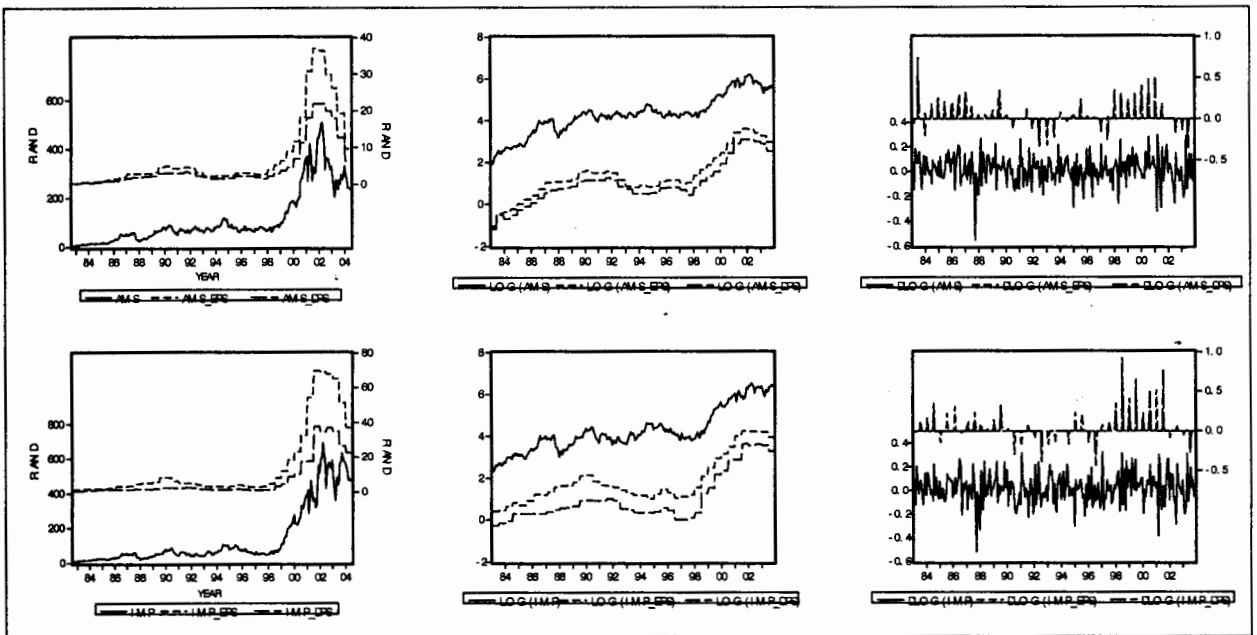


Figure 1: Platinum Shares (AMS and IMP) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms and First Differences of Logarithms

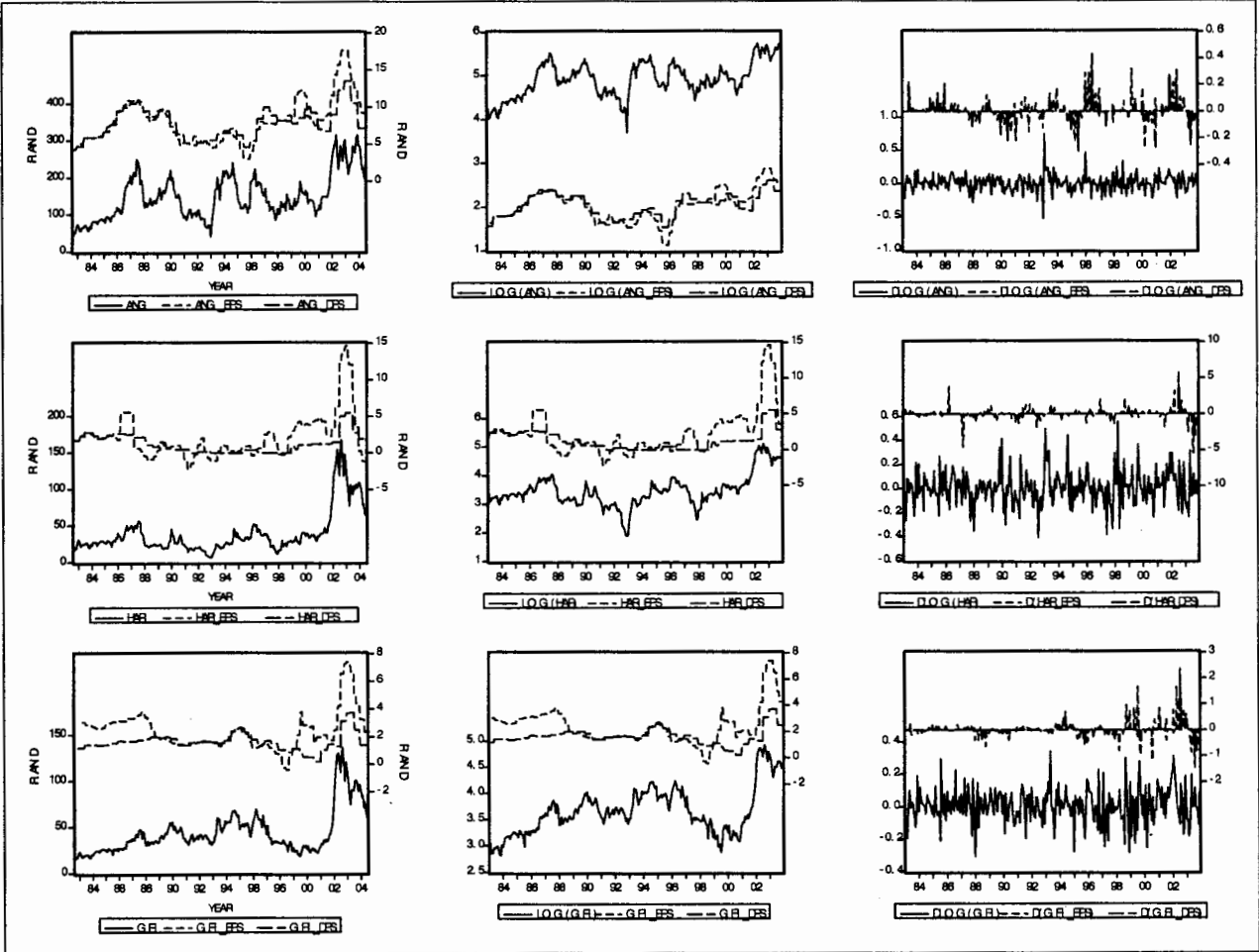


Figure 2: Gold Shares (ANG, HAR and GFI) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms, First Differences and First Differences of Logarithms

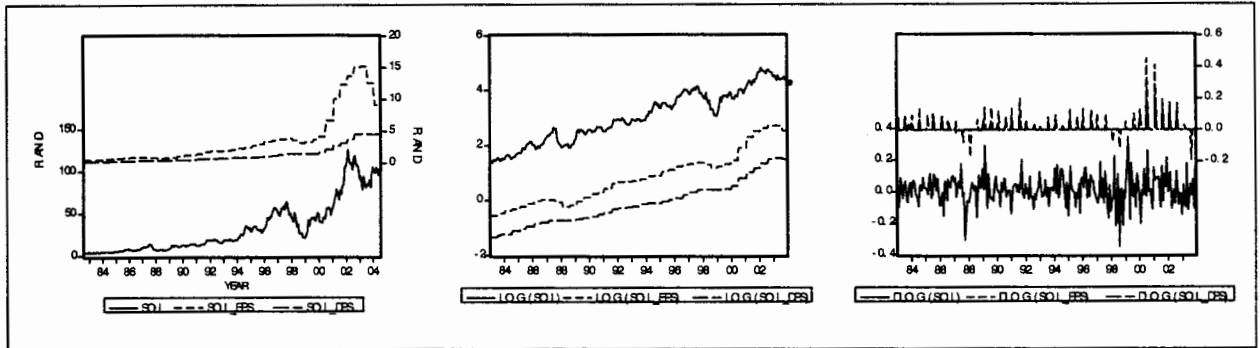


Figure 3: Oil & Gas Share (SOL) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms, and First Differences of Logarithms

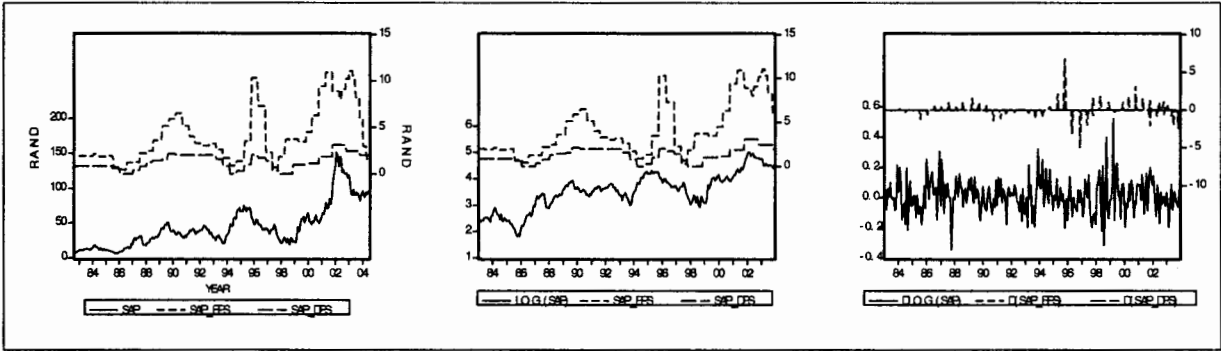


Figure 4: Paper Share (SAP) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms, First Differences and First Differences of Logarithms

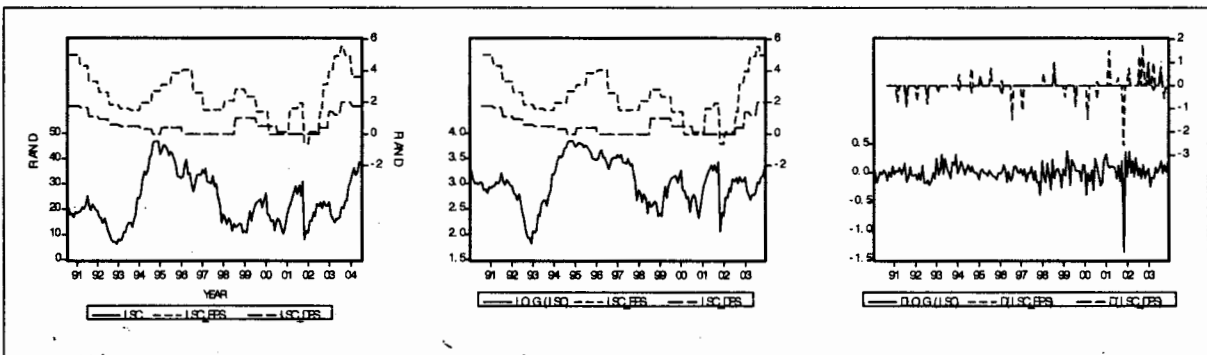


Figure 5: Steel Share (ISC) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms, First Differences and First Differences of Logarithms

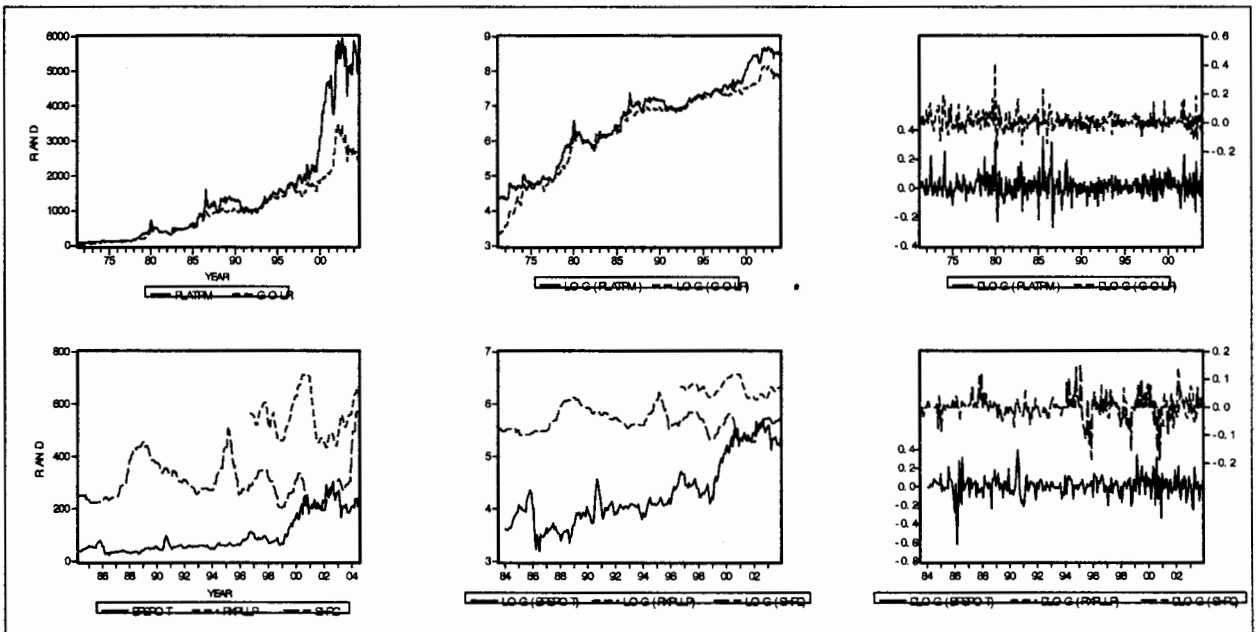


Figure 6: Commodities (PLATPM, GOLR, BRSPOT, PXPULP and SHRC) Prices in Levels, Logarithms, and First Differences of Logarithms

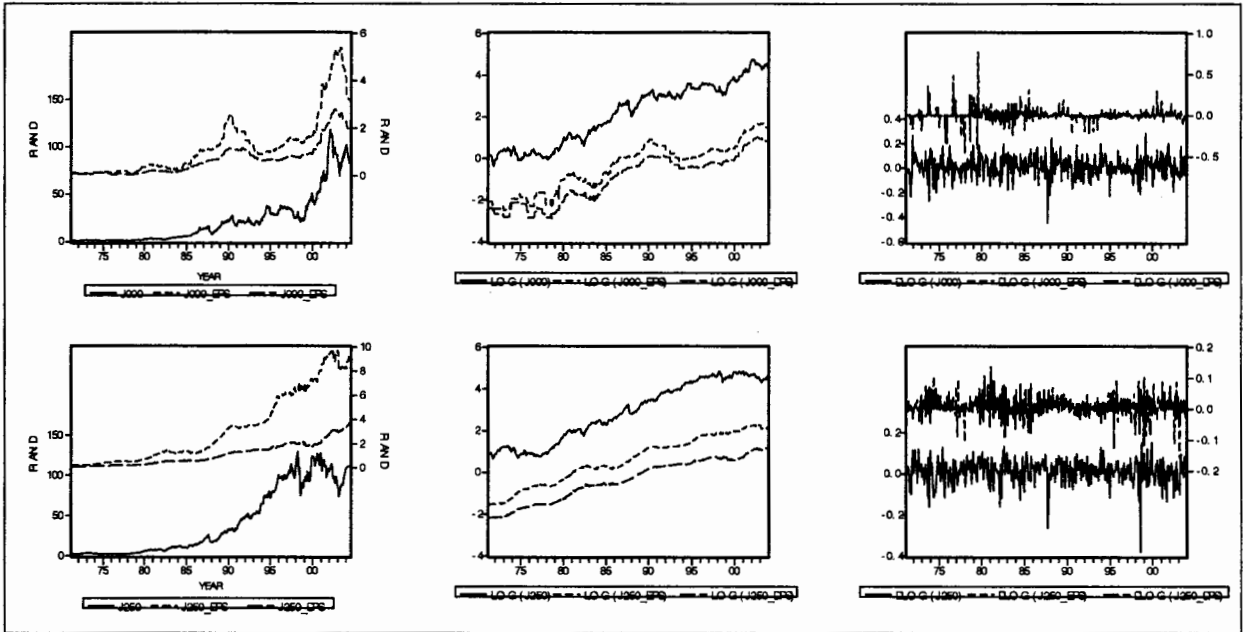


Figure 7: Index Shares (J000 and J250) Share Price, Earnings Per Share and Dividends Per Share in Levels, Logarithms, and First Differences of Logarithms

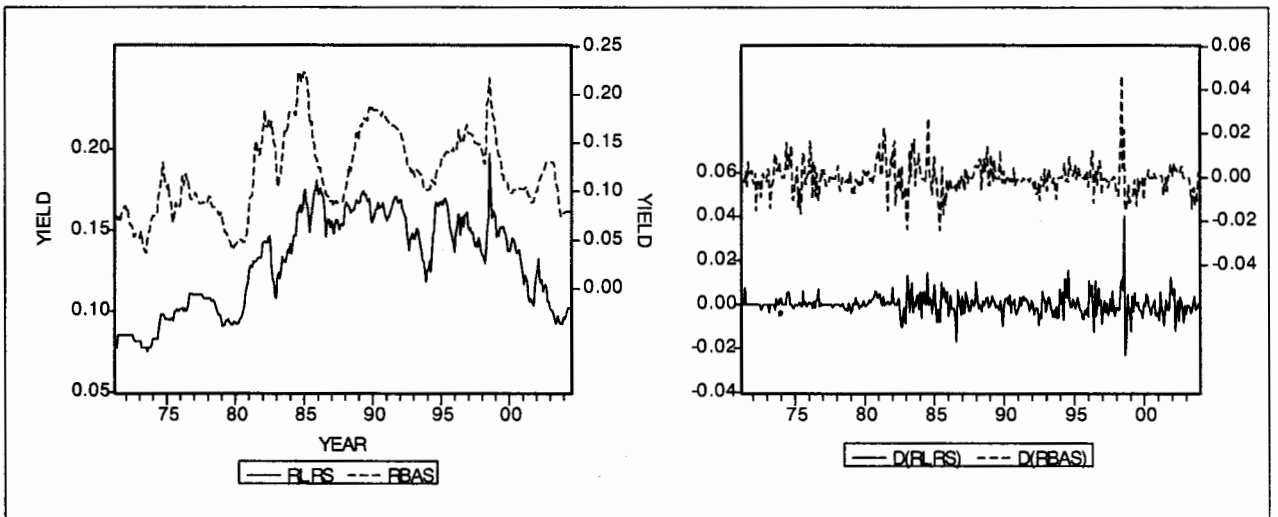


Figure 8: Interest Rates (RLRS and RBAS) in Levels and First Differences

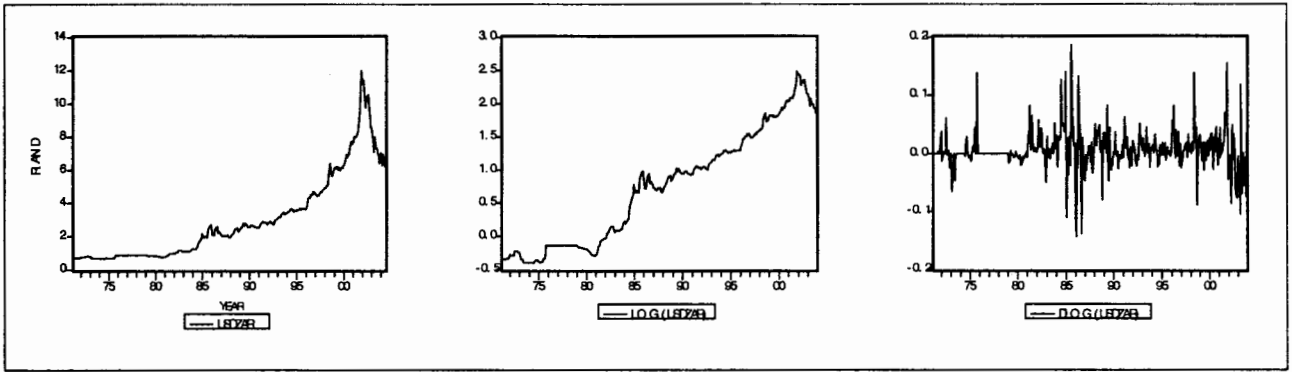


Figure 9: R/\$ Exchange Rate (USDZAR) in Level, Logarithm and First Difference of Logarithm

Before any modeling procedures can be initiated, it is required that all the variables are integrated of the same order, i.e. $I(1)$ or stationary first differences. The third plot of each row in Figures 1 to 9 (second plot in Figure 8) clearly shows that first differences are stationary. Another method of testing a series for stationarity is to plot the sample autocorrelation function (ACF) as covariance stationary series can also be distinguished in terms of correlations. The ACF graphs the values of autocorrelation at successive lags against the length of the lag. It follows from the requirements of covariance stationarity that the correlation between Y_t and Y_{t+h} as in [4] depends only on h . The series is weakly stationary if the correlation between Y_t and Y_{t+h} goes to zero “sufficiently quickly” as $h \rightarrow \infty$ and the correlations between the time periods are said to be asymptotically uncorrelated. The plots of the ACF for the first differences of each of the series as it is being used in the regression, i.e. in log transformation or level, can be found in Appendix A. These plots are called correlograms. From these plots it can also be seen that the first differences of all these variables follow a stable autoregressive process as in [6] with $|\rho| < 1$. The partial autocorrelation function (PACF) allows one to determine the exact nature of the AR process.

4.2. Formulation of the Models

The next step is to attempt to find meaningful long-term equilibrium relationships by estimating the regression as in [1] using various combinations (that make economic sense) of the variables presented in Table 1. Only the significant models will be presented.

The following models were found to be co-integrated and can formally be written as (stochastic error terms are omitted):

1. $\log(IMP) = C_0 + C_1 \log(PLATPM) + C_2 \log(IMP_EPS) + C_3 \log(IMP_DPS) + C_4 RLRS$
2. $\log(HAR) = C_0 + C_1 \log(GOLR) + C_2 HAR_EPS + C_3 HAR_DPS + C_4 RLRS$
3. $\log(GFI) = C_0 + C_1 \log(GOLR) + C_2 \log(GFI_EPS) + C_3 \log(GFI_DPS) + C_4 RLRS$
4. $\log(SOL) = C_0 + C_1 \log(SOL_EPS) + C_2 \log(SOL_DPS) + C_3 RLRS$
5. $\log(SAP) = C_0 + C_1 PXPULP + C_2 SAP_EPS + C_3 SAP_DPS + C_4 RLRS$

In Models 1, 2, 3, and 5, a long-term relationship was found between share price, commodity price, earnings per share, dividends per share and the long-term interest rate. Models 1, 2, 3 and 5 were also co-integrated with the short-term interest rate, RBAS but since this variable is highly correlated with the long-term rate, RLRS, the results are very similar and are therefore not presented. Including the commodity BRSPOT or RBAS in Model 4 fails to pass the co-integration test. Also in Model 5, a co-integrating relationship is only found when I do not take the log of PXPULP. This is acceptable, as PXPULP does not display any strong trend. Unfortunately no co-integrating relationships could be found for AMS, ANG and ISC.

The next step is to construct an ECM for each co-integrating relationship. Three generalizations of each model (as in [10]) were estimated and the best model was chosen by evaluating and comparing the models' forecasting performance based on information criteria. A program was implemented in Eviews to carry out the rolling window

forecasting procedure. The sample program implemented for Model 1 ($\log(IMP)$) along with explanation can be found in Appendix D. The next section presents the results.

5. Results

All models were estimated using Ordinary Least Squares (OLS). A full report of all results can be found in Appendix C.

5.1. Model 1 – $\Delta \log(IMP)$

Dependent Variable: LOG(IMP)				
Method: Least Squares				
Sample(adjusted): 1982:08 2004:07				
Included observations: 264 after adjusting endpoints				
Explanatory Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.266261	0.340085	-12.54468	0.0000
LOG(PLATPM)	1.141981	0.050249	22.72630	0.0000
LOG(IMP_EPS)	-0.407330	0.091560	-4.448789	0.0000
LOG(IMP_DPS)	0.651860	0.078105	8.345911	0.0000
RLRS	1.643201	0.868123	1.892821	0.0595
R-squared	0.953267	Mean dependent var		4.275604
Adjusted R-squared	0.952546	S.D. dependent var		1.099551
S.E. of regression	0.239526	Akaike info criterion		-0.001550
Sum squared resid	14.85956	Schwarz criterion		0.066177
Log likelihood	5.204544	F-statistic		1320.793
Durbin-Watson stat	0.257529	Prob(F-statistic)		0.000000

Table 2: OLS coefficient estimates obtained from the regression of dependent variable $\log(IMP)$ on explanatory variables $\log(PLATPM)$, $\log(IMP_EPS)$, $\log(IMP_DPS)$, $RLRS$ and constant C . It needs to be established that the residual series obtained from this regression is stationary and consequently that the variables in this model are co-integrated.

OLS regression produced the coefficient estimates shown in Table 2 for the regression of dependent variable $\log(IMP)$ on explanatory variables $\log(PLATPM)$, $\log(IMP_EPS)$, $\log(IMP_DPS)$, $RLRS$ and a constant C . The regression yields a vector of residuals, obtained by subtracting the fitted values (product of estimated coefficients and actual values of the explanatory variables) from the actual values of $\log(IMP)$. This is the vector u_t in [5], which determines whether the variables are co-integrated or not. The first plot in Figure 10 displays the residual series, together with the actual and fitted values of $\log(IMP)$. At the points where the residual series u_t is positive, the OLS regression under

predicted $\log(IMP)$ and when u_t is negative, the regression over predicted $\log(IMP)$. At the points where $u_t = 0$, the actual value of $\log(IMP)$ equals the fitted value. In the plot, u_t frequently crosses the zero line thus one can say the regression frequently moves toward equilibrium. The second plot in Figure 10 displays the correlogram of the residuals. The ACF values are all less than one in absolute value and the plot converges to zero fairly quickly. These plots show that the residual series is stationary and follows a stable AR(1) process. The Augmented Engle & Granger test results depicted in Table 3 confirms this conclusion. The EG critical values are tabulated for m , the number of regressors equal to 5. The complete test results are shown in Appendix C. One lagged difference term of the residual series was added to remove serial correlation. The test produced a τ statistic of -4.208717 , which is greater in absolute value than the EG critical values at the 10% significance level (-4.13). The null hypothesis that the residual series contains a unit root and therefore stationary is rejected and thus $\log(IMP)$, $\log(PLATPM)$, $\log(IMP_EPS)$, $\log(IMP_DPS)$ and $RLRS$, despite being individually non-stationary, are co-integrated.³

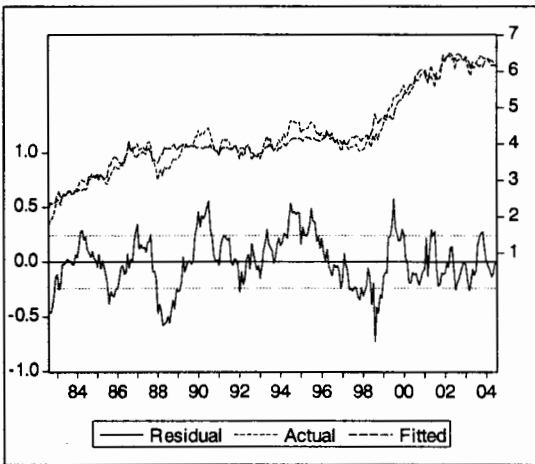


Figure 10: The first diagram displays the actual, fitted and residual values obtained from the OLS regression for dependent variable $\log(IMP)$ in Table 2. The second diagram on the right displays the correlogram of the residuals obtained from this regression. These diagrams both show stationarity of the residuals.

Sample: 1971:04 2004:07 Included observations: 264		
Autocorrelation	Partial Correlation	AC
*****	*****	1 0.864
*****	*	2 0.770
*****	*	3 0.661
****	*	4 0.553
****	.	5 0.469
***	.	6 0.399
**	.	7 0.327
**	*	8 0.250
*	.	9 0.194
*	.	10 0.138
*	*	11 0.081
.	.	12 0.031
.	.	13 -0.023
*	.	14 -0.065
*	.	15 -0.109
*	.	16 -0.149
*	.	17 -0.173
**	.	18 -0.203
**	.	19 -0.218
**	*	20 -0.244
**	.	21 -0.250
**	.	22 -0.248

³ The series is also found to be co-integrated in the in-sample estimation period at approximately 80% confidence level with a τ statistic of -3.686488 . Look-ahead bias is consequently avoided.

Augmented Engle & Granger Unit Root Test				
ADF Test Statistic	-4.208717	1%	Critical Value	-4.96
		5%	Critical Value	-4.42
		10%	Critical Value	-4.13

Table 3: Augmented Engle & Granger Unit Root Test on the residuals obtained from the regression in Table 2 for $\log(IMP)$. The critical values on the right are the Engle & Granger critical values ($m=5$) for rejection of hypothesis of a unit root. The τ statistic is greater (in absolute value) than the EG critical values at the 10% significance level.

Since it was established that the variables in Table 2 are linked by a stable long-term equilibrium relationship, one can now use the residual series obtained as an additional $I(0)$ regressor to construct the Error Correction Model's (ECM). The purpose of the construction of these models is to correct for the short-term disequilibrium that exists between the variables in their level form and also to determine whether the model could be useful in explaining future share price returns. The following three ECM's were constructed for $\log(IMP)$:

$$\Delta \log(IMP_t) = c_1 + c_2 res_{t-1} + c_3 \Delta \log(IMP_{t-1}) + c_4 \Delta \log(PLATPM_{t-1}) + c_5 \Delta(RLRS_{t-1}) + c_6 \Delta \log(IMP_EPS_{t-1}) \quad [26]$$

$$\Delta \log(IMP_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^3 c_{2+k} \Delta \log(IMP_{t-k}) + \sum_{k=1}^3 c_{5+k} \Delta \log(PLATPM_{t-k}) + \sum_{k=1}^3 c_{8+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^3 c_{11+k} \Delta \log(IMP_EPS_{t-k}) \quad [27]$$

$$\Delta \log(IMP_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^6 c_{2+k} \Delta \log(IMP_{t-k}) + \sum_{k=1}^6 c_{8+k} \Delta \log(PLATPM_{t-k}) + \sum_{k=1}^6 c_{14+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^6 c_{20+k} \Delta \log(IMP_EPS_{t-k}) \quad [28]$$

The ECM in [26] estimates a model for the log return of IMP share price using one lag of the residual series obtained from the co-integrating relationship (RES_{t-1}), one lag of the log return of IMP ($\Delta \log(IMP_{t-1})$), one lag of the log return of $PLATPM$ ($\Delta \log(IMP_{t-1})$), one lag of the log return of IMP_EPS ($\Delta \log(IMP_EPS_{t-1})$), and one lag of the first

difference of RLRS ($\Delta(RLRS_{t-1})$). The ECM's in [27] and [28] estimates the same model generalized to include three and six lags respectively of each of the dependent and explanatory variables (only one lag of *RES* is added in each case). The models in [26], [27] and [28] estimate a total of 5, 14 and 26 coefficients respectively. To model the average log returns over two and three months, change the dependent variable of each model to

$$(\Delta \log(IMP_t) + \Delta \log(IMP_{t+1}))/2 \quad [29]$$

and

$$(\Delta \log(IMP_t) + \Delta \log(IMP_{t+1}) + \Delta \log(IMP_{t+2}))/3 \quad [30]$$

respectively. The right-hand side of each model remains the same as in [26], [27] and [28]. The coefficients of each of the above models were estimated in the in-sample estimation period and the models forecasting ability was tested in the out-of-sample forecast evaluation period. The in-sample estimation period spanned 1983:04 to 1999:12 and the out-of-sample forecast evaluation period spanned 2000:01 to 2004:07. OLS regression results are given in Appendix C.

All the variables in these models are now stationary and therefore the standard inference procedures can be used to draw conclusions about the model. The reason why *IMP_DPS* was not included in this model is because of the almost collinear relationship it has with *IMP_EPS*. Since the regression statistics now matters, one cannot allow collinearity effects to obstruct performance of the model. Also notice in the results for each model, the coefficient of the error correction term (*RES*) for each model is significant with the proper negative sign as expected, meaning the adjustment back to long run equilibrium definitely has an effect on short run changes in $\log(IMP)$.

The model that displays the best forecasting properties is chosen to explain future behaviour of *IMP* log returns. The forecast evaluation criteria results are presented in Table 4, where the values in bold indicate the best model based on the corresponding criteria.

FORECAST EVALUATION CRITERIA RESULTS			
Dependent variable: One-month return [$\Delta \log(IMP_t)$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.065768	0.057078	0.087584
AIC	-1.280617	-1.236032	-1.231238
CC	0.289489	0.323689	0.421175
RMSE	0.134432	0.133731	0.143788
% Correct Sign Prediction	0.648148	0.685185	0.574074
Dependent variable: Two-month average return [$(\Delta \log(IMP_t) + \Delta \log(IMP_{t+1}))/2$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.097993	0.099979	0.147486
AIC	-2.055676	-2.030819	-2.054959
CC	0.339715	0.381451	0.481035
RMSE	0.085356	0.080526	0.077377
% Correct Sign Prediction	0.703704	0.703704	0.759259
Dependent variable: Three-month average return [$(\Delta \log(IMP_t) + \Delta \log(IMP_{t+1}) + \Delta \log(IMP_{t+2}))/3$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.148179	0.178339	0.193024
AIC	-2.557813	-2.582681	-2.554592
CC	0.405739	0.468937	0.521968
RMSE	0.062410	0.060830	0.058935
% Correct Sign Prediction	0.722222	0.759259	0.666667

Table 4: Forecast evaluation criteria results for each ECM, modelling one, two and three month average log returns for IMP respectively. ECM1, ECM2 and ECM3 models $\Delta \log(IMP)$ with one, three and six lags of each dependent and explanatory variables respectively.

Between ECM2 and ECM3, there is a significant difference in forecast accuracy predicting one-month returns based on RMSE and % correct sign prediction. ECM2 displays better forecasting properties for one-month returns, whereas ECM3 displays better forecasting performance for two and three month returns. The difference in forecast accuracy between the two models is more significant predicting one-month returns than predicting two and three month returns. The graphical illustration of ECM3 in Appendix C shows unstable behaviour for one-month returns. ECM2 will therefore be chosen to display the strongest forecasting performance. The models forecasting accuracy

also improves significantly with forecasting over two and three months. Note the model predicted the correct sign 76% of the time when predicting the average return over three months. The correlation coefficient (CC) of 0.32, 0.38 and 0.47 for one, two and three-month average returns imply a definite significant relationship between the dependent variables (as in Table 4) and the explanatory variables (in [27]). The model may not have achieved the most efficient results under Adj_R^2 , CC or AIC, but as explained in the methodology the RMSE and % correct sign predictions are clearly more important measures of forecast accuracy. It was also explained that forecasts with a higher RMSE may be risky if there is a cost associated with the forecast errors and the % of correct sign prediction criterion is self-explanatory. Thus the explanatory variables in [27] have significant explanatory power in the prediction of one, two and three month average future log returns of *IMP*.

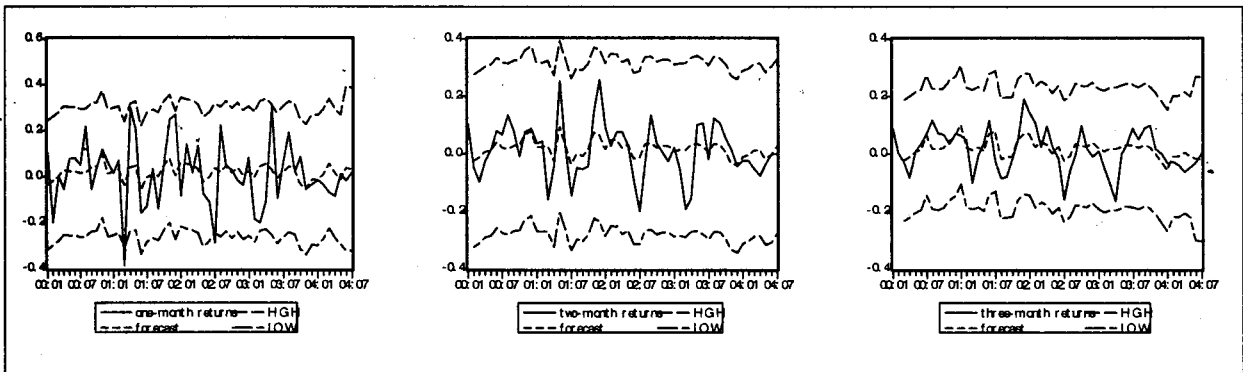


Figure 11: Forecasting performance of the ECM for $\log(IMP)$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three-month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

The forecasting performance of ECM2 is illustrated in Figure 11. The first diagram depicts the forecast for one-month-ahead rolling window returns. The second diagram depicts the average of one and two-month-ahead returns. The third diagram depicts the average of one, two and three-month-ahead returns. Each forecast is compared with the actual values of the corresponding average log returns for *IMP* together with the 95% confidence interval. These plots clearly show that this model possess significant forecasting properties. Forecasting performance for ECM1 and ECM3 can be found in Appendix C.

5.2. Model 2- $\Delta \log(HAR)$

Dependent Variable: LOG(HAR)				
Method: Least Squares				
Sample(adjusted): 1983:04 2004:07				
Included observations: 256 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.732542	0.580103	-4.710444	0.0000
LOG(GOLR)	0.796117	0.061073	13.03543	0.0000
HAR_EPS	-0.023949	0.011949	-2.004207	0.0461
HAR_DPS	0.306185	0.028227	10.84729	0.0000
RLRS	1.358842	1.308808	1.038229	0.3002
R-squared	0.701368	Mean dependent var		3.488498
Adjusted R-squared	0.696609	S.D. dependent var		0.581486
S.E. of regression	0.320288	Akaike info criterion		0.580146
Sum squared resid	25.74868	Schwarz criterion		0.649387
Log likelihood	-69.25864	F-statistic		147.3747
Durbin-Watson stat	0.252657	Prob(F-statistic)		0.000000

Table 5: OLS coefficient estimates obtained from the regression of dependent variable $\log(HAR)$ on explanatory variables $\log(GOLR)$, HAR_EPS , HAR_DPS , $RLRS$ and constant C . It needs to be established that the residual series obtained from this regression is stationary and consequently that the variables in this model are co-integrated.

OLS regression produced the coefficient estimates shown in Table 5 for the regression of dependent variable $\log(HAR)$ on explanatory variables $\log(GOLR)$, HAR_EPS , HAR_DPS , $RLRS$ and a constant C . The residual series obtained from the regression, together with corresponding correlogram, is plotted in Figure 12. The ACF converges to zero fairly quickly. The Augmented Engle & Granger test results are depicted in Table 6. The test produced a τ statistic of -4.428810, which is greater in absolute value than the EG critical values at the 5% significance level (-4.42). One lagged difference term of the residual series was added to remove serial correlation. This confirms stationarity of the residuals and therefore $\log(HAR)$, $\log(GOLR)$, HAR_EPS , HAR_DPS and $RLRS$, despite being individually non-stationary, are co-integrated.⁴

⁴ The series is also co-integrated in the in-sample estimation period at the 90% confidence level ($\tau = -4.351198$).

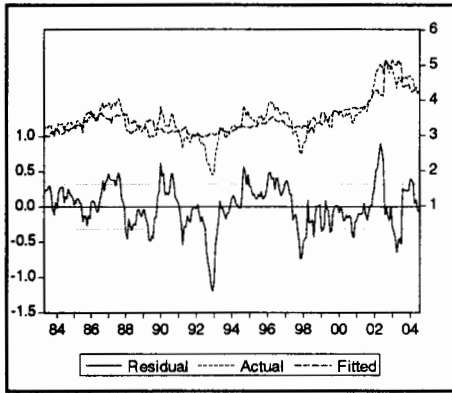


Figure 12: The first diagram displays the actual, fitted and residual values obtained from the OLS regression for dependent variable $\log(HAR)$ in Table 5. The second diagram on the right displays the correlogram of the residuals obtained from this regression. These diagrams both show stationarity of the residuals.

Sample: 1983:04 2004:07 Included observations: 256		
Autocorrelation	Partial Correlation	AC
*****	*****	1 0.873
*****	*	2 0.739
****	*	3 0.586
***	*	4 0.438
***	*	5 0.338
**	*	6 0.236
*	.	7 0.149
.	.	8 0.076
.	.	9 0.011
.	.	10 -0.037
*	.	11 -0.059
*	.	12 -0.078
*	.	13 -0.091
*	*	14 -0.078
*	.	15 -0.064
.	.	16 -0.043
.	.	17 -0.034
.	.	18 -0.024
.	.	19 -0.023
.	.	20 -0.026
*	*	21 -0.064
*	.	22 -0.107
*	.	23 -0.150
**	.	24 -0.191

Augmented Engle & Granger Unit Root Test			
AEG Test Statistic (τ)	-4.428810	1% Critical Value	-4.96
		5% Critical Value	-4.42
		10% Critical Value	-4.13

Table 6: Augmented Engle & Granger Unit Root Test on the residuals obtained from the regression in Table 5 for $\log(HAR)$. The critical values on the right are the Engle & Granger critical values ($m=5$) for rejection of hypothesis of a unit root. The τ statistic is greater (in absolute value) than the EG critical values at the 5% significance level.

The following three ECM's were constructed to model log returns for HAR :

$$\Delta \log(HAR_t) = c_1 + c_2 res_{t-1} + c_3 \Delta \log(HAR_{t-1}) + c_4 \Delta \log(GOLR_{t-1}) + c_5 \Delta(RLRS_{t-1}) + c_6 \Delta(HAR_EPS_{t-1}) \quad [31]$$

$$\begin{aligned} \Delta \log(HAR_t) = & c_1 + c_2 res_{t-1} + \sum_{k=1}^3 c_{2+k} \Delta \log(HAR_{t-k}) + \sum_{k=1}^3 c_{5+k} \Delta \log(GOLR_{t-k}) \\ & + \sum_{k=1}^3 c_{8+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^3 c_{11+k} \Delta(HAR_EPS_{t-k}) \end{aligned} \quad [32]$$

$$\begin{aligned} \Delta \log(HAR_t) = & c_1 + c_2 res_{t-1} + \sum_{k=1}^6 c_{2+k} \Delta \log(HAR_{t-k}) + \sum_{k=1}^6 c_{8+k} \Delta \log(GOLR_{t-k}) \\ & + \sum_{k=1}^6 c_{14+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^6 c_{20+k} \Delta(HAR_EPS_{t-k}) \end{aligned} \quad [33]$$

The residual series (*res*) is the series obtained from the co-integrating regression. The ECM in [31] estimates a model for the log return of *HAR* share price using one lag of the residual series obtained from the co-integrating relationship (RES_{t-1}), one lag of the log return of *HAR* ($\Delta \log(HAR_{t-1})$), one lag of the log return of *GOLR* ($\Delta \log(GOLR_{t-1})$), one lag of the first difference of *HAR_EPS* ($\Delta(HAR_EPS_{t-1})$), and one lag of the first difference of *RLRS* ($\Delta(RLRS_{t-1})$). The ECM's in [32] and [33] estimates the same model generalized to include three and six lags respectively of each of the dependent and explanatory variables (only one lag of *RES* is added in each case).

OLS regression results for the above models can be found in Appendix C. The parameters were estimated in the in-sample estimation period (1983:04 to 1999:12) and the models forecasting ability was tested in the out-of-sample forecast evaluation period (2000:01 to 2004:07). The coefficient of the error correction term (*RES*) for each model is negative as expected, indicating adjustment back to long run equilibrium. Each ECM generated forecasts for one, two and three month average returns. The forecast evaluation criteria results are presented in Table 7.

The ECM in [33] (ECM3 containing 6 lags of dependent and explanatory variables) is chosen to represent the best model. It achieved the highest correlation coefficient (CC) and the highest proportion of correct sign prediction for one, two and three month forecasts. It also achieved the lowest RMSE for two and three month forecasts.

FORECAST EVALUATION CRITERIA RESULTS			
Dependent variable: One-month return [$\Delta\log(HAR_t)$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.030976	0.041369	0.036042
AIC	-1.007766	-0.980331	-0.928122
CC	0.224230	0.302354	0.366067
RMSE	0.142501	0.144841	0.151384
% Correct Sign Prediction	0.500000	0.500000	0.555556
Dependent variable: Two-month average return [$(\Delta\log(HAR_t) + \Delta\log(HAR_{t+1}))/2$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.073444	0.093687	0.062048
AIC	-1.696687	-1.680360	-1.602398
CC	0.303152	0.375506	0.396697
RMSE	0.101821	0.094578	0.088516
% Correct Sign Prediction	0.555556	0.555556	0.648148
Dependent variable: Three-month average return [$(\Delta\log(HAR_t) + \Delta\log(HAR_{t+1}) + \Delta\log(HAR_{t+2}))/3$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.139502	0.147654	0.114256
AIC	-2.135275	-2.106252	-2.019252
CC	0.395782	0.438354	0.451963
RMSE	0.079175	0.073302	0.068987
% Correct Sign Prediction	0.481481	0.537037	0.574074

Table 7: Forecast evaluation criteria results for each ECM, modelling one, two and three month average log returns for HAR respectively. ECM1, ECM2 and ECM3 models $\Delta\log(HAR)$ with one, three and six lags of each dependent and explanatory variables respectively.

Forecasting performance for ECM3 is depicted in Figure 13. The ECM chosen uses six lags of each of the dependent and explanatory variables and one lag of the residual series obtained from the co-integrating model to predict the average log return of HAR share over one, two and three months into the future. Each diagram also plots the 95% confidence interval associated with the forecast made. The ECM in [33] definitely contains significant predictive power in explaining future share price returns. Graphical illustrations of the forecasting performance for ECM1 and ECM2 can be found in Appendix C.

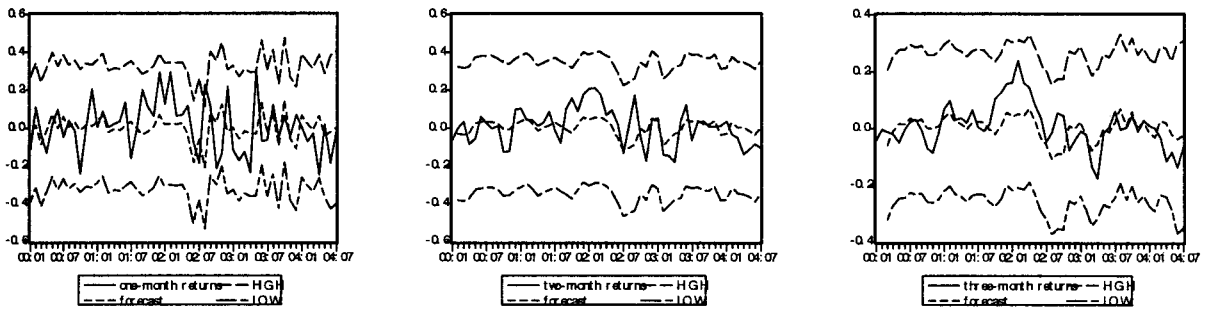


Figure 13: Forecasting performance of the ECM for $\log(\text{HAR})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

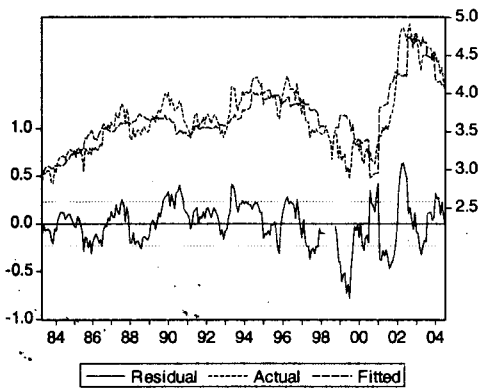
5.3. Model 3 – $\Delta \log(\text{GFI})$

Dependent Variable: LOG(GFI)					
Method: Least Squares					
Sample(adjusted): 1983:04 2004:07					
Included observations: 250					
Excluded observations: 6 after adjusting endpoints					
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
C	-0.988541	0.378826	-2.609489	0.0096	
LOG(GOLR)	0.630366	0.038208	16.49846	0.0000	
LOG(GFI_EPS)	0.029381	0.033273	0.883031	0.3781	
LOG(GFI_DPS)	0.524080	0.032404	16.17335	0.0000	
RLRS	-0.392670	0.915573	-0.428879	0.6684	
R-squared	0.747917	Mean dependent var	3.693067		
Adjusted R-squared	0.743801	S.D. dependent var	0.456304		
S.E. of regression	0.230963	Akaike info criterion	-0.073320		
Sum squared resid	13.06928	Schwarz criterion	-0.002890		
Log likelihood	14.16495	F-statistic	181.7255		
Durbin-Watson stat	0.297568	Prob(F-statistic)	0.000000		

Table 8: OLS coefficient estimates obtained from the regression of dependent variable $\log(\text{GFI})$ on explanatory variables $\log(\text{GOLR})$, $\text{LOG}(\text{GFI_EPS})$, $\text{LOG}(\text{GFI_DPS})$, RLRS and constant C . It needs to be established that the residual series obtained from this regression is stationary and consequently that the variables in this model are co-integrated.

OLS regression produced the coefficient estimates shown in Table 8 for the regression of dependent variable $\log(\text{GFI})$ on explanatory variables $\log(\text{GOLR})$, $\log(\text{GFI_EPS})$, $\log(\text{GFI_DPS})$, RLRS and a constant C . Figure 14 plots the residual series along with the actual and fitted values of $\log(\text{GFI})$ and also the correlogram of residuals. The variables

in the model are co-integrated if the residual series of the regression is stationary. The ACF values are all less than one in absolute value and the plot of the autocorrelations converges to zero fairly quickly. The AEG test (in Table 9) produced a τ statistic of -4.633376, which is greater in absolute value than the EG critical values at the 5% significance level (-4.42). Two lagged difference terms of the residual series was included to eliminate serial correlation. This confirms stationarity of the residuals and therefore $\log(GFI)$, $\log(GOLR)$, $\log(GFI_EPS)$, $\log(GFI_DPS)$ and $RLRS$, despite being individually non-stationary, are co-integrated.⁵



Sample: 1971:04 2004:07		
Included observations: 250		
Autocorrelation	Partial Correlation	AC
*****	*****	1 0.851
*****	..	2 0.724
*****	*	3 0.588
***	*	4 0.443
**	*	5 0.304
*	*	6 0.171
*	..	7 0.078
..	..	8 0.003
*	..	9 -0.064
*	..	10 -0.097
*	*	11 -0.139
*	..	12 -0.168
*	*	13 -0.146
*	*	14 -0.103
..	..	15 -0.047
..	..	16 0.018
*	..	17 0.076
*	..	18 0.137
*	..	19 0.172
**	..	20 0.209
**	..	21 0.225
**	*	22 0.241
**	..	23 0.261
**	..	24 0.264

Figure 14: The first diagram displays the actual, fitted and residual values obtained from the OLS regression for dependent variable $\log(GFI)$ in Table 8. The second diagram on the right displays the correlogram of the residuals obtained from this regression. These diagrams both show stationarity of the residuals.

⁵ The series is also co-integrated in the in-sample estimation period at the 95% confidence level ($\tau = -4.526757$)

Augmented Engle & Granger Unit Root Test			
ADF Test Statistic	-4.633376	1% Critical Value	-4.96
		5% Critical Value	-4.42
		10% Critical Value	-4.13

Table 9: Augmented Engle & Granger Unit Root Test on the residuals obtained from the regression in Table 8 for $\log(GFI)$. The critical values on the right are the Engle & Granger critical values ($m=5$) for rejection of hypothesis of a unit root. The τ statistic is greater (in absolute value) than the EG critical values at the 5% significance level.

The following ECM's were constructed to model log returns for GFI :

$$\begin{aligned} \Delta \log(GFI_t) = & c_1 + c_2 res_{t-1} + c_3 \Delta \log(GFI_{t-1}) + c_4 \Delta \log(GOLR_{t-1}) \\ & + c_5 \Delta(RLRS_{t-1}) + c_6 \Delta \log(GFI_EPS_{t-1}) \end{aligned} \quad [34]$$

$$\begin{aligned} \Delta \log(GFI_t) = & c_1 + c_2 res_{t-1} + \sum_{k=1}^3 c_{2+k} \Delta \log(GFI_{t-k}) + \sum_{k=1}^3 c_{5+k} \Delta \log(GOLR_{t-k}) \\ & + \sum_{k=1}^3 c_{8+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^3 c_{11+k} \Delta \log(GFI_EPS_{t-k}) \end{aligned} \quad [35]$$

$$\begin{aligned} \Delta \log(GFI_t) = & c_1 + c_2 res_{t-1} + \sum_{k=1}^6 c_{2+k} \Delta \log(GFI_{t-k}) + \sum_{k=1}^6 c_{8+k} \Delta \log(GOLR_{t-k}) \\ & + \sum_{k=1}^6 c_{14+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^6 c_{20+k} \Delta \log(GFI_EPS_{t-k}) \end{aligned} \quad [36]$$

The ECM in [34] estimates a model for the log return of GFI share price using one lag of the residual series obtained from the co-integrating relationship (RES_{t-1}), one lag of the log return of GFI ($\Delta \log(GFI_{t-1})$), one lag of the log return of $GOLR$ ($\Delta \log(GOLR_{t-1})$), one lag of the log return of GFI_EPS ($\Delta \log(GFI_EPS_{t-1})$), and one lag of the first difference of $RLRS$ ($\Delta(RLRS_{t-1})$). The ECM's in [35] and [36] estimates the same model generalized to include three and six lags respectively of each of the dependent and explanatory variables (only one lag of RES is added in each case).

OLS regression results for the above models can be found in Appendix C. The parameters were estimated in the in-sample estimation period (1983:04 to 1999:12) and the models forecasting ability was tested in the out-of-sample forecast evaluation period

(2000:01 to 2004:07). The coefficient of the error correction term (*RES*) for each model is negative as expected, indicating adjustment back to long run equilibrium. Each ECM generated forecasts for one, two and three month average returns. The forecast evaluation criteria results are presented in Table 10.

Undoubtedly ECM3 (ECM containing 6 lags of dependent and explanatory variables) is the best model. It achieved the absolute best results across all information criteria. The correlation coefficient is significant and the proportion of correct sign prediction is high and RMSE is low. This is clearly the best model with the most efficient forecasting abilities.

FORECAST EVALUATION CRITERIA RESULTS			
Dependent variable: One-month return [$\Delta\log(GFI_t)$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.028683	0.024982	0.118853
AIC	-1.609283	-1.594285	-1.644497
CC	0.220426	0.278918	0.461512
RMSE	0.120487	0.119909	0.114679
% Correct Sign Prediction	0.537037	0.555556	0.648148
Dependent variable: Two-month average return [$(\Delta\log(GFI_t) + \Delta\log(GFI_{t+1}))/2$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.065287	0.067372	0.151484
AIC	-2.419637	-2.378099	-2.424162
CC	0.290587	0.343351	0.492075
RMSE	0.085393	0.080851	0.070701
% Correct Sign Prediction	0.555556	0.611111	0.759259
Dependent variable: Three-month average return [$(\Delta\log(GFI_t) + \Delta\log(GFI_{t+1}) + \Delta\log(GFI_{t+2}))/3$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.108090	0.121163	0.207776
AIC	-2.838077	-2.818518	-2.866225
CC	0.355481	0.410812	0.540754
RMSE	0.070882	0.065868	0.055502
% Correct Sign Prediction	0.574074	0.592593	0.685185

Table 10: Forecast evaluation criteria results for each ECM, modelling one, two and three month average log returns for GFI respectively. ECM1, ECM2 and ECM3 models $\Delta\log(GFI)$ with one, three and six lags of each dependent and explanatory variables respectively.

Forecasting performance for ECM3 is depicted in Figure 15. It is evident that this model contains significant predictive power in explaining future share price returns of *GFI*. The forecasting performance for ECM1 and ECM2 can be found in Appendix C.

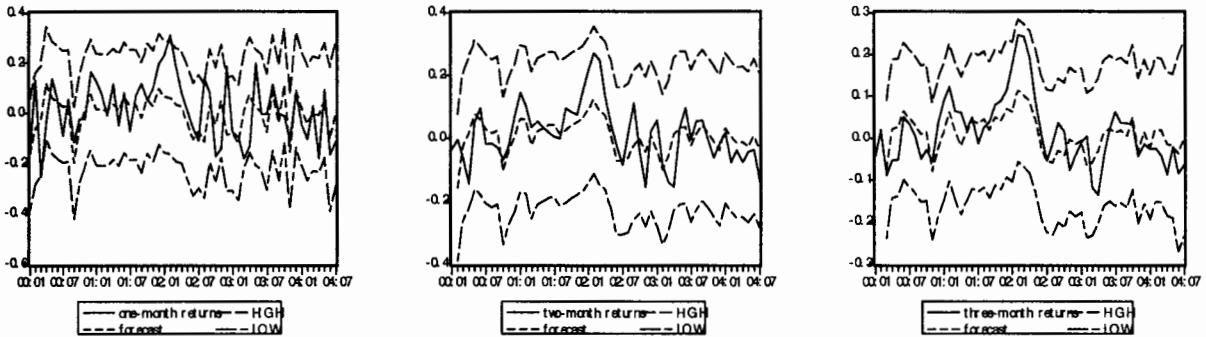


Figure 15: Forecasting performance of the ECM for $\log(GFI)$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

5.4. Model 4 – $\Delta \log(SOL)$

OLS regression produced the coefficient estimates shown in Table 11 for the regression of dependent variable $\log(SOL)$ on explanatory variables $\log(SOL_EPS)$, $\log(SOL_DPS)$, $RLRS$ and a constant C . Figure 16 plots the residual series along with the actual and fitted values of $\log(SOL)$ and also the correlogram of residuals. The ACF values are all less than one in absolute value and the plot of the autocorrelations converges to zero fairly quickly. The AEG test (in Table 12) produced a τ statistic of -4.128368, which is greater in absolute value than the EG critical values at the 5% significance level (-4.10). One lagged difference term of the residual series was included to eliminate serial correlation. This confirms stationarity of the residuals and therefore $\log(SOL)$, $\log(SOL_EPS)$, $\log(SOL_DPS)$ and $RLRS$, despite being individually non-stationary, are co-integrated.⁶

⁶ The series is also co-integrated in the in-sample estimation period at the 95% confidence level ($\tau = -4.227958$)

Dependent Variable: LOG(SOL)
 Method: Least Squares
 Sample(adjusted): 1982:02 2004:07
 Included observations: 270 after adjusting endpoints

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.385461	0.153005	9.055013	0.0000
LOG(SOL_EPS)	0.830390	0.097275	8.536502	0.0000
LOG(SOL_DPS)	0.313135	0.111566	2.806726	0.0054
RLRS	7.008143	0.766302	9.145400	0.0000
R-squared	0.955021	Mean dependent var	3.019166	
Adjusted R-squared	0.954514	S.D. dependent var	1.017724	
S.E. of regression	0.217055	Akaike info criterion	-0.202629	
Sum squared resid	12.53201	Schwarz criterion	-0.149320	
Log likelihood	31.35498	F-statistic	1882.630	
Durbin-Watson stat	0.282383	Prob(F-statistic)	0.000000	

Table 11: OLS coefficient estimates obtained from the regression of dependent variable log(SOL) on explanatory variables LOG(SOL_EPS), LOG(SOL_DPS), RLRS and constant C. It needs to be established that the residual series obtained from this regression is stationary and consequently that the variables in this model are co-integrated.

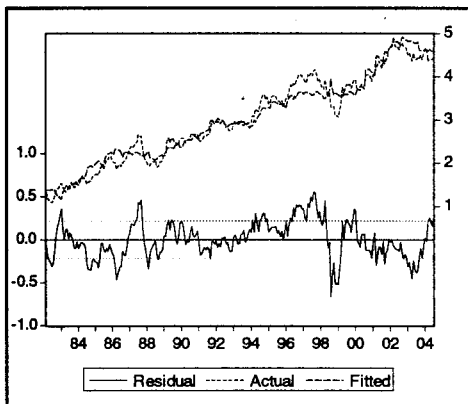


Figure 16: The first diagram displays the actual, fitted and residual values obtained from the OLS regression for dependent variable log(SOL) in Table 11. The second diagram on the right displays the correlogram of the residuals obtained from this regression. These diagrams both show stationarity of the residuals.

Sample: 1971:04 2004:07		Included observations: 270	
Autocorrelation	Partial Correlation	AC	
*****	*****	1	0.856
*****		2	0.744
*****		3	0.646
****	*	4	0.528
***		5	0.442
***		6	0.377
**	*	7	0.287
**	*	8	0.201
*		9	0.139
*		10	0.075
		11	0.022
		12	-0.001
		13	-0.014
		14	-0.035
		15	-0.030
		16	-0.027
	*	17	0.010
*	*	18	0.069
*		19	0.108
*		20	0.131
*	*	21	0.135
*		22	0.131
*		23	0.120
*		24	0.118

Augmented Engle & Granger Unit Root Test			
ADF Test Statistic	-4.128368	1% Critical Value	-3.81
		5% Critical Value	-4.10
		10% Critical Value	-4.64

Table 12: Augmented Engle & Granger Unit Root Test on the residuals obtained from the regression in Table 11 for $\log(SOL)$. The critical values on the right are the Engle & Granger critical values ($m=4$) for rejection of hypothesis of a unit root. The τ statistic is greater (in absolute value) than the EG critical values at the 5% significance level.

The following ECM's were constructed to model log returns for SOL :

$$\Delta \log(SOL_t) = c_1 + c_2 res_{t-1} + c_3 \Delta \log(SOL_{t-1}) + c_4 \Delta(RLRS_{t-1}) + c_5 \Delta \log(SOL_EPS_{t-1}) \quad [37]$$

$$\Delta \log(SOL_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^3 c_{2+k} \Delta \log(SOL_{t-k}) + \sum_{k=1}^3 c_{5+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^3 c_{8+k} \Delta \log(SOL_EPS_{t-k}) \quad [38]$$

$$\Delta \log(SOL_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^6 c_{2+k} \Delta \log(SOL_{t-k}) + \sum_{k=1}^6 c_{8+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^6 c_{14+k} \Delta \log(SOL_EPS_{t-k}) \quad [39]$$

The ECM in [37] estimates a model for the log return of SOL share price using one lag of the residual series obtained from the co-integrating relationship (RES_{t-1}), one lag of the log return of SOL ($\Delta \log(SOL_{t-1})$), one lag of the log return of SOL_EPS ($\Delta \log(SOL_EPS_{t-1})$), and one lag of the first difference of RLRS ($\Delta(RLRS_{t-1})$). The ECM's in [38] and [39] estimates the same model generalized to include three and six lags respectively of each of the dependent and explanatory variables (only one lag of RES is added in each case).

OLS regression results for the above models can be found in Appendix C. The parameters were estimated in the in-sample estimation period (1982:02 to 1999:12) and

the models forecasting ability was tested in the out-of-sample forecast evaluation period (2000:01 to 2004:07). The coefficient of the error correction term (*RES*) for each model is negative as expected, indicating adjustment back to long run equilibrium. Each ECM generated forecasts for one, two and three month average returns. The forecast evaluation criteria results are presented in Table 13.

FORECAST EVALUATION CRITERIA RESULTS			
Dependent variable: One-month return [$\Delta \log(SOL_t)$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.024510	0.048139	0.083769
AIC	-1.921094	-1.917908	-1.916636
CC	0.198077	0.290398	0.388233
RMSE	0.099542	0.103364	0.102861
% Correct Sign Prediction	0.481481	0.500000	0.518519
Dependent variable: Two-month average return [$(\Delta \log(SOL_t) + \Delta \log(SOL_{t+1}))/2$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.066233	0.098744	0.132064
AIC	-2.653047	-2.662470	-2.665466
CC	0.283422	0.364709	0.442142
RMSE	0.064023	0.061143	0.059648
% Correct Sign Prediction	0.611111	0.666667	0.666667
Dependent variable: Three-month average return [$(\Delta \log(SOL_t) + \Delta \log(SOL_{t+1}) + \Delta \log(SOL_{t+2}))/3$]			
	ECM1 (1-lag)	ECM2 (3-lags)	ECM3 (6-lags)
Adj-R ²	0.106451	0.126069	0.150843
AIC	-3.078693	-3.074302	-3.072886
CC	0.346322	0.399122	0.461407
RMSE	0.050368	0.050543	0.049446
% Correct Sign Prediction	0.574074	0.574074	0.555556

Table 13: Forecast evaluation criteria results for each ECM, modelling one, two and three month average log returns for SOL respectively. ECM1, ECM2 and ECM3 models $\Delta \log(SOL)$ with one, three and six lags of each dependent and explanatory variables respectively.

Again ECM3 (ECM containing 6 lags of dependent and explanatory variables) is chosen to be the best model. The difference in forecast accuracy based on RMSE and % correct sign prediction is relatively small, which made this decision harder than the other models.

ECM3 was chosen because of the significant improvement in Adj-R² and correlation coefficient for each forecast.

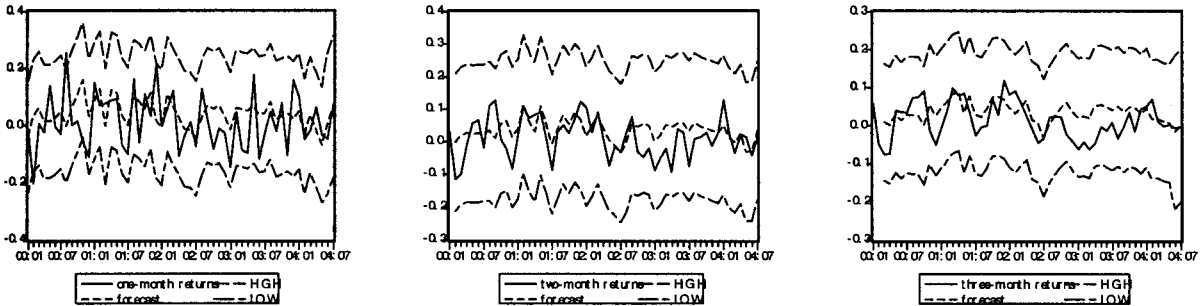


Figure 17: Forecasting performance of the ECM for log(SOL) containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three-month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

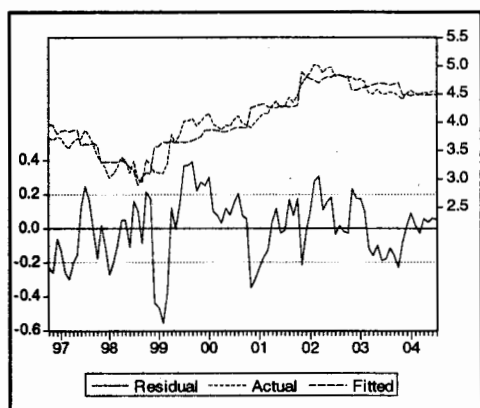
The forecasting performance of ECM3 is graphically illustrated in Figure 17. The model clearly demonstrates significant forecasting abilities.

5.5. Model 5 – $\Delta \log(SAP)$

Dependent Variable: LOG(SAP)				
Method: Least Squares				
Sample(adjusted): 1996:10 2004:07				
Included observations: 94 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.845335	0.285496	13.46895	0.0000
PXPULP	0.000510	0.000279	1.829546	0.0707
SAP_EPS	-0.002005	0.008888	-0.225558	0.8221
SAP_DPS	0.465457	0.037037	12.56721	0.0000
RLRS	-6.088709	1.284317	-4.740816	0.0000
R-squared	0.882591	Mean dependent var	4.063327	
Adjusted R-squared	0.877315	S.D. dependent var	0.569026	
S.E. of regression	0.199310	Akaike info criterion	-0.336188	
Sum squared resid	3.535471	Schwarz criterion	-0.200907	
Log likelihood	20.80085	F-statistic	167.2591	
Durbin-Watson stat	0.641995	Prob(F-statistic)	0.000000	

Table 14: OLS coefficient estimates obtained from the regression of dependent variable log(SAP) on explanatory variables PXPULP, SAP_EPS, SAP_DPS, RLRS and constant C. It needs to be established that the residual series obtained from this regression is stationary and consequently that the variables in this model are co-integrated.

OLS regression produced the coefficient estimates shown in Table 14 for the regression of dependent variable $\log(SAP)$ on explanatory variables $PXPULP$, SAP_EPS , SAP_DPS , $RLRS$ and a constant C . Figure 18 plots the residual series along with the actual and fitted values of $\log(SAP)$ and also the correlogram of residuals. The ACF values are all less than one in absolute value and the plot of the autocorrelations converges to zero fairly quickly. The AEG test (Table 15) produced a τ statistic of -4.479323, which is greater in absolute value than the EG critical values at the 5% significance level (-4.42). One lagged difference term of the residual series was included to eliminate serial correlation. This confirms stationarity of the residuals and therefore $\log(SAP)$, $PXPULP$, SAP_EPS , SAP_DPS and $RLRS$, despite being individually non-stationary, are co-integrated.⁷



Sample: 1971:04 2004:07 Included observations: 94		
Autocorrelation	Partial Correlation	AC
. *****	. *****	1 0.671
. ***	. *	2 0.379
. *	. .	3 0.195
. .	. *	4 -0.002
. *	. *	5 -0.067
. *	. *	6 -0.150
. **	. .	7 -0.199
. *	. *	8 -0.111
. *	. .	9 -0.070
. .	. *	10 -0.040
. .	. *	11 0.041
. .	. *	12 0.039
. .	. *	13 -0.025
. *	. .	14 -0.067
. *	. *	15 -0.126
. *	. *	16 -0.180
. **	. *	17 -0.259
. **	. .	18 -0.304
. **	. .	19 -0.220
. *	. *	20 -0.072

Figure 18: The first diagram displays the actual, fitted and residual values obtained from the OLS regression for dependent variable $\log(SAP)$ in Table 14. The second diagram on the right displays the correlogram of the residuals obtained from this regression. These diagrams both show stationarity of the residuals.

Augmented Engle & Granger Unit Root Test			
ADF Test Statistic	-4.479323	1% Critical Value	-4.96
		5% Critical Value	-4.42
		10% Critical Value	-4.13

Table 15: Augmented Engle & Granger Unit Root Test on the residuals obtained from the regression in Table 14 for $\log(SAP)$. The critical values on the right are the Engle & Granger critical values ($m=5$) for rejection of hypothesis of a unit root. The τ statistic is greater (in absolute value) than the EG critical values at the 5% significance level

⁷ The series is also co-integrated in the in-sample estimation period at approximately 85% confidence level ($\tau = -3.550487$)

The following ECM's were constructed to model log returns for *SAP*:

$$\Delta \log(SAP_t) = c_1 + c_2 res_{t-1} + c_3 \Delta \log(SAP_{t-1}) + c_4 \Delta(PXPULP_{t-1}) + c_5 \Delta(RLRS_{t-1}) + c_6 \Delta(SAP_EPS_{t-1}) \quad [40]$$

$$\Delta \log(SAP_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^3 c_{2+k} \Delta \log(SAP_{t-k}) + \sum_{k=1}^3 c_{5+k} \Delta(PXPULP_{t-k}) + \sum_{k=1}^3 c_{8+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^3 c_{11+k} \Delta(SAP_EPS_{t-k}) \quad [41]$$

$$\Delta \log(SAP_t) = c_1 + c_2 res_{t-1} + \sum_{k=1}^6 c_{2+k} \Delta \log(SAP_{t-k}) + \sum_{k=1}^6 c_{8+k} \Delta(PXPULP_{t-k}) + \sum_{k=1}^6 c_{14+k} \Delta(RLRS_{t-k}) + \sum_{k=1}^6 c_{20+k} \Delta(SAP_EPS_{t-k}) \quad [42]$$

The ECM in [40] estimates a model for the log return of *SAP* share price using one lag of the residual series obtained from the co-integrating relationship (*RES*_{*t-1*}), one lag of the log return of *SAP* ($\Delta \log(SAP_{t-1})$), one lag of the first difference of *PXPULP* ($\Delta(PXPULP_{t-1})$), one lag of the first difference of *SAP_EPS* ($\Delta(SAP_EPS_{t-1})$), and one lag of the first difference of *RLRS* ($\Delta(RLRS_{t-1})$). The ECM's in [41] and [42] estimates the same model generalized to include three and six lags respectively of each of the dependent and explanatory variables (only one lag of *RES* is added in each case).

OLS regression results for the above models can be found in Appendix C. The parameters were estimated in the in-sample estimation period (1996:10 to 2002:01) and the models forecasting ability was tested in the out-of-sample forecast evaluation period (2002:02 to 2004:07). Data for *PXPULP* was only available as of 1996:10; therefore this models estimation and forecasting periods contain significantly fewer observations than the other models. The coefficient of the error correction term (*RES*) for each model is negative as expected, indicating adjustment back to long run equilibrium. Each ECM generated forecasts for one, two and three month average returns. The forecast evaluation criteria results are presented in Table 16.

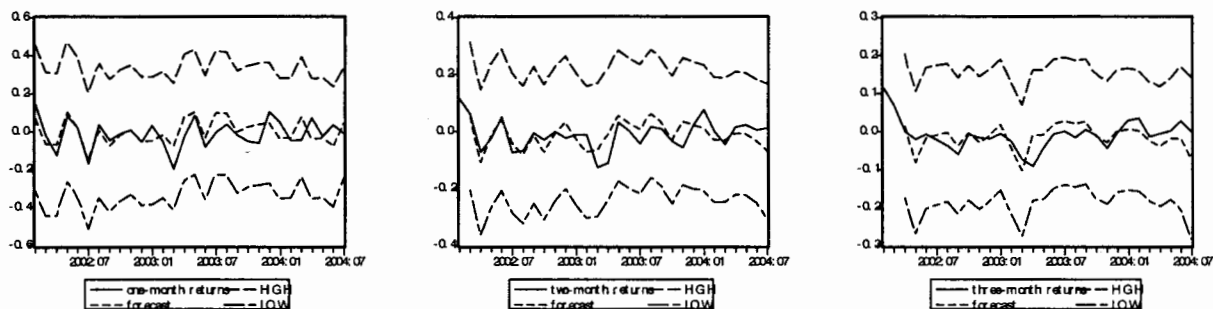


Figure 19: Forecasting performance of the ECM for log(SAP) containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three-month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

6. Summary and Conclusion

The primary purpose of this paper was to develop models that contain predictive power in explaining future share price returns. Models were developed for resource shares IMPLATS, HARMONY, GOLDFIELDS, SASOL and SAPPI. This was achieved first by finding long term equilibrium relationships between easily observed variables that mostly affect share price movements, namely company earnings, dividends, commodity price and long and short term interest rates. An error correction model (ECM) is then developed to model the short run changes in share price. Essentially, variables that are linked by a stable long-term equilibrium relationship are allowed to move away from equilibrium in the short term but economic forces are likely to push these variables back toward equilibrium in the long run. The ECM is developed to capture the short run changes, which is then evaluated via a one-month rolling window approach to test whether it has any forecasting abilities. Forecasts were generated for average returns over one, two and three months into the future. Forecasting average returns over two and three months give a better approximation of the general direction of the return on the share further than one-month ahead.

Findings suggest that changes in the above-mentioned variables together with changes in past share price returns contains significant explanatory power in predicting future share

price returns. This also implies that there is definite correlation between past and future share price changes thereby contradicting the Random Walk Hypothesis. An attempt was made to exclude past behaviour of share price changes in the models but resulted in no improvement of forecasting performance.

It is important to note that due to the very unpredictable nature of share prices, the uncertainty surrounding forecasts will always be high no matter what method is being implemented. The process is however necessary to guide investment decision-making.

An area that deserves further research, which was very briefly considered, is the area of investigating relative returns of shares. This means that share price movements are modeled relative to share price movements in a competitive counterpart share. If the share is found to be over or undervalued compared its competitive counterpart then arbitrage opportunities might exist. The study can also be extended to using the information found to develop to an appropriate investment strategy by selecting a portfolio of stocks that have been modeled to perform well.

APPENDICES

A: Correlograms of Returns

B: Asymptotic Engle & Granger Critical Values

C: Addendum of all Results

D: Eviews Program with Explanation

7. APPENDIX A

Correlograms of log returns or first differences of all variables

Diagrams show that first differences of levels or log are stationary and consequently confirms that all variables in their level or log-level form are random walks and therefore are $I(1)$.

Sample: 1971:04 2004:07							
Included observations: 399							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
.*	.*	1	0.119	0.119	5.6870	0.017	
. .	. .	2	-0.004	-0.018	5.6929	0.058	
. .	. .	3	0.013	0.016	5.7610	0.124	
. .	. .	4	0.044	0.041	6.5435	0.162	
*.	*.	5	-0.117	-0.129	12.068	0.034	
*.	. .	6	-0.083	-0.054	14.854	0.021	
. .	. .	7	-0.003	0.011	14.857	0.038	
. .	. .	8	0.025	0.023	15.108	0.057	
. .	. .	9	-0.019	-0.012	15.256	0.084	
. .	. .	10	-0.024	-0.029	15.500	0.115	
. .	. .	11	0.020	0.009	15.666	0.154	
. .	. .	12	0.063	0.055	17.296	0.139	
. .	. .	13	0.008	0.003	17.325	0.185	
. .	. .	14	0.008	0.009	17.350	0.238	
. .	*.	15	-0.045	-0.060	18.194	0.253	
. .	. .	16	0.007	0.013	18.214	0.312	
. .	. .	17	0.010	0.024	18.259	0.373	
*.	*.	18	-0.064	-0.061	19.984	0.334	
. .	. .	19	-0.010	0.010	20.029	0.393	
. .	. .	20	-0.020	-0.038	20.191	0.446	
. .	. .	21	-0.025	-0.022	20.446	0.493	
. .	. .	22	-0.056	-0.037	21.792	0.472	
. .	. .	23	-0.038	-0.040	22.420	0.495	
. .	. .	24	0.006	0.006	22.438	0.553	

Figure 20: Correlogram of DLOG(AMS)

Sample: 1971:04 2004:07							
Included observations: 262							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
. .	. .	1	-0.016	-0.016	0.0703	0.791	
. .	. .	2	-0.015	-0.015	0.1317	0.936	
. .	. .	3	-0.015	-0.016	0.1941	0.979	
. .	. .	4	-0.028	-0.029	0.4037	0.982	
. .	. .	5	-0.005	-0.007	0.4115	0.995	
***	***	6	0.395	0.394	42.594	0.000	
*	*	7	0.104	0.137	45.517	0.000	
. .	. .	8	-0.017	0.000	45.594	0.000	
. .	. .	9	-0.019	-0.011	45.698	0.000	
. .	. .	10	-0.016	0.005	45.768	0.000	
. .	. .	11	-0.005	0.002	45.776	0.000	
**	*	12	0.241	0.101	61.790	0.000	
. .	. .	13	0.034	-0.049	62.109	0.000	
. .	. .	14	-0.016	-0.028	62.179	0.000	
. .	. .	15	-0.017	-0.005	62.264	0.000	
. .	. .	16	-0.019	-0.005	62.362	0.000	
. .	. .	17	-0.011	-0.012	62.399	0.000	
**	*	18	0.205	0.094	74.281	0.000	
. .	. .	19	0.033	0.012	74.591	0.000	
. .	. .	20	-0.017	0.000	74.676	0.000	
. .	. .	21	-0.018	-0.003	74.767	0.000	
. .	. .	22	-0.020	-0.005	74.882	0.000	
. .	. .	23	-0.025	-0.017	75.057	0.000	
*	. .	24	0.135	0.012	80.341	0.000	

Figure 21: Correlogram of DLOG(AMS_EPS)

Sample: 1971:04 2004:07						
Included observations: 273						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.008	-0.008	0.0195	0.889
. .	. .	2	-0.011	-0.011	0.0536	0.974
. .	. .	3	-0.009	-0.010	0.0782	0.994
. .	. .	4	-0.009	-0.010	0.1031	0.999
. .	. .	5	-0.001	-0.002	0.1037	1.000
****	****	6	0.355	0.354	35.445	0.000
*.	*.	7	0.092	0.112	37.852	0.000
. .	. .	8	-0.010	0.002	37.882	0.000
. .	. .	9	-0.012	-0.006	37.926	0.000
*.	*.	10	-0.066	-0.070	39.172	0.000
. .	. .	11	-0.015	-0.023	39.232	0.000
**	**	12	0.293	0.191	63.855	0.000
. .	. .	13	0.016	-0.043	63.926	0.000
. .	. .	14	-0.016	-0.026	63.997	0.000
. .	. .	15	-0.015	-0.010	64.061	0.000
. .	. .	16	0.001	0.050	64.061	0.000
. .	. .	17	-0.014	0.017	64.121	0.000
**	**	18	0.232	0.100	80.010	0.000
. .	. .	19	-0.005	-0.047	80.018	0.000
. .	. .	20	-0.016	-0.012	80.091	0.000
. .	. .	21	-0.014	-0.002	80.148	0.000
. .	. .	22	-0.032	-0.018	80.456	0.000
. .	. .	23	-0.038	-0.044	80.897	0.000
*	.	24	0.134	-0.022	86.321	0.000

Figure 22: Correlogram of DLOG(AMS_DPS)

Sample: 1971:04 2004:07						
Included observations: 377						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.036	0.036	0.4893	0.484
. .	. .	2	-0.015	-0.017	0.5802	0.748
. .	. .	3	0.063	0.065	2.1145	0.549
. .	. .	4	0.000	-0.005	2.1145	0.715
*.	*.	5	-0.090	-0.088	5.2028	0.392
*.	*.	6	-0.079	-0.077	7.5909	0.270
*.	*.	7	0.076	0.080	9.8175	0.199
. .	. .	8	0.037	0.042	10.349	0.241
. .	. .	9	0.002	0.011	10.351	0.323
. .	. .	10	0.021	0.002	10.519	0.396
. .	. .	11	0.019	-0.001	10.653	0.473
. .	. .	12	0.026	0.033	10.908	0.537
. .	. .	13	0.041	0.059	11.580	0.562
. .	. .	14	-0.035	-0.039	12.068	0.601
*.	*.	15	-0.069	-0.075	13.924	0.531
. .	. .	16	0.037	0.037	14.467	0.564
. .	. .	17	-0.018	-0.011	14.596	0.625
*.	*.	18	-0.076	-0.056	16.890	0.531
. .	. .	19	-0.036	-0.044	17.418	0.562
. .	. .	20	-0.051	-0.079	18.472	0.556
. .	. .	21	0.045	0.058	19.285	0.567
*.	*.	22	-0.076	-0.060	21.628	0.482
. .	. .	23	-0.056	-0.063	22.902	0.467
. .	. .	24	0.063	0.042	24.528	0.432

Figure 23: Correlogram of DLOG(IMP)

Sample: 1971:04 2004:07
 Included observations: 263

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.017	-0.017	0.0778	0.780
. .	. .	2	-0.017	-0.018	0.1595	0.923
. .	. .	3	-0.017	-0.018	0.2412	0.971
. .	. .	4	-0.018	-0.019	0.3243	0.988
. .	. .	5	-0.017	-0.018	0.4033	0.995
****	****	6	0.589	0.589	94.590	0.000
. .	. .	7	0.012	0.039	94.627	0.000
. .	. .	8	-0.020	-0.007	94.734	0.000
. .	. .	9	-0.020	-0.008	94.840	0.000
. .	. .	10	-0.020	-0.008	94.950	0.000
. .	. .	11	-0.013	0.001	94.997	0.000
**	. .	12	0.328	-0.030	124.79	0.000
. .	*	13	-0.042	-0.097	125.28	0.000
. .	. .	14	-0.021	-0.014	125.41	0.000
. .	. .	15	-0.021	-0.007	125.53	0.000
. .	. .	16	-0.022	-0.007	125.66	0.000
. .	. .	17	0.005	0.021	125.67	0.000
**	*	18	0.285	0.161	148.81	0.000
. .	*	19	0.020	0.133	148.92	0.000
. .	. .	20	-0.021	0.019	149.04	0.000
. .	. .	21	-0.021	-0.002	149.17	0.000
. .	. .	22	-0.021	-0.004	149.30	0.000
. .	. .	23	0.021	0.014	149.43	0.000
*	*	24	0.188	-0.070	159.74	0.000

Figure 24: Correlogram of DLOG(IMP_EPS)

Sample: 1971:04 2004:07
 Included observations: 275

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.011	-0.011	0.0349	0.852
. .	. .	2	-0.011	-0.011	0.0704	0.965
. .	. .	3	-0.010	-0.010	0.0975	0.992
. .	. .	4	-0.011	-0.012	0.1343	0.998
. .	. .	5	-0.012	-0.012	0.1733	0.999
***	***	6	0.335	0.335	31.954	0.000
. .	. .	7	-0.013	-0.008	32.004	0.000
. .	. .	8	-0.012	-0.007	32.046	0.000
. .	. .	9	-0.011	-0.006	32.080	0.000
. .	. .	10	-0.013	-0.008	32.129	0.000
. .	. .	11	-0.012	-0.007	32.173	0.001
****	***	12	0.460	0.392	93.545	0.000
. .	. .	13	-0.013	-0.004	93.593	0.000
. .	. .	14	-0.015	-0.007	93.655	0.000
. .	. .	15	-0.014	-0.007	93.708	0.000
. .	. .	16	-0.016	-0.009	93.788	0.000
. .	. .	17	-0.012	-0.003	93.833	0.000
*	*	18	0.115	-0.146	97.779	0.000
. .	. .	19	-0.013	-0.003	97.833	0.000
. .	. .	20	-0.015	-0.006	97.902	0.000
. .	. .	21	-0.016	-0.008	97.976	0.000
. .	. .	22	-0.015	-0.003	98.040	0.000
. .	. .	23	-0.013	-0.004	98.091	0.000
*	*	24	0.111	-0.088	101.86	0.000

Figure 25: Correlogram of DLOG(IMP_DPS)

Autocorrelation		Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	0.021	0.021	0.1791	0.672	
. .	. .	2	0.001	0.000	0.1794	0.914	
* .	* .	3	-0.070	-0.070	2.1817	0.536	
. .	. .	4	-0.050	-0.048	3.2133	0.523	
. .	. .	5	-0.014	-0.012	3.2876	0.656	
* .	* .	6	-0.163	-0.169	14.152	0.028	
. .	. .	7	0.059	0.059	15.550	0.030	
. .	. .	8	0.047	0.042	16.467	0.036	
. .	. .	9	0.065	0.039	18.213	0.033	
. .	. .	10	-0.004	-0.013	18.219	0.051	
* .	* .	11	0.069	0.081	20.160	0.043	
. .	. .	12	0.057	0.041	21.514	0.043	
. .	. .	13	-0.049	-0.028	22.496	0.048	
. .	. .	14	-0.003	0.022	22.501	0.069	
. .	. .	15	-0.039	-0.014	23.133	0.081	
. .	* .	16	-0.051	-0.065	24.217	0.085	
. .	. .	17	-0.036	-0.017	24.752	0.100	
* .	* .	18	-0.088	-0.090	28.020	0.062	
* .	* .	19	0.121	0.095	34.142	0.018	
. .	. .	20	0.056	0.039	35.488	0.018	
* .	. .	21	0.075	0.054	37.897	0.013	
. .	. .	22	-0.033	-0.046	38.362	0.017	
. .	. .	23	0.001	0.013	38.362	0.023	
. .	. .	24	-0.019	-0.022	38.522	0.031	

Figure 26: Correlogram of DLOG(PLATPM)

Autocorrelation		Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	0.036	0.036	0.5187	0.471	
. .	. .	2	-0.025	-0.026	0.7734	0.679	
. .	. .	3	0.047	0.049	1.6785	0.642	
. .	. .	4	0.035	0.031	2.1886	0.701	
. .	. .	5	0.003	0.003	2.1924	0.822	
* .	* .	6	-0.091	-0.092	5.5378	0.477	
. .	. .	7	-0.025	-0.021	5.7836	0.565	
* .	* .	8	0.085	0.082	8.7745	0.362	
. .	. .	9	0.028	0.030	9.0883	0.429	
. .	. .	10	-0.019	-0.009	9.2309	0.510	
. .	. .	11	0.008	0.003	9.2557	0.598	
. .	. .	12	0.045	0.029	10.111	0.606	
* .	* .	13	-0.085	-0.095	13.119	0.439	
* .	* .	14	-0.131	-0.112	20.206	0.124	
. .	. .	15	-0.050	-0.042	21.239	0.129	
. .	. .	16	0.039	0.039	21.861	0.148	
. .	* .	17	0.062	0.076	23.492	0.134	
* .	* .	18	-0.096	-0.081	27.338	0.073	
. .	. .	19	-0.042	-0.052	28.069	0.082	
. .	. .	20	0.043	0.003	28.856	0.091	
* .	* .	21	-0.061	-0.063	30.438	0.084	
. .	. .	22	-0.032	0.008	30.877	0.099	
. .	. .	23	-0.025	0.000	31.148	0.119	
. .	. .	24	-0.006	-0.014	31.162	0.149	

Figure 27: Correlogram of DLOG(ANG)

Sample: 1971:04 2004:07						
Included observations: 255						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
.	1	0.001	0.001	8.E-05	0.993
.	2	0.031	0.031	0.2510	0.882
****	****	3	0.499	0.500	65.103	0.000
.	4	-0.005	0.002	65.109	0.000
.	5	0.018	-0.017	65.193	0.000
**	. . .	6	0.221	-0.037	78.103	0.000
.	7	0.006	0.014	78.114	0.000
.	8	0.012	0.006	78.154	0.000
*	**	9	-0.071	-0.225	79.502	0.000
.	10	-0.008	-0.030	79.518	0.000
*	*	11	-0.070	-0.091	80.844	0.000
**	*	12	-0.237	-0.154	96.017	0.000
.	13	-0.031	-0.039	96.271	0.000
.	14	-0.009	0.099	96.291	0.000
**	*	15	-0.271	-0.059	116.42	0.000
.	16	-0.015	0.014	116.48	0.000
.	17	-0.026	-0.025	116.67	0.000
**	*	18	-0.253	-0.079	134.34	0.000
.	19	-0.008	0.005	134.36	0.000
.	20	0.022	0.039	134.50	0.000
**	*	21	-0.197	-0.086	145.34	0.000
.	22	-0.008	-0.046	145.36	0.000
. . .	*	23	-0.021	-0.080	145.48	0.000
*	. . .	24	-0.058	0.031	146.43	0.000

Figure 28: Correlogram of DLOG(ANG_EPS)

Sample: 1971:04 2004:07						
Included observations: 288						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
.	1	-0.002	-0.002	0.0008	0.977
.	2	0.002	0.002	0.0026	0.999
.	3	-0.003	-0.003	0.0050	1.000
.	4	0.000	0.000	0.0050	1.000
.	5	-0.003	-0.003	0.0080	1.000
***	***	6	0.337	0.337	33.626	0.000
.	7	0.033	0.038	33.954	0.000
.	8	-0.003	-0.005	33.957	0.000
.	9	0.000	0.001	33.957	0.000
.	10	-0.013	-0.015	34.011	0.000
.	11	-0.046	-0.050	34.641	0.000
**	****	12	-0.295	-0.464	60.930	0.000
.	13	0.028	-0.021	61.177	0.000
.	14	-0.008	-0.010	61.199	0.000
.	15	0.001	-0.001	61.199	0.000
.	16	-0.016	-0.004	61.277	0.000
.	17	-0.030	0.029	61.553	0.000
***	*	18	-0.384	-0.114	107.16	0.000
.	19	-0.002	0.002	107.16	0.000
.	20	-0.001	0.002	107.16	0.000
.	21	0.001	-0.001	107.16	0.000
.	22	0.000	-0.004	107.16	0.000
.	23	0.025	0.015	107.36	0.000
*	. . .	24	-0.101	-0.015	110.59	0.000

Figure 29: Correlogram of DLOG(ANG_DPS)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.030	0.030	0.3586	0.549
. .	. .	2	-0.004	-0.004	0.3636	0.834
. .	. .	3	-0.007	-0.007	0.3839	0.944
. .	. .	4	0.007	0.008	0.4047	0.982
. .	. .	5	-0.056	-0.056	1.6581	0.894
* .	* .	6	-0.063	-0.060	3.2722	0.774
. .	. .	7	0.009	0.012	3.3039	0.856
. .	. .	8	0.036	0.034	3.8384	0.871
. .	. .	9	0.018	0.016	3.9742	0.913
. .	. .	10	0.027	0.025	4.2766	0.934
* .	* .	11	0.076	0.069	6.6784	0.825
. .	. .	12	0.051	0.045	7.7363	0.805
* .	* .	13	-0.087	-0.085	10.843	0.624
. .	. .	14	-0.046	-0.036	11.730	0.628
. .	. .	15	-0.016	-0.011	11.831	0.692
. .	. .	16	0.040	0.049	12.504	0.709
. .	. .	17	-0.010	0.001	12.544	0.766
. .	. .	18	-0.022	-0.028	12.747	0.806
. .	. .	19	-0.019	-0.039	12.904	0.843
* .	* .	20	0.082	0.074	15.717	0.734
* .	* .	21	-0.075	-0.077	18.072	0.644
. .	. .	22	-0.040	-0.036	18.768	0.660
. .	. .	23	0.039	0.040	19.418	0.677
. .	. .	24	-0.032	-0.032	19.858	0.705

Figure 30: Correlogram of DLOG(GFI)

Sample: 1971:04 2004:07						
Included observations: 248						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.000	0.000	4.E-05	0.995
* .	* .	2	-0.072	-0.072	1.3098	0.519
. ***	. ***	3	0.362	0.364	34.474	0.000
* .	* .	4	0.158	0.166	40.785	0.000
. .	. .	5	-0.014	0.047	40.832	0.000
* .	. .	6	0.087	-0.025	42.770	0.000
* .	. .	7	0.156	0.052	49.027	0.000
. .	. .	8	0.009	-0.020	49.046	0.000
* .	* .	9	-0.084	-0.118	50.890	0.000
. .	* .	10	0.034	-0.071	51.182	0.000
. .	* .	11	-0.003	-0.061	51.184	0.000
** .	** .	12	-0.262	-0.250	69.223	0.000
. .	. .	13	-0.011	-0.011	69.254	0.000
. .	. .	14	0.007	-0.014	69.268	0.000
** .	. .	15	-0.209	-0.034	80.886	0.000
. .	* .	16	-0.026	0.085	81.066	0.000
. .	. .	17	-0.029	-0.001	81.290	0.000
* .	. .	18	-0.134	-0.014	86.097	0.000
** .	* .	19	-0.192	-0.160	96.046	0.000
* .	* .	20	-0.058	-0.077	96.964	0.000
. .	* .	21	-0.045	-0.060	97.528	0.000
. .	. *	22	-0.024	0.123	97.681	0.000
. .	* .	23	-0.028	0.073	97.891	0.000
* .	* .	24	-0.075	-0.084	99.443	0.000

Figure 31: Correlogram of DLOG(GFI_EPS)

Autocorrelation		Partial Correlation		AC	PAC	Q-Stat	Prob
. .	. .	1	0.002	0.002	0.0008	0.977	
. .	. .	2	0.021	0.021	0.1191	0.942	
. .	. .	3	0.001	0.001	0.1194	0.989	
. .	. .	4	0.005	0.004	0.1258	0.998	
. .	. .	5	0.063	0.063	1.1849	0.946	
* .	* .	6	-0.146	-0.147	6.8731	0.333	
. .	. .	7	-0.013	-0.015	6.9209	0.437	
. .	. .	8	0.001	0.008	6.9212	0.545	
. .	. .	9	-0.014	-0.014	6.9708	0.640	
. .	. .	10	0.058	0.058	7.8913	0.639	
. .	. .	11	-0.004	0.015	7.8952	0.723	
* .	* .	12	-0.110	-0.137	11.202	0.512	
. .	. .	13	-0.006	-0.008	11.211	0.593	
. .	. .	14	0.000	0.008	11.212	0.669	
. .	. .	15	0.009	-0.003	11.234	0.736	
* .	* .	16	-0.104	-0.088	14.220	0.582	
* .	* .	17	-0.078	-0.061	15.923	0.529	
* .	* .	18	0.166	0.143	23.606	0.168	
. .	. .	19	-0.038	-0.044	24.006	0.196	
. .	. .	20	0.018	0.009	24.103	0.238	
. .	. .	21	0.003	0.018	24.105	0.288	
. .	. .	22	0.001	-0.012	24.105	0.342	
. .	. .	23	0.059	0.023	25.114	0.344	
* .	* .	24	-0.171	-0.148	33.515	0.094	

Figure 32: Correlogram of DLOG(GFI_DPS)

Autocorrelation		Partial Correlation		AC	PAC	Q-Stat	Prob
* .	* .	1	0.146	0.146	8.5604	0.003	
. .	. .	2	0.036	0.015	9.0697	0.011	
. .	. .	3	0.033	0.026	9.4966	0.023	
* .	* .	4	-0.076	-0.086	11.809	0.019	
. .	. .	5	-0.008	0.015	11.832	0.037	
* .	* .	6	-0.074	-0.074	14.032	0.029	
. .	. .	7	-0.006	0.022	14.045	0.050	
. .	. .	8	0.032	0.027	14.474	0.070	
. .	. .	9	0.038	0.037	15.071	0.089	
. .	. .	10	-0.007	-0.032	15.088	0.129	
. .	. .	11	0.013	0.018	15.160	0.175	
* .	* .	12	0.082	0.077	17.924	0.118	
* .	* .	13	-0.132	-0.155	25.185	0.022	
* .	. .	14	-0.067	-0.030	27.071	0.019	
. .	. .	15	-0.032	-0.011	27.501	0.025	
. .	* .	16	0.040	0.074	28.174	0.030	
. .	. .	17	0.052	0.015	29.313	0.032	
. .	. .	18	0.037	0.037	29.902	0.038	
. .	. .	19	-0.008	-0.051	29.928	0.053	
. .	. .	20	0.050	0.055	30.980	0.055	
* .	* .	21	-0.080	-0.102	33.700	0.039	
* .	* .	22	-0.169	-0.124	45.798	0.002	
. .	. .	23	-0.022	0.020	45.998	0.003	
* .	. .	24	-0.059	-0.043	47.499	0.003	

Figure 33: Correlogram of DLOG(HAR)

Sample: 1971:04 2004:07
 Included observations: 255

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.001	-0.001	8.E-05	0.993
* .	* .	2	0.150	0.150	5.7912	0.055
* .	* .	3	0.165	0.169	12.880	0.005
* .	* .	4	0.181	0.172	21.443	0.000
* .	* .	5	0.106	0.075	24.384	0.000
. .	. .	6	0.056	-0.011	25.207	0.000
. .	* .	7	0.010	-0.075	25.234	0.001
* .	* .	8	-0.071	-0.156	26.576	0.001
* .	* .	9	-0.018	-0.075	26.661	0.002
. .	. .	10	-0.061	-0.056	27.661	0.002
. .	. .	11	0.000	0.053	27.661	0.004
**** .	**** .	12	-0.495	-0.468	93.693	0.000
. .	. .	13	-0.004	-0.020	93.696	0.000
* .	. .	14	-0.114	0.013	97.257	0.000
* .	* .	15	-0.060	0.136	98.240	0.000
* .	* .	16	-0.106	0.099	101.32	0.000
* .	. .	17	-0.109	0.000	104.59	0.000
. .	. .	18	-0.035	0.009	104.94	0.000
. .	* .	19	-0.021	-0.013	105.07	0.000
. .	. .	20	-0.019	-0.088	105.16	0.000
. .	. .	21	-0.016	-0.016	105.23	0.000
. .	. .	22	0.019	-0.002	105.34	0.000
. .	. .	23	0.001	0.039	105.34	0.000
. .	*** .	24	-0.006	-0.347	105.35	0.000

Figure 34: Correlogram of D(HAR_EPS)

Sample: 1971:04 2004:07
 Included observations: 280

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.001	-0.001	0.0006	0.981
. .	. .	2	0.001	0.001	0.0007	1.000
. .	. .	3	-0.029	-0.029	0.2482	0.969
. .	. .	4	0.000	0.000	0.2482	0.993
* .	* .	5	0.147	0.147	6.4795	0.262
. .	. .	6	0.035	0.035	6.8264	0.337
. .	. .	7	-0.017	-0.018	6.9088	0.438
. .	. .	8	-0.001	0.007	6.9090	0.546
. .	. .	9	0.000	0.002	6.9090	0.647
. .	. .	10	0.000	-0.023	6.9090	0.734
. .	. .	11	0.001	-0.010	6.9090	0.806
*** .	*** .	12	-0.398	-0.404	53.500	0.000
. .	. .	13	0.000	-0.008	53.500	0.000
. .	. .	14	0.000	0.002	53.500	0.000
. .	. .	15	0.000	-0.024	53.500	0.000
. .	. .	16	0.002	0.006	53.501	0.000
* .	. .	17	-0.108	0.012	56.971	0.000
. .	. .	18	0.019	0.064	57.081	0.000
. .	. .	19	-0.024	-0.015	57.256	0.000
. .	. .	20	0.000	0.004	57.256	0.000
. .	. .	21	0.001	0.000	57.256	0.000
. .	. .	22	0.014	0.023	57.320	0.000
. .	. .	23	0.001	-0.011	57.320	0.000
. .	** .	24	-0.001	-0.193	57.320	0.000

Figure 35: Correlogram of D(HAR_DPS)

Sample: 1971:04 2004:07							
Included observations: 399							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
*	*	1	0.151	0.151	9.1503	0.002	
.	.	2	-0.016	-0.040	9.2546	0.010	
.	.	3	-0.012	-0.004	9.3176	0.025	
*	*	4	-0.089	-0.089	12.490	0.014	
.	.	5	-0.045	-0.019	13.322	0.021	
*	*	6	-0.144	-0.143	21.714	0.001	
.	*	7	0.061	0.107	23.230	0.002	
*	.	8	0.102	0.061	27.458	0.001	
*	*	9	0.102	0.084	31.766	0.000	
*	*	10	0.079	0.032	34.315	0.000	
*	*	11	0.149	0.157	43.464	0.000	
.	.	12	0.024	-0.026	43.702	0.000	
*	*	13	-0.115	-0.069	49.146	0.000	
*	*	14	-0.103	-0.059	53.568	0.000	
.	.	15	-0.009	0.050	53.599	0.000	
.	.	16	0.004	-0.014	53.607	0.000	
.	.	17	-0.012	-0.001	53.668	0.000	
.	*	18	-0.022	-0.077	53.864	0.000	
.	*	19	-0.030	-0.076	54.253	0.000	
*	.	20	0.074	0.055	56.592	0.000	
.	.	21	0.012	0.010	56.654	0.000	
.	.	22	0.017	0.017	56.772	0.000	
.	.	23	0.035	0.039	57.302	0.000	
.	.	24	0.002	0.027	57.303	0.000	

Figure 36: Correlogram of DLOG(GOLR)

Sample: 1971:04 2004:07							
Included observations: 296							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
.	.	1	0.048	0.048	0.6767	0.411	
.	.	2	-0.009	-0.011	0.6989	0.705	
*	*	3	0.071	0.072	2.2087	0.530	
*	*	4	-0.111	-0.118	5.8989	0.207	
.	.	5	-0.032	-0.019	6.2110	0.286	
.	.	6	-0.026	-0.032	6.4123	0.379	
*	*	7	-0.089	-0.071	8.8081	0.267	
.	.	8	0.037	0.037	9.2372	0.323	
.	.	9	0.065	0.059	10.549	0.308	
*	*	10	-0.062	-0.065	11.741	0.303	
.	*	11	-0.057	-0.076	12.754	0.310	
.	*	12	-0.053	-0.055	13.626	0.325	
*	*	13	-0.154	-0.136	21.005	0.073	
.	.	14	-0.013	-0.007	21.060	0.100	
*	*	15	-0.064	-0.072	22.347	0.099	
.	.	16	0.038	0.056	22.801	0.119	
*	*	17	-0.060	-0.127	23.952	0.121	
.	.	18	0.020	0.017	24.083	0.152	
.	.	19	0.042	0.004	24.636	0.173	
.	.	20	0.032	0.035	24.961	0.203	
.	.	21	-0.018	-0.044	25.064	0.244	
.	.	22	0.000	0.001	25.064	0.294	
.	.	23	-0.011	-0.032	25.102	0.345	
.	.	24	-0.008	-0.029	25.120	0.399	

Figure 37: Correlogram of DLOG(SOL)

Sample: 1971:04 2004:07						
Included observations: 269						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.034	-0.034	0.3225	0.570
. .	. .	2	-0.035	-0.036	0.6491	0.723
. .	. .	3	-0.036	-0.038	0.9981	0.802
. .	. .	4	-0.035	-0.039	1.3406	0.854
. .	. .	5	0.016	0.010	1.4103	0.923
***	***	6	0.353	0.352	35.941	0.000
**	**	7	0.246	0.312	52.755	0.000
. .	. .	8	-0.040	0.042	53.193	0.000
. .	. .	9	-0.041	-0.003	53.663	0.000
. .	. .	10	-0.039	-0.016	54.095	0.000
. .	. .	11	0.043	0.039	54.606	0.000
. .	. .	12	0.091	-0.052	56.961	0.000
*	*	13	0.137	-0.071	62.300	0.000
. .	*	14	-0.042	-0.131	62.804	0.000
. .	. .	15	-0.042	-0.050	63.301	0.000
. .	. .	16	-0.042	-0.034	63.820	0.000
. .	*	17	-0.019	-0.060	63.925	0.000
. .	. .	18	0.044	-0.018	64.478	0.000
*	. .	19	0.068	0.033	65.819	0.000
. .	. .	20	-0.041	0.000	66.312	0.000
. .	. .	21	-0.043	0.026	66.847	0.000
. .	. .	22	-0.041	0.006	67.344	0.000
*	. .	23	-0.065	-0.036	68.608	0.000
*	*	24	-0.076	-0.119	70.328	0.000

Figure 38: Correlogram of DLOG(SOL_EPS)

Sample: 1971:04 2004:07						
Included observations: 275						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
*	*	1	-0.104	-0.104	3.0348	0.081
*	*	2	-0.099	-0.111	5.7584	0.056
*	*	3	-0.102	-0.128	8.6516	0.034
*	*	4	-0.105	-0.150	11.735	0.019
. .	. .	5	0.023	-0.040	11.879	0.036
***	**	6	0.354	0.327	47.385	0.000
**	***	7	0.226	0.348	61.846	0.000
*	*	8	-0.104	0.085	64.927	0.000
*	. .	9	-0.083	0.046	66.910	0.000
*	. .	10	-0.109	-0.018	70.319	0.000
*	*	11	-0.072	-0.121	71.819	0.000
***	**	12	0.392	0.238	116.35	0.000
*	. .	13	0.095	0.014	118.98	0.000
*	*	14	-0.096	-0.128	121.67	0.000
*	*	15	-0.098	-0.088	124.46	0.000
*	*	16	-0.098	-0.058	127.26	0.000
. .	. .	17	-0.049	-0.037	127.97	0.000
. .	*	18	0.126	-0.117	132.65	0.000
**	. .	19	0.205	-0.024	145.20	0.000
*	. .	20	-0.101	-0.053	148.22	0.000
*	. .	21	-0.086	0.000	150.45	0.000
*	. .	22	-0.105	-0.007	153.76	0.000
*	. .	23	-0.064	0.013	154.99	0.000
*	. .	24	0.117	0.003	159.17	0.000

Figure 39: Correlogram of DLOG(SOL_DPS)

Sample: 1971:04 2004:07						
Included observations: 246						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.000	0.000	4.E-07	0.999
* .	* .	2	-0.078	-0.078	1.5026	0.472
* .	* .	3	0.122	0.123	5.2379	0.155
* .	* .	4	-0.137	-0.147	9.9504	0.041
* .	* .	5	-0.174	-0.157	17.641	0.003
. .	. .	6	0.008	-0.027	17.657	0.007
* .	* .	7	-0.094	-0.092	19.914	0.006
. .	. .	8	0.009	0.028	19.932	0.011
. .	. .	9	0.064	0.006	20.977	0.013
. .	. .	10	0.024	0.018	21.127	0.020
* .	* .	11	0.150	0.133	26.934	0.005
. .	. .	12	-0.051	-0.089	27.605	0.006
* .	* .	13	-0.074	-0.045	29.049	0.006
. .	. .	14	0.005	-0.029	29.056	0.010
* .	* .	15	-0.176	-0.142	37.239	0.001
. .	. .	16	-0.019	0.035	37.329	0.002
. .	. .	17	0.061	0.002	38.307	0.002
* .	* .	18	-0.119	-0.096	42.116	0.001
* .	* .	19	0.136	0.105	47.092	0.000
. .	. .	20	0.027	-0.085	47.288	0.001
. .	. .	21	-0.039	0.015	47.697	0.001
* .	* .	22	0.090	0.019	49.891	0.001
* .	* .	23	-0.067	-0.077	51.108	0.001
* .	* .	24	-0.132	-0.053	55.923	0.000

Figure 40: Correlogram of DLOG(BRSPOT)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	0.086	0.086	2.9993	0.083
. .	. .	2	0.007	0.000	3.0203	0.221
* .	* .	3	0.129	0.129	9.7364	0.021
* .	* .	4	-0.078	-0.103	12.223	0.016
. .	. .	5	-0.037	-0.020	12.780	0.026
* .	* .	6	0.091	0.082	16.183	0.013
. .	. .	7	-0.025	-0.019	16.444	0.021
. .	. .	8	0.020	0.026	16.610	0.034
. .	. .	9	0.057	0.025	17.938	0.036
. .	. .	10	-0.054	-0.045	19.158	0.038
. .	. .	11	0.011	0.017	19.205	0.058
* .	* .	12	0.070	0.055	21.252	0.047
. .	. .	13	-0.016	-0.004	21.356	0.066
. .	. .	14	-0.030	-0.044	21.740	0.084
. .	* .	15	-0.040	-0.058	22.413	0.097
* .	* .	16	-0.085	-0.055	25.420	0.063
* .	* .	17	-0.083	-0.067	28.302	0.042
* .	* .	18	-0.095	-0.089	32.082	0.022
* .	* .	19	-0.118	-0.094	37.921	0.006
* .	* .	20	-0.112	-0.101	43.198	0.002
* .	. .	21	-0.066	-0.049	45.060	0.002
. .	. .	22	-0.013	0.014	45.135	0.003
. .	. .	23	-0.043	-0.037	45.925	0.003
* .	* .	24	0.102	0.116	50.358	0.001

Figure 41: Correlogram of DLOG(SAP)

Sample: 1971:04 2004:07
 Included observations: 258

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
. .	. .	1 -0.001	-0.001	0.0002	0.990
. .	. .	2 0.005	0.005	0.0063	0.997
*	*	3 0.073	0.073	1.4058	0.704
. .	. .	4 0.040	0.040	1.8318	0.767
. .	. .	5 -0.014	-0.015	1.8853	0.865
*	*	6 0.147	0.143	7.6681	0.263
*	*	7 0.152	0.151	13.870	0.054
. .	. .	8 -0.018	-0.015	13.953	0.083
. .	. .	9 -0.004	-0.025	13.957	0.124
. .	. .	10 0.014	-0.018	14.008	0.173
. .	. .	11 -0.048	-0.055	14.637	0.200
*	*	12 -0.127	-0.152	19.055	0.087
*	**	13 -0.169	-0.237	26.915	0.013
. .	. .	14 0.028	-0.004	27.126	0.019
. .	. .	15 -0.039	-0.012	27.554	0.025
. .	. .	16 -0.016	0.020	27.628	0.035
. .	. .	17 -0.055	-0.029	28.466	0.040
*	. .	18 -0.077	-0.016	30.121	0.036
**	*	19 -0.219	-0.124	43.626	0.001
. .	*	20 0.064	0.124	44.768	0.001
. .	. .	21 0.024	0.045	44.929	0.002
. .	. .	22 -0.009	0.031	44.953	0.003
. .	. .	23 -0.013	-0.009	45.001	0.004
*	*	24 0.086	0.087	47.143	0.003

Figure 42: Correlogram of D(SAP_EPS)

Sample: 1971:04 2004:07
 Included observations: 276

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
. .	. .	1 -0.001	-0.001	0.0003	0.986
. .	. .	2 -0.001	-0.001	0.0006	1.000
. .	. .	3 0.000	0.000	0.0006	1.000
. .	. .	4 -0.002	-0.002	0.0017	1.000
*	*	5 0.068	0.068	1.2926	0.936
*	*	6 0.179	0.180	10.447	0.107
. .	. .	7 0.039	0.043	10.876	0.144
. .	. .	8 0.000	0.002	10.876	0.209
. .	. .	9 0.001	0.002	10.877	0.284
. .	. .	10 -0.001	-0.005	10.877	0.367
. .	. .	11 0.042	0.018	11.376	0.412
. .	. .	12 0.038	0.001	11.788	0.463
*	*	13 -0.114	-0.133	15.591	0.272
. .	. .	14 0.014	0.007	15.647	0.335
. .	. .	15 0.000	0.000	15.647	0.406
. .	. .	16 -0.002	-0.005	15.648	0.478
. .	. .	17 0.006	-0.008	15.658	0.548
*	*	18 -0.090	-0.089	18.070	0.451
**	**	19 -0.241	-0.217	35.365	0.013
. .	. .	20 0.005	0.000	35.372	0.018
. .	. .	21 -0.004	-0.006	35.378	0.026
. .	. .	22 -0.001	-0.002	35.378	0.035
*	*	23 0.095	0.116	38.101	0.025
**	**	24 -0.257	-0.210	58.217	0.000

Figure 43: Correlogram of D(SAP_DPS)

Sample: 1971:04 2004:07
 Included observations: 93

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
*****	*****	1	0.675	0.675	43.738	0.000
**	**	2	0.315	-0.257	53.398	0.000
.	.	3	-0.001	-0.186	53.398	0.000
*	*	4	-0.095	0.128	54.287	0.000
.	.	5	-0.029	0.111	54.371	0.000
*	*	6	0.067	-0.003	54.829	0.000
.	.	7	0.160	0.091	57.450	0.000
*	*	8	0.120	-0.094	58.956	0.000
.	.	9	0.111	0.135	60.249	0.000
*	*	10	0.067	-0.010	60.725	0.000
.	.	11	0.007	-0.097	60.730	0.000
*	*	12	-0.115	-0.167	62.165	0.000
.	.	13	-0.230	-0.090	68.004	0.000
**	**	14	-0.264	-0.034	75.776	0.000
**	**	15	-0.214	-0.003	80.958	0.000
.	.	16	-0.056	0.079	81.315	0.000
*	*	17	-0.066	-0.290	81.824	0.000
.	.	18	-0.078	0.064	82.535	0.000
*	*	19	-0.171	-0.064	86.020	0.000
.	.	20	-0.246	-0.126	93.353	0.000
**	**	21	-0.230	0.051	99.828	0.000
**	**	22	-0.202	-0.096	104.92	0.000
*	*	23	-0.146	-0.074	107.60	0.000
*	*	24	-0.151	0.000	110.50	0.000

Figure 44: Correlogram of DLOG(PXPULP)

Sample: 1971:04 2004:07
 Included observations: 176

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
*	*	1	-0.171	-0.171	5.2643	0.022
*	*	2	0.185	0.160	11.398	0.003
*	.	3	-0.097	-0.045	13.095	0.004
*	*	4	0.120	0.074	15.701	0.003
*	*	5	-0.092	-0.046	17.264	0.004
*	*	6	0.134	0.087	20.564	0.002
*	*	7	-0.128	-0.074	23.612	0.001
.	.	8	0.033	-0.041	23.818	0.002
.	.	9	-0.055	-0.007	24.389	0.004
*	*	10	-0.087	-0.132	25.803	0.004
*	*	11	-0.103	-0.105	27.817	0.003
.	.	12	0.057	0.044	28.434	0.005
.	*	13	0.020	0.081	28.513	0.008
.	.	14	-0.026	-0.032	28.642	0.012
.	.	15	-0.010	-0.021	28.663	0.018
*	*	16	-0.110	-0.109	31.038	0.013
*	*	17	0.150	0.132	35.475	0.005
.	.	18	-0.037	0.007	35.749	0.008
.	*	19	0.000	-0.072	35.749	0.011
*	*	20	-0.078	-0.070	36.962	0.012
.	.	21	0.064	0.007	37.802	0.014
.	.	22	-0.021	0.051	37.895	0.019
.	*	23	-0.048	-0.097	38.358	0.023
.	.	24	0.037	0.057	38.637	0.030

Figure 45: Correlogram of DLOG(ISC)

Sample: 1971:04 2004:07							
Included observations: 166							
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob	
. .	. .	1	0.000	0.000	4.E-05	0.995	
. .	. .	2	0.061	0.061	0.6407	0.726	
. .	. .	3	-0.019	-0.019	0.7019	0.873	
. .	. .	4	0.045	0.041	1.0484	0.902	
* .	* .	5	0.075	0.077	2.0115	0.848	
* .	* .	6	0.172	0.169	7.1934	0.303	
* .	* .	7	0.084	0.082	8.4221	0.297	
* .	* .	8	-0.043	-0.060	8.7422	0.365	
* .	* .	9	-0.124	-0.141	11.471	0.245	
* .	* .	10	-0.009	-0.028	11.486	0.321	
* .	* .	11	-0.058	-0.082	12.089	0.357	
* .	* .	12	-0.126	-0.182	14.956	0.244	
. .	. .	13	-0.016	-0.036	15.005	0.307	
. .	. .	14	-0.051	-0.006	15.482	0.346	
. .	. .	15	-0.013	0.053	15.514	0.415	
* .	* .	16	-0.080	-0.023	16.705	0.405	
. .	. .	17	-0.003	0.041	16.708	0.474	
* .	* .	18	-0.150	-0.091	20.931	0.283	
. .	. .	19	-0.004	0.015	20.935	0.340	
* .	* .	20	0.123	0.136	23.814	0.251	
. .	* .	21	-0.051	-0.090	24.317	0.278	
. .	. .	22	0.041	0.034	24.639	0.315	
. .	. .	23	-0.019	-0.005	24.709	0.365	
* .	* .	24	-0.066	-0.079	25.571	0.375	

Figure 46: Correlogram of D(ISC_EPS)

Sample: 1971:04 2004:07							
Included observations: 167							
Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob	
. .	. .	1	0.000	0.000	2.E-06	0.999	
. .	. .	2	0.000	0.000	2.E-05	1.000	
. .	. .	3	-0.046	-0.046	0.3698	0.946	
. .	. .	4	-0.038	-0.038	0.6220	0.961	
* .	* .	5	0.078	0.078	1.6692	0.893	
. .	. .	6	-0.006	-0.008	1.6761	0.947	
** .	** .	7	0.197	0.195	8.5520	0.286	
. .	. .	8	-0.018	-0.014	8.6084	0.376	
. .	. .	9	0.000	0.007	8.6084	0.474	
. .	. .	10	0.012	0.023	8.6329	0.567	
. .	. .	11	0.003	0.017	8.6345	0.656	
. .	. .	12	0.015	-0.016	8.6764	0.730	
. .	. .	13	-0.057	-0.053	9.2767	0.752	
. .	. .	14	-0.001	-0.040	9.2769	0.813	
. .	. .	15	0.001	0.004	9.2769	0.863	
. .	. .	16	-0.001	-0.009	9.2770	0.902	
. .	. .	17	0.035	0.025	9.5091	0.923	
. .	. .	18	0.007	0.011	9.5186	0.946	
. .	. .	19	0.007	0.011	9.5267	0.964	
. .	. .	20	0.000	0.025	9.5267	0.976	
. .	. .	21	-0.001	0.010	9.5267	0.984	
. .	. .	22	0.000	-0.005	9.5267	0.990	
. .	. .	23	0.002	0.006	9.5275	0.994	
* .	* .	24	-0.145	-0.164	13.653	0.954	

Figure 47: Correlogram of D(ISC_DPS)

Sample: 1971:04 2004:07							
Included observations: 270							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
**	**	1	0.294	0.294	23.648	0.000	
**	*	2	0.266	0.197	43.052	0.000	
*	.	3	0.175	0.061	51.446	0.000	
*	.	4	0.135	0.034	56.481	0.000	
.	.	5	0.054	-0.036	57.283	0.000	
*	*	6	0.108	0.070	60.525	0.000	
.	.	7	0.018	-0.040	60.619	0.000	
*	.	8	-0.063	-0.109	61.715	0.000	
*	*	9	-0.097	-0.082	64.389	0.000	
*	.	10	-0.064	0.001	65.532	0.000	
*	*	11	-0.138	-0.080	70.956	0.000	
.	*	12	0.009	0.105	70.980	0.000	
*	*	13	-0.154	-0.140	77.724	0.000	
*	.	14	-0.065	0.016	78.920	0.000	
*	.	15	-0.066	0.016	80.189	0.000	
*	.	16	-0.073	-0.045	81.715	0.000	
*	*	17	-0.184	-0.150	91.539	0.000	
*	.	18	-0.090	-0.022	93.899	0.000	
*	*	19	-0.160	-0.083	101.39	0.000	
.	*	20	-0.006	0.125	101.40	0.000	
.	.	21	-0.054	-0.027	102.26	0.000	
*	*	22	0.112	0.143	105.99	0.000	
.	.	23	0.047	0.046	106.64	0.000	
.	*	24	0.029	-0.074	106.89	0.000	

Figure 48: Correlogram of DLOG(SHRC)

Sample: 1971:04 2004:07							
Included observations: 399							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
.	.	1	0.036	0.036	0.5199	0.471	
.	.	2	0.018	0.017	0.6541	0.721	
.	.	3	0.054	0.053	1.8464	0.605	
.	.	4	-0.008	-0.012	1.8708	0.759	
*	*	5	-0.134	-0.136	9.1643	0.103	
.	.	6	-0.057	-0.051	10.482	0.106	
.	.	7	0.025	0.035	10.733	0.151	
.	.	8	-0.024	-0.008	10.964	0.204	
.	.	9	0.019	0.024	11.119	0.268	
.	.	10	-0.018	-0.042	11.259	0.338	
.	.	11	-0.008	-0.021	11.287	0.420	
.	.	12	-0.004	0.000	11.295	0.504	
.	.	13	0.018	0.023	11.435	0.574	
.	.	14	-0.025	-0.022	11.702	0.630	
.	.	15	-0.034	-0.040	12.187	0.665	
.	.	16	-0.032	-0.042	12.620	0.700	
.	.	17	0.001	0.009	12.621	0.761	
.	.	18	-0.029	-0.019	12.967	0.794	
.	.	19	-0.054	-0.053	14.172	0.774	
.	.	20	-0.022	-0.035	14.385	0.810	
.	.	21	-0.020	-0.027	14.554	0.845	
.	.	22	-0.050	-0.046	15.613	0.835	
.	.	23	-0.038	-0.037	16.239	0.845	
.	.	24	0.040	0.029	16.923	0.852	

Figure 49: Correlogram of DLOG(J00)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.050	-0.050	0.9917	0.319
. .	. .	2	-0.004	-0.006	0.9979	0.607
*.	*.	3	0.107	0.107	5.6043	0.133
. .	. .	4	0.040	0.051	6.2369	0.182
. .	. .	5	-0.005	0.000	6.2483	0.283
*.	*.	6	0.158	0.149	16.466	0.011
. .	. .	7	0.023	0.031	16.681	0.020
. .	. .	8	0.022	0.025	16.870	0.031
. .	. .	9	0.022	-0.006	17.063	0.048
. .	. .	10	0.024	0.007	17.299	0.068
*.	*.	11	-0.103	-0.113	21.694	0.027
*.	*.	12	0.126	0.091	28.281	0.005
. .	. .	13	-0.033	-0.039	28.745	0.007
. .	. .	14	-0.020	-0.011	28.906	0.011
. .	*.	15	-0.051	-0.073	29.981	0.012
*.	*.	16	-0.109	-0.129	34.904	0.004
. .	. .	17	0.006	0.028	34.919	0.006
*.	*.	18	0.111	0.106	40.136	0.002
*.	*.	19	-0.095	-0.051	43.926	0.001
*.	*.	20	-0.117	-0.124	49.657	0.000
. .	. .	21	-0.001	-0.013	49.657	0.000
. .	. .	22	-0.013	0.019	49.725	0.001
. .	. .	23	-0.015	0.052	49.818	0.001
. .	*.	24	-0.052	-0.091	50.989	0.001

Figure 50: Correlogram of DLOG(J000_EPS)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
. .	. .	1	-0.023	-0.023	0.2144	0.643
*.	*.	2	0.080	0.079	2.7761	0.250
*.	*.	3	0.183	0.188	16.281	0.001
*.	*.	4	0.084	0.092	19.124	0.001
. .	. .	5	0.040	0.018	19.761	0.001
*.	*.	6	0.142	0.102	27.969	0.000
*.	. .	7	0.080	0.059	30.567	0.000
. .	. .	8	0.007	-0.021	30.589	0.000
. .	. .	9	0.029	-0.030	30.943	0.000
. .	. .	10	-0.002	-0.048	30.944	0.001
*.	*.	11	-0.078	-0.104	33.463	0.000
. .	. .	12	0.001	-0.027	33.464	0.001
*.	*.	13	0.080	0.087	36.105	0.001
*.	. .	14	-0.086	-0.047	39.210	0.000
. .	. .	15	-0.037	-0.038	39.790	0.000
. .	. .	16	0.033	0.029	40.239	0.001
. .	. .	17	-0.015	0.035	40.339	0.001
. .	. .	18	0.000	0.034	40.339	0.002
. .	. .	19	0.041	0.029	41.049	0.002
. .	. .	20	0.009	0.014	41.086	0.004
. .	. .	21	-0.051	-0.053	42.172	0.004
. .	. .	22	-0.019	-0.057	42.328	0.006
. .	*.	23	-0.055	-0.074	43.637	0.006
*.	*.	24	-0.159	-0.167	54.487	0.000

Figure 51: Correlogram of DLOG(J000_DPS)

Sample: 1971:04 2004:07							
Included observations: 399							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
.*	.*	1	0.118	0.118	5.6168	0.018	
.	.	2	-0.024	-0.039	5.8559	0.054	
.	.	3	-0.013	-0.005	5.9225	0.115	
.*	.*	4	-0.075	-0.075	8.2245	0.084	
.	.	5	-0.034	-0.016	8.6820	0.122	
.	.	6	0.039	0.041	9.2959	0.158	
.	.*	7	-0.046	-0.060	10.165	0.179	
.	.	8	0.021	0.031	10.342	0.242	
.	.	9	0.045	0.033	11.185	0.263	
.	.	10	-0.019	-0.023	11.334	0.332	
.	.	11	0.007	0.010	11.352	0.414	
.	.	12	0.013	0.010	11.427	0.493	
.	.	13	-0.034	-0.025	11.893	0.536	
.	.	14	-0.047	-0.046	12.799	0.542	
.	.	15	-0.004	0.005	12.806	0.617	
.	.	16	-0.050	-0.047	13.870	0.608	
.	.	17	0.017	0.021	13.990	0.668	
.	.	18	0.011	-0.005	14.045	0.726	
.	.	19	0.001	0.003	14.045	0.781	
.	.*	20	-0.057	-0.066	15.395	0.753	
.	.	21	-0.043	-0.034	16.191	0.759	
.	.	22	0.004	0.021	16.199	0.806	
.	.	23	0.029	0.019	16.554	0.831	
.	.	24	-0.006	-0.018	16.567	0.867	

Figure 52: Correlogram of DLOG(J250)

Sample: 1971:04 2004:07							
Included observations: 399							
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob		
.*	.*	1	-0.176	-0.176	12.466	0.000	
.	.	2	-0.024	-0.056	12.692	0.002	
.*	.*	3	0.191	0.183	27.403	0.000	
.	.*	4	-0.002	0.067	27.405	0.000	
.*	.*	5	0.078	0.106	29.883	0.000	
.*	.*	6	0.157	0.169	39.980	0.000	
.	.*	7	0.031	0.095	40.373	0.000	
.	.	8	0.028	0.031	40.685	0.000	
.*	.*	9	0.148	0.112	49.690	0.000	
.	.	10	-0.024	-0.011	49.921	0.000	
.	.*	11	-0.055	-0.111	51.151	0.000	
.*	.*	12	0.180	0.070	64.585	0.000	
.	.*	13	-0.016	-0.001	64.689	0.000	
.*	.*	14	-0.066	-0.088	66.517	0.000	
.	.*	15	0.049	-0.067	67.502	0.000	
.	.	16	-0.015	-0.035	67.596	0.000	
.	.	17	0.006	0.004	67.613	0.000	
.	.	18	0.064	0.034	69.322	0.000	
.*	.	19	-0.061	-0.028	70.913	0.000	
.	.	20	-0.057	-0.051	72.295	0.000	
.*	.*	21	0.115	0.072	77.901	0.000	
.*	.*	22	-0.137	-0.092	85.880	0.000	
.	.	23	-0.037	-0.041	86.466	0.000	
.	.	24	0.017	-0.055	86.592	0.000	

Figure 53: Correlogram of DLOG(J250_EPS)

Sample: 1971:04 2004:07
 Included observations: 399

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
** .	** .	1	-0.263	-0.263	27.836	0.000
* .	* .	2	-0.064	-0.144	29.512	0.000
* .	* .	3	0.168	0.121	40.906	0.000
.	4	-0.042	0.035	41.607	0.000
.	5	0.003	0.029	41.610	0.000
. . ** .	. . ** .	6	0.208	0.215	59.289	0.000
*	7	-0.080	0.044	61.906	0.000
.	8	0.009	0.026	61.939	0.000
. . ** .	. . * .	9	0.197	0.169	77.938	0.000
*	10	-0.084	0.024	80.834	0.000
* .	* .	11	-0.067	-0.089	82.666	0.000
. . ** .	. . * .	12	0.209	0.096	100.74	0.000
.	13	-0.028	0.065	101.06	0.000
* .	* .	14	-0.097	-0.090	104.94	0.000
.	15	0.123	-0.021	111.21	0.000
.	16	-0.050	-0.021	112.27	0.000
.	17	0.003	0.005	112.28	0.000
.	18	0.083	-0.015	115.18	0.000
.	19	-0.039	0.008	115.81	0.000
* .	* .	20	-0.161	-0.161	126.74	0.000
. . ** .	. . * .	21	0.244	0.096	151.88	0.000
* .	* .	22	-0.140	-0.064	160.20	0.000
.	23	-0.028	0.002	160.54	0.000
.	24	0.049	-0.056	161.57	0.000

Figure 54: Correlogram of DLOG(J250_DPS)

Sample: 1971:04 2004:07
 Included observations: 399

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
.	1	0.147	0.147	8.7260	0.003
.	2	0.128	0.108	15.307	0.000
.	3	0.073	0.041	17.441	0.001
* .	* .	4	-0.101	-0.134	21.533	0.000
*	5	-0.064	-0.049	23.175	0.000
.	6	-0.080	-0.043	25.766	0.000
.	7	0.109	0.163	30.609	0.000
.	8	0.121	0.106	36.623	0.000
.	9	0.101	0.040	40.772	0.000
. . .	* .	10	0.023	-0.070	40.996	0.000
.	11	0.179	0.181	54.190	0.000
.	12	0.003	-0.011	54.193	0.000
*	13	-0.058	-0.052	55.600	0.000
.	14	0.037	0.024	56.154	0.000
* .	* .	15	-0.078	-0.059	58.687	0.000
* .	* .	16	-0.080	-0.088	61.352	0.000
*	17	-0.060	-0.023	62.836	0.000
. . .	* .	18	-0.116	-0.135	68.465	0.000
.	19	-0.016	-0.018	68.578	0.000
.	20	-0.017	-0.001	68.697	0.000
.	21	0.018	0.035	68.838	0.000
.	22	0.066	0.009	70.680	0.000
.	23	0.006	0.002	70.693	0.000
* .	* .	24	-0.104	-0.100	75.345	0.000

Figure 55: Correlogram of DLOG(UDSZAR)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
.*	.*	1	0.091	0.091	3.3036	0.069
.*	.*	2	-0.004	-0.013	3.3109	0.191
.*	.*	3	0.070	0.072	5.2648	0.153
.*	.*	4	-0.070	-0.084	7.2598	0.123
.*	.*	5	-0.007	0.010	7.2777	0.201
.*	.*	6	-0.091	-0.100	10.618	0.101
.*	.*	7	0.029	0.061	10.955	0.141
.*	.*	8	-0.120	-0.145	16.882	0.031
.*	.*	9	-0.041	0.006	17.575	0.040
.*	.*	10	0.040	0.013	18.223	0.051
.*	.*	11	-0.077	-0.056	20.691	0.037
.*	.*	12	0.007	-0.006	20.709	0.055
.*	.*	13	-0.039	-0.042	21.345	0.066
.*	.*	14	0.017	0.017	21.468	0.090
.*	.*	15	0.047	0.037	22.377	0.098
.*	.*	16	-0.064	-0.076	24.097	0.087
.*	.*	17	0.012	-0.001	24.161	0.115
.*	.*	18	-0.059	-0.057	25.607	0.109
.*	.*	19	-0.029	-0.023	25.956	0.131
.*	.*	20	0.103	0.101	30.395	0.064
.*	.*	21	0.047	0.035	31.314	0.069
.*	.*	22	-0.001	-0.031	31.315	0.090
.*	.*	23	-0.062	-0.059	32.974	0.082
.*	.*	24	-0.115	-0.137	38.599	0.030

Figure 56: Correlogram of D(RLRS)

Sample: 1971:04 2004:07						
Included observations: 399						
Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob	
.***	.***	1	0.379	0.379	57.804	0.000
.*	.*	2	0.179	0.042	70.765	0.000
.*	.*	3	0.087	0.008	73.848	0.000
.*	.*	4	0.047	0.006	74.731	0.000
.*	.*	5	0.049	0.030	75.725	0.000
.*	.*	6	0.102	0.084	79.978	0.000
.*	.*	7	0.080	0.012	82.609	0.000
.*	.*	8	-0.028	-0.093	82.920	0.000
.*	.*	9	-0.023	0.004	83.137	0.000
.*	.*	10	-0.074	-0.066	85.366	0.000
.*	.*	11	-0.048	0.002	86.333	0.000
.*	.*	12	0.037	0.072	86.896	0.000
.*	.*	13	-0.017	-0.063	87.016	0.000
.*	.*	14	-0.014	0.010	87.101	0.000
.*	.*	15	-0.027	-0.011	87.402	0.000
.*	.*	16	-0.041	-0.022	88.110	0.000
.*	.*	17	-0.028	0.010	88.435	0.000
.*	.*	18	-0.080	-0.098	91.120	0.000
.*	.*	19	-0.098	-0.054	95.204	0.000
.*	.*	20	-0.072	0.007	97.375	0.000
.*	.*	21	-0.073	-0.044	99.655	0.000
.*	.*	22	-0.077	-0.018	102.20	0.000
.*	.*	23	-0.079	-0.039	104.85	0.000
.*	.*	24	-0.026	0.030	105.15	0.000

Figure 57: Correlogram of D(RBAS)

8. APPENDIX B

Test Statistic	1%	2.5%	5%	10%
m = 2				
τ_c	-3.90	-3.59	-3.34	-3.04
τ_{ct}	-4.32	-4.03	-3.73	-3.50
τ_{ctt}	-4.69	-4.40	-4.15	-3.87
m = 3				
τ_c	-4.29	-4.00	-3.74	-3.45
τ_{ct}	-4.66	-4.37	-4.12	-3.84
τ_{ctt}	-4.99	-4.70	-4.45	-4.17
m = 4				
τ_c	-4.64	-4.35	-4.10	-3.81
τ_{ct}	-4.97	-4.68	-4.43	-4.15
τ_{ctt}	-5.27	-4.98	-4.73	-4.45
m = 5				
τ_c	-4.96	-4.66	-4.42	-4.13
τ_{ct}	-5.25	-4.96	-4.72	-4.43
τ_{ctt}	-5.53	-5.24	-4.99	-4.72
m = 6				
τ_c	-5.25	-4.96	-4.71	-4.42
τ_{ct}	-5.52	-5.23	-4.98	-4.70
τ_{ctt}	-5.77	-5.49	-5.24	-4.96

Table 17: Asymptotic Critical Values for Augmented Engle & Granger Test

9. APPENDIX C

Addendum of all Results for all Models

- OLS regression output for co-integrating models
- Augmented Engle & Granger (AEG) test results confirming co-integration
- OLS regression output for Error Correction Models (ECM)
- Rolling Window forecasting performance of each ECM forecasting log returns over one, two and three months respectively.

9.1. MODEL 1 – $\Delta \log(IMP)$

Dependent Variable: LOG(IMP)				
Method: Least Squares				
Sample(adjusted): 1982:08 2004:07				
Included observations: 264 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-4.266261	0.340085	-12.54468	0.0000
LOG(PLATPM)	1.141981	0.050249	22.72630	0.0000
LOG(IMP_EPS)	-0.407330	0.091560	-4.448789	0.0000
LOG(IMP_DPS)	0.651860	0.078105	8.345911	0.0000
RLRS	1.643201	0.868123	1.892821	0.0595
R-squared	0.953267	Mean dependent var		4.275604
Adjusted R-squared	0.952546	S.D. dependent var		1.099551
S.E. of regression	0.239526	Akaike info criterion		-0.001550
Sum squared resid	14.85956	Schwarz criterion		0.066177
Log likelihood	5.204544	F-statistic		1320.793
Durbin-Watson stat	0.257529	Prob(F-statistic)		0.000000

Table 18: OLS Regression Results for dependent variable $\log(IMP)$ regressed on explanatory variables $\log(PLATPM)$, $\log(IMP_EPS)$, $\log(IMP_DPS)$ and RLRS

ADF Test Statistic	-4.208717	1% Critical Value	-4.96	
		5% Critical Value	-4.42	
		10% Critical Value	-4.13	
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RES)				
Method: Least Squares				
Sample(adjusted): 1982:11 2004:07				
Included observations: 261 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES(-1)	-0.135494	0.032194	-4.208717	0.0000
D(RES(-1))	-0.084322	0.062582	-1.347376	0.1790
D(RES(-2))	0.097093	0.061556	1.577322	0.1159
R-squared	0.091066	Mean dependent var		0.001504
Adjusted R-squared	0.084020	S.D. dependent var		0.121256
S.E. of regression	0.116051	Akaike info criterion		-1.458150
Sum squared resid	3.474687	Schwarz criterion		-1.417179
Log likelihood	193.2886	Durbin-Watson stat		2.015717

Table 19: Augmented Engle & Granger Unit Root Test Results on Residuals for Model 1. The τ statistic is greater in absolute value than the EG critical values at the 10% significance level thus the null of no co-integration is rejected.

ERROR CORRECTION MODELS for $\Delta \log(IMP)$

Dependent Variable: DLOG(IMP)				
Method: Least Squares				
Sample(adjusted): 1982:10 1999:12				
Included observations: 207 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.019228	0.008814	2.181593	0.0303
RES(-1)	-0.120966	0.035283	-3.428466	0.0007
DLOG(IMP(-1))	0.055469	0.081880	0.677444	0.4989
DLOG(PLATPM(-1))	-0.176142	0.145803	-1.208079	0.2284
D(RLRS(-1))	2.049002	1.454165	1.409057	0.1604
DLOG(IMP_EPS(-1))	-0.010457	0.101634	-0.102889	0.9182
R-squared	0.067086	Mean dependent var		0.017337
Adjusted R-squared	0.043879	S.D. dependent var		0.127088
S.E. of regression	0.124268	Akaike info criterion		-1.304190
Sum squared resid	3.103967	Schwarz criterion		-1.207589
Log likelihood	140.9836	F-statistic		2.890767
Durbin-Watson stat	1.984609	Prob(F-statistic)		0.015226

Table 20: ECM adding one lag of residual from co-integrating relationship and one lag of each dependent and explanatory variables

Dependent Variable: DLOG(IMP)				
Method: Least Squares				
Sample(adjusted): 1982:12 1999:12				
Included observations: 205 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016441	0.009381	1.752533	0.0813
RES(-1)	-0.125220	0.038640	-3.240668	0.0014
DLOG(IMP(-1))	0.053170	0.085129	0.624579	0.5330
DLOG(IMP(-2))	0.021574	0.085754	0.251577	0.8016
DLOG(IMP(-3))	0.114736	0.085823	1.336892	0.1828
DLOG(PLATPM(-1))	-0.152378	0.157067	-0.970142	0.3332
DLOG(PLATPM(-2))	-0.063402	0.160660	-0.394633	0.6936
DLOG(PLATPM(-3))	-0.078714	0.157273	-0.500493	0.6173
D(RLRS(-1))	2.526429	1.544922	1.635311	0.1036
D(RLRS(-2))	-0.598131	1.537959	-0.388912	0.6978
D(RLRS(-3))	0.176845	1.507225	0.117332	0.9067
DLOG(IMP_EPS(-1))	-0.017956	0.104478	-0.171866	0.8637
DLOG(IMP_EPS(-2))	0.017285	0.105076	0.164501	0.8695
DLOG(IMP_EPS(-3))	0.105780	0.104860	1.008778	0.3144
R-squared	0.081835	Mean dependent var		0.016814
Adjusted R-squared	0.019343	S.D. dependent var		0.127514
S.E. of regression	0.126275	Akaike info criterion		-1.234863
Sum squared resid	3.045560	Schwarz criterion		-1.007926
Log likelihood	140.5734	F-statistic		1.309515
Durbin-Watson stat	1.999008	Prob(F-statistic)		0.210006

Table 21: ECM adding one lag of residual from co-integrating relationship and three lags of each dependent and explanatory variables

Dependent Variable: DLOG(IMP)				
Method: Least Squares				
Sample(adjusted): 1983:03 1999:12				
Included observations: 202 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.015578	0.009619	1.619480	0.1071
RES(-1)	-0.107284	0.042559	-2.520856	0.0126
DLOG(IMP(-1))	0.037827	0.088842	0.425775	0.6708
DLOG(IMP(-2))	0.001225	0.085397	0.014349	0.9886
DLOG(IMP(-3))	0.137814	0.086238	1.598060	0.1118
DLOG(IMP(-4))	0.043437	0.086145	0.504236	0.6147
DLOG(IMP(-5))	-0.038142	0.087618	-0.435322	0.6639
DLOG(IMP(-6))	-0.108405	0.086456	-1.253883	0.2115
DLOG(PLATPM(-1))	-0.147368	0.156260	-0.943092	0.3469
DLOG(PLATPM(-2))	-0.102196	0.161013	-0.634706	0.5264
DLOG(PLATPM(-3))	-0.118856	0.162041	-0.733492	0.4642
DLOG(PLATPM(-4))	-0.125799	0.165953	-0.758045	0.4494
DLOG(PLATPM(-5))	-0.077862	0.167490	-0.464872	0.6426
DLOG(PLATPM(-6))	-0.098636	0.159288	-0.619230	0.5366
D(RLRS(-1))	2.813233	1.537617	1.829605	0.0690
D(RLRS(-2))	-0.549466	1.548921	-0.354741	0.7232
D(RLRS(-3))	1.557449	1.543743	1.008878	0.3144
D(RLRS(-4))	-1.339372	1.534873	-0.872627	0.3841
D(RLRS(-5))	-2.074106	1.522762	-1.362068	0.1749
D(RLRS(-6))	-0.060513	1.493035	-0.040530	0.9677
DLOG(IMP_EPS(-1))	0.006784	0.105643	0.064215	0.9489
DLOG(IMP_EPS(-2))	0.047450	0.104278	0.455032	0.6496
DLOG(IMP_EPS(-3))	0.101199	0.102456	0.987730	0.3246
DLOG(IMP_EPS(-4))	0.089826	0.103143	0.870888	0.3850
DLOG(IMP_EPS(-5))	0.425726	0.109504	3.887770	0.0001
DLOG(IMP_EPS(-6))	-0.141143	0.113825	-1.239993	0.2166
R-squared	0.201194	Mean dependent var		0.015210
Adjusted R-squared	0.087728	S.D. dependent var		0.126968
S.E. of regression	0.121271	Akaike info criterion		-1.261932
Sum squared resid	2.588382	Schwarz criterion		-0.836115
Log likelihood	153.4551	F-statistic		1.773157
Durbin-Watson stat	1.954601	Prob(F-statistic)		0.017795

Table 22: ECM adding one lag of residual from co-integrating relationship and six lags of each dependent and independent variables

FORECASTING PERFORMANCE OF ECM'S

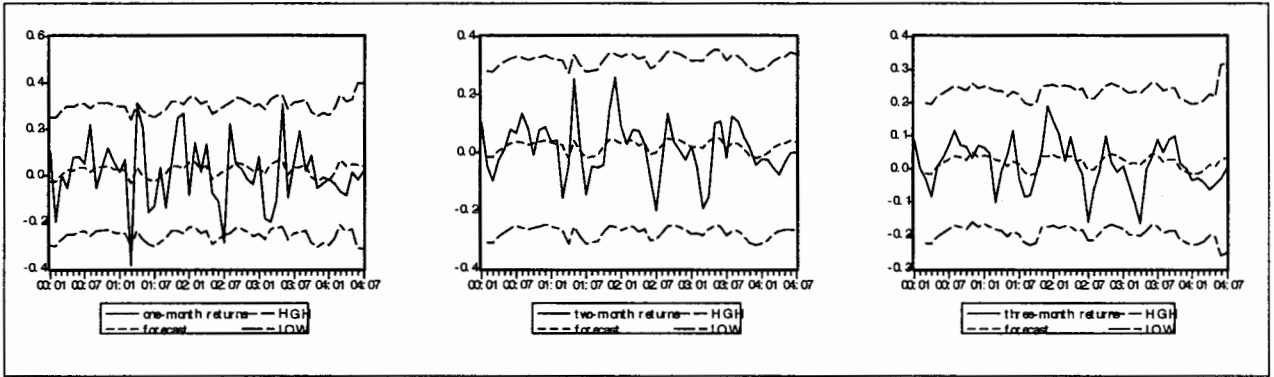


Figure 58: Forecasting performance of the ECM for $\Delta \log(\text{IMP})$ containing one lag of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

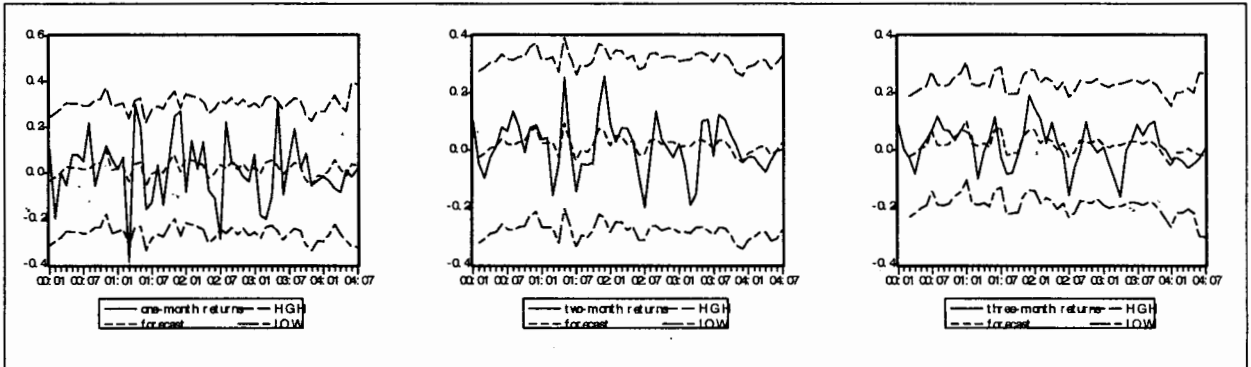


Figure 59: Forecasting performance of the ECM for $\Delta \log(\text{IMP})$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

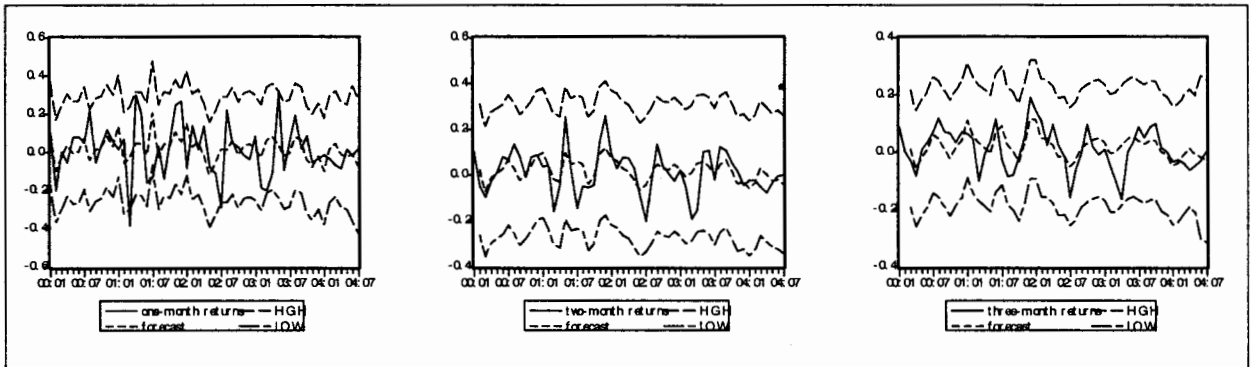


Figure 60: Forecasting performance of the ECM for $\Delta \log(\text{IMP})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

9.2. MODEL 2 – $\Delta\log(HAR)$

Dependent Variable: LOG(HAR)				
Method: Least Squares				
Sample(adjusted): 1983:04 2004:07				
Included observations: 256 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-2.732542	0.580103	-4.710444	0.0000
LOG(GOLR)	0.796117	0.061073	13.03543	0.0000
HAR_EPS	-0.023949	0.011949	-2.004207	0.0461
HAR_DPS	0.306185	0.028227	10.84729	0.0000
RLRS	1.358842	1.308808	1.038229	0.3002
R-squared	0.701368	Mean dependent var		3.488498
Adjusted R-squared	0.696609	S.D. dependent var		0.581486
S.E. of regression	0.320288	Akaike info criterion		0.580146
Sum squared resid	25.74868	Schwarz criterion		0.649387
Log likelihood	-69.25864	F-statistic		147.3747
Durbin-Watson stat	0.252657	Prob(F-statistic)		0.000000

Table 23: OLS Regression Results for dependent variable $\log(HAR)$ regressed on explanatory variables $\log(GOLR)$, HAR_EPS, HAR_DPS and RLRS

ADF Test Statistic	-4.428810	1% Critical Value	-4.96	
		5% Critical Value	-4.42	
		10% Critical Value	-4.13	
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RES)				
Method: Least Squares				
Sample(adjusted): 1983:06 2004:07				
Included observations: 254 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES(-1)	-0.139544	0.031508	-4.428810	0.0000
D(RES(-1))	0.095659	0.062637	1.527201	0.1280
R-squared	0.072799	Mean dependent var	-0.001219	
Adjusted R-squared	0.069119	S.D. dependent var	0.160314	
S.E. of regression	0.154675	Akaike info criterion	-0.887143	
Sum squared resid	6.028912	Schwarz criterion	-0.859290	
Log likelihood	114.6671	Durbin-Watson stat	2.030698	

Table 24: Augmented Engle & Granger Unit Root Test Results on Residuals for Model 2. The τ statistic is greater in absolute value than the EG critical values at the 5% significance level thus the null of no co-integration is rejected.

ERROR CORRECTION MODELS for $\Delta \log(HAR)$

Dependent Variable: DLOG(HAR)				
Method: Least Squares				
Sample(adjusted): 1983:06 1999:12				
Included observations: 199 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.000548	0.010446	0.052427	0.9582
RES(-1)	-0.119210	0.033919	-3.514584	0.0005
DLOG(HAR(-1))	0.097131	0.078791	1.232776	0.2192
DLOG(GOLR(-1))	0.136833	0.263691	0.518915	0.6044
D(RLRS(-1))	1.497105	1.763663	0.848861	0.3970
D(HAR_EPS(-1))	0.012698	0.017209	0.737876	0.4615
R-squared	0.071829	Mean dependent var		0.002183
Adjusted R-squared	0.047783	S.D. dependent var		0.148996
S.E. of regression	0.145393	Akaike info criterion		-0.989065
Sum squared resid	4.079854	Schwarz criterion		-0.889769
Log likelihood	104.4120	F-statistic		2.987170
Durbin-Watson stat	2.030069	Prob(F-statistic)		0.012743

Table 25: ECM adding one lag of residual from co-integrating relationship and one lag of each dependent and independent variables

Dependent Variable: DLOG(HAR)				
Method: Least Squares				
Sample(adjusted): 1983:08 1999:12				
Included observations: 197 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.000890	0.010865	-0.081889	0.9348
RES(-1)	-0.139454	0.036906	-3.778646	0.0002
DLOG(HAR(-1))	0.094878	0.080369	1.180528	0.2393
DLOG(HAR(-2))	0.146022	0.081762	1.785941	0.0758
DLOG(HAR(-3))	0.023140	0.082485	0.280539	0.7794
DLOG(GOLR(-1))	0.155013	0.274958	0.563772	0.5736
DLOG(GOLR(-2))	-0.247837	0.273649	-0.905676	0.3663
DLOG(GOLR(-3))	0.265012	0.279558	0.947966	0.3444
D(RLRS(-1))	1.178000	1.804556	0.652792	0.5147
D(RLRS(-2))	0.715634	1.791056	0.399560	0.6899
D(RLRS(-3))	2.417336	1.834420	1.317766	0.1892
D(HAR_EPS(-1))	0.006314	0.018085	0.349147	0.7274
D(HAR_EPS(-2))	0.013841	0.017622	0.785463	0.4332
D(HAR_EPS(-3))	-0.001086	0.017505	-0.062062	0.9506
R-squared	0.112848	Mean dependent var		0.002123
Adjusted R-squared	0.049826	S.D. dependent var		0.149696
S.E. of regression	0.145919	Akaike info criterion		-0.943119
Sum squared resid	3.896488	Schwarz criterion		-0.709795
Log likelihood	106.8972	F-statistic		1.790617
Durbin-Watson stat	2.009255	Prob(F-statistic)		0.047272

Table 26: ECM adding one lag of residual from co-integrating relationship and three lags of each dependent and independent variables

Dependent Variable: DLOG(HAR)				
Method: Least Squares				
Sample(adjusted): 1983:11 1999:12				
Included observations: 194 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005370	0.011700	0.458974	0.6468
RES(-1)	-0.126914	0.041380	-3.067031	0.0025
DLOG(HAR(-1))	0.106057	0.085956	1.233857	0.2190
DLOG(HAR(-2))	0.138808	0.086455	1.605548	0.1103
DLOG(HAR(-3))	0.057755	0.085726	0.673713	0.5014
DLOG(HAR(-4))	-0.081153	0.085191	-0.952596	0.3422
DLOG(HAR(-5))	0.023236	0.086044	0.270046	0.7875
DLOG(HAR(-6))	0.000457	0.085026	0.005377	0.9957
DLOG(GOLR(-1))	0.085333	0.295642	0.288635	0.7732
DLOG(GOLR(-2))	-0.301630	0.299602	-1.006768	0.3155
DLOG(GOLR(-3))	0.143803	0.296889	0.484366	0.6288
DLOG(GOLR(-4))	-0.102613	0.303705	-0.337871	0.7359
DLOG(GOLR(-5))	0.119845	0.304617	0.393427	0.6945
DLOG(GOLR(-6))	-0.591938	0.300327	-1.970976	0.0504
D(RLRS(-1))	0.959068	1.901521	0.504369	0.6147
D(RLRS(-2))	1.112912	1.904429	0.584381	0.5597
D(RLRS(-3))	2.213363	1.902497	1.163399	0.2463
D(RLRS(-4))	2.534832	1.902947	1.332056	0.1846
D(RLRS(-5))	-1.489862	1.915650	-0.777732	0.4378
D(RLRS(-6))	-0.536521	1.904647	-0.281691	0.7785
D(HAR_EPS(-1))	0.012482	0.019094	0.653733	0.5142
D(HAR_EPS(-2))	0.010105	0.019209	0.526058	0.5995
D(HAR_EPS(-3))	0.008420	0.019104	0.440765	0.6600
D(HAR_EPS(-4))	-0.008005	0.019114	-0.418796	0.6759
D(HAR_EPS(-5))	-0.002929	0.018931	-0.154740	0.8772
D(HAR_EPS(-6))	-0.004400	0.018788	-0.234224	0.8151
R-squared	0.160793	Mean dependent var		0.003196
Adjusted R-squared	0.035911	S.D. dependent var		0.149909
S.E. of regression	0.147193	Akaike info criterion		-0.869998
Sum squared resid	3.639847	Schwarz criterion		-0.432038
Log likelihood	110.3898	F-statistic		1.287561
Durbin-Watson stat	1.962169	Prob(F-statistic)		0.175760

Table 27: ECM adding one lag of residual from co-integrating relationship and six lags of each dependent and independent variables

FORECASTING PERFORMANCE OF ECM'S

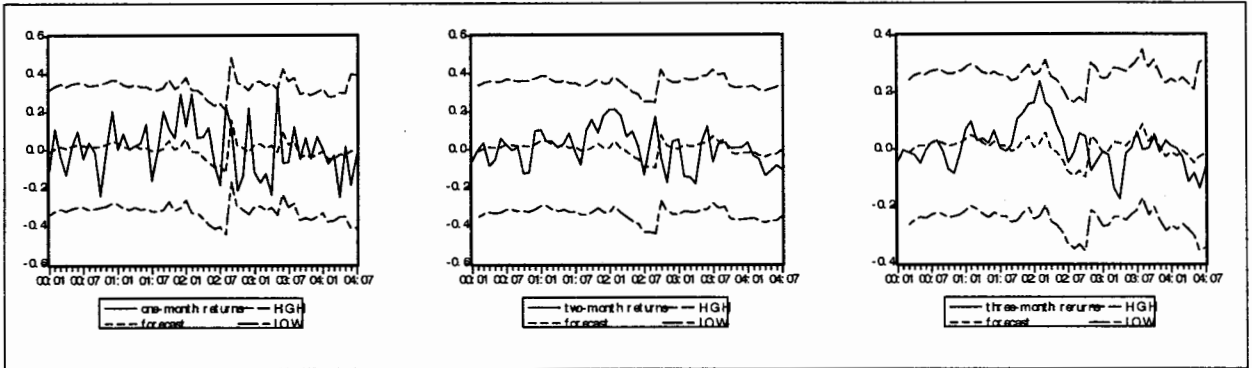


Figure 61: Forecasting performance of the ECM for $\Delta \log(\text{HAR})$ containing one lag of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

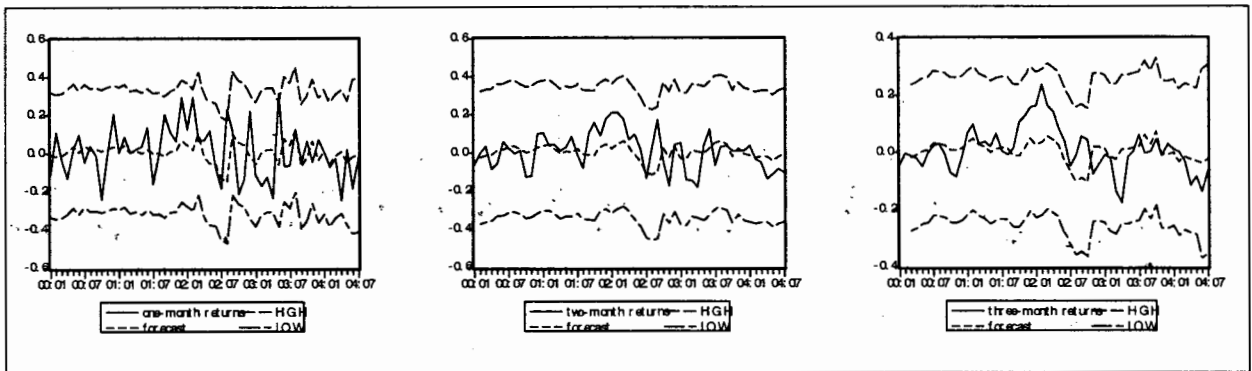


Figure 62: Forecasting performance of the ECM for $\Delta \log(\text{HAR})$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

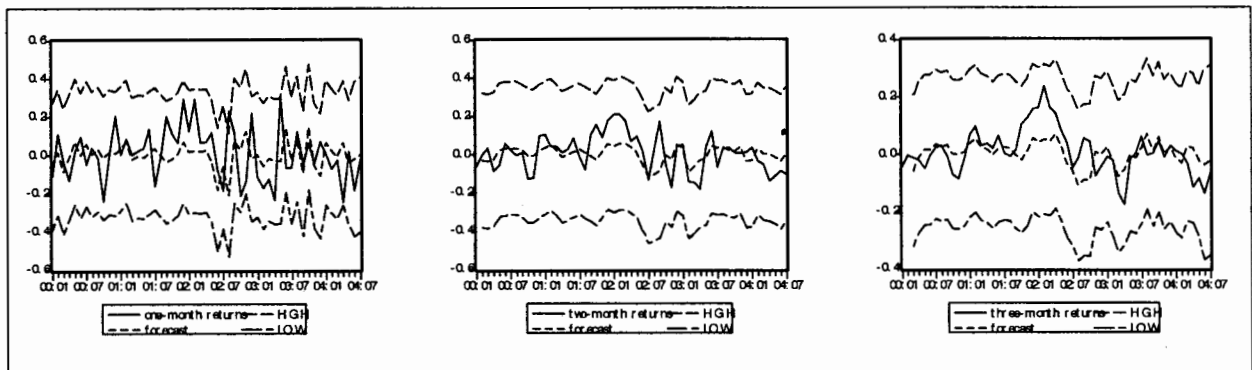


Figure 63: Forecasting performance of the ECM for $\Delta \log(\text{HAR})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

9.3. MODEL 3 – $\Delta \log(GFI)$

Dependent Variable: LOG(GFI)				
Method: Least Squares				
Sample(adjusted): 1983:04 2004:07				
Included observations: 250				
Excluded observations: 6 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.988541	0.378826	-2.609489	0.0096
LOG(GOLR)	0.630366	0.038208	16.49846	0.0000
LOG(GFI_EPS)	0.029381	0.033273	0.883031	0.3781
LOG(GFI_DPS)	0.524080	0.032404	16.17335	0.0000
RLRS	-0.392670	0.915573	-0.428879	0.6684
R-squared	0.747917	Mean dependent var	3.693067	
Adjusted R-squared	0.743801	S.D. dependent var	0.456304	
S.E. of regression	0.230963	Akaike info criterion	-0.073320	
Sum squared resid	13.06928	Schwarz criterion	-0.002890	
Log likelihood	14.16495	F-statistic	181.7255	
Durbin-Watson stat	0.297568	Prob(F-statistic)	0.000000	

Table 28: OLS Regression Results for dependent variable $\log(GFI)$ regressed on explanatory variables $\log(GOLR)$, $\log(GFI_EPS)$, $\log(GFI_DPS)$ and RLRS

ADF Test Statistic	-4.633376	1% Critical Value	-4.96	
		.5% Critical Value	-4.42	
		10% Critical Value	-4.13	
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RES)				
Method: Least Squares				
Sample(adjusted): 1983:07 2004:07				
Included observations: 244				
Excluded observations: 9 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES(-1)	-0.165219	0.035659	-4.633376	0.0000
D(RES(-1))	0.011843	0.064025	0.184981	0.8534
D(RES(-2))	0.101560	0.063388	1.602196	0.1104
R-squared	0.088009	Mean dependent var	0.001418	
Adjusted R-squared	0.080441	S.D. dependent var	0.124581	
S.E. of regression	0.119466	Akaike info criterion	-1.399356	
Sum squared resid	3.439566	Schwarz criterion	-1.356358	
Log likelihood	173.7214	Durbin-Watson stat	2.039439	

Table 29: Augmented Engle & Granger Unit Root Test Results on Residuals for Model 3. The τ statistic is greater in absolute value than the EG critical values at the 5% significance level thus the null of no co-integration is rejected.

ERROR CORRECTION MODELS for $\Delta \log(GFI)$

Dependent Variable: DLOG(GFI)				
Method: Least Squares				
Sample(adjusted): 1983:06 1999:12				
Included observations: 192				
Excluded observations: 7 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.002522	0.007544	0.334336	0.7385
RES(-1)	-0.079161	0.037026	-2.138001	0.0338
DLOG(GFI(-1))	-0.105420	0.084093	-1.253615	0.2116
DLOG(GOLR(-1))	0.082737	0.198109	0.417632	0.6767
D(RLRS(-1))	1.295774	1.564273	0.828356	0.4085
DLOG(GFI_EPS(-1))	0.012273	0.070946	0.172994	0.8628
R-squared	0.045939	Mean dependent var		0.002947
Adjusted R-squared	0.020292	S.D. dependent var		0.104210
S.E. of regression	0.103147	Akaike info criterion		-1.674570
Sum squared resid	1.978913	Schwarz criterion		-1.572774
Log likelihood	166.7588	F-statistic		1.791216
Durbin-Watson stat	1.988860	Prob(F-statistic)		0.116582

Table 30: ECM adding one lag of residual from co-integrating relationship and one lag of each dependent and independent variables

Dependent Variable: DLOG(GFI)				
Method: Least Squares				
Sample(adjusted): 1983:08 1999:12				
Included observations: 188				
Excluded observations: 9 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.003238	0.007811	0.414550	0.6790
RES(-1)	-0.101783	0.040479	-2.514458	0.0128
DLOG(GFI(-1))	-0.096696	0.088629	-1.091022	0.2768
DLOG(GFI(-2))	0.043906	0.088497	0.496134	0.6204
DLOG(GFI(-3))	0.040854	0.087087	0.469113	0.6396
DLOG(GOLR(-1))	0.101384	0.204634	0.495443	0.6209
DLOG(GOLR(-2))	0.042708	0.201064	0.212409	0.8320
DLOG(GOLR(-3))	-0.006195	0.201051	-0.030811	0.9755
D(RLRS(-1))	1.477053	1.621860	0.910716	0.3637
D(RLRS(-2))	0.687269	1.613362	0.425985	0.6706
D(RLRS(-3))	1.178955	1.602885	0.735521	0.4630
DLOG(GFI_EPS(-1))	0.005735	0.072797	0.078783	0.9373
DLOG(GFI_EPS(-2))	-0.035743	0.072614	-0.492233	0.6232
DLOG(GFI_EPS(-3))	-0.078874	0.074507	-1.058607	0.2912
R-squared	0.063846	Mean dependent var		0.003654
Adjusted R-squared	-0.006097	S.D. dependent var		0.102624
S.E. of regression	0.102937	Akaike info criterion		-1.637853
Sum squared resid	1.843702	Schwarz criterion		-1.396841
Log likelihood	167.9582	F-statistic		0.912834
Durbin-Watson stat	1.969877	Prob(F-statistic)		0.540968

Table 31: ECM adding one lag of residual from co-integrating relationship and three lags of each dependent and independent variables

Dependent Variable: DLOG(GFI)				
Method: Least Squares				
Date: 05/08/05 Time: 14:33				
Sample(adjusted): 1983:11 1999:12				
Included observations: 182				
Excluded observations: 12 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012898	0.008153	1.582056	0.1157
RES(-1)	-0.138224	0.046802	-2.953370	0.0036
DLOG(GFI(-1))	-0.049460	0.092485	-0.534785	0.5936
DLOG(GFI(-2))	0.038446	0.091079	0.422120	0.6735
DLOG(GFI(-3))	0.063909	0.088766	0.719969	0.4726
DLOG(GFI(-4))	0.007256	0.089665	0.080924	0.9356
DLOG(GFI(-5))	-0.054826	0.091505	-0.599157	0.5499
DLOG(GFI(-6))	0.072956	0.089285	0.817106	0.4151
DLOG(GOLR(-1))	-0.012656	0.215831	-0.058641	0.9533
DLOG(GOLR(-2))	-0.024067	0.210705	-0.114223	0.9092
DLOG(GOLR(-3))	0.026241	0.205726	0.127554	0.8987
DLOG(GOLR(-4))	-0.143841	0.209710	-0.685903	0.4938
DLOG(GOLR(-5))	0.106057	0.212315	0.499524	0.6181
DLOG(GOLR(-6))	-0.598883	0.215275	-2.781941	0.0061
D(RLRS(-1))	1.556696	1.649845	0.943541	0.3469
D(RLRS(-2))	1.076491	1.668630	0.645134	0.5198
D(RLRS(-3))	1.614131	1.649897	0.978322	0.3294
D(RLRS(-4))	-1.011874	1.644126	-0.615448	0.5392
D(RLRS(-5))	-1.828663	1.637919	-1.116455	0.2659
D(RLRS(-6))	-0.263129	1.590384	-0.165450	0.8688
DLOG(GFI_EPS(-1))	0.252105	0.106782	2.360942	0.0195
DLOG(GFI_EPS(-2))	0.091775	0.112282	0.817362	0.4150
DLOG(GFI_EPS(-3))	0.112832	0.107598	1.048646	0.2960
DLOG(GFI_EPS(-4))	-0.150323	0.087925	-1.709679	0.0893
DLOG(GFI_EPS(-5))	-0.146374	0.104403	-1.402011	0.1629
DLOG(GFI_EPS(-6))	-0.273678	0.104891	-2.609162	0.0100
R-squared	0.187181	Mean dependent var		0.005126
Adjusted R-squared	0.056921	S.D. dependent var		0.102752
S.E. of regression	0.099785	Akaike info criterion		-1.640041
Sum squared resid	1.553289	Schwarz criterion		-1.182326
Log likelihood	175.2437	F-statistic		1.436983
Durbin-Watson stat	1.950541	Prob(F-statistic)		0.094910

Table 32: ECM adding one lag of residual from co-integrating relationship and six lags of each dependent and independent variables

FORECASTING PERFORMANCE OF ECM'S

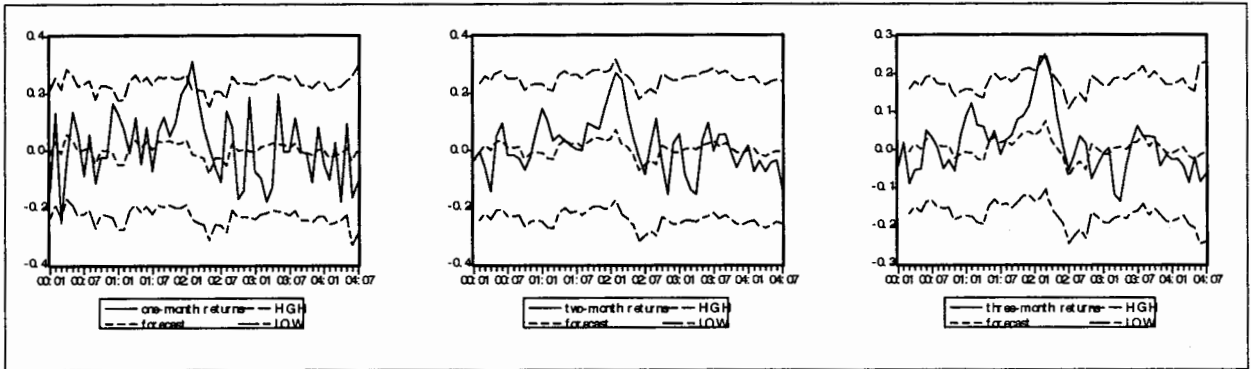


Figure 64: Forecasting performance of the ECM for $\Delta \log(\text{GFI})$ containing one lag of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

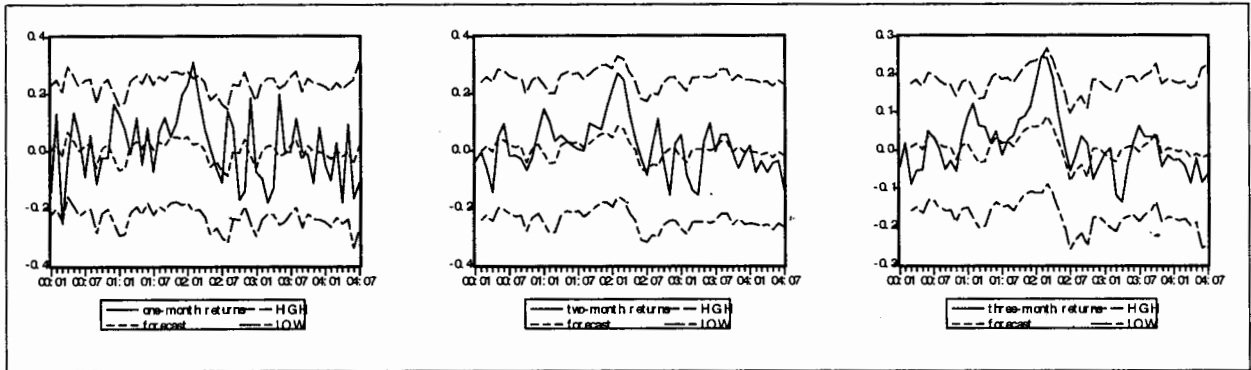


Figure 65: Forecasting performance of the ECM for $\Delta \log(\text{GFI})$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

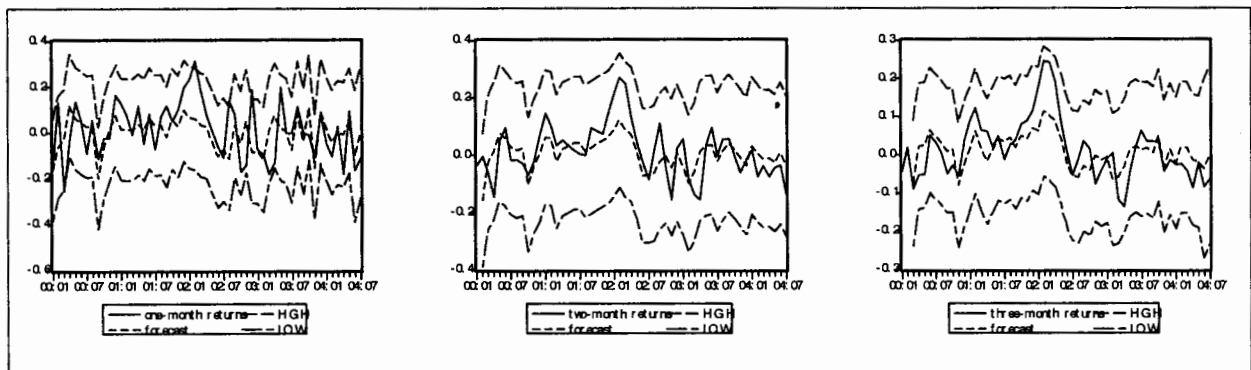


Figure 66: Forecasting performance of the ECM for $\Delta \log(\text{GFI})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

9.4. MODEL 4 – $\Delta\log(SOL)$

Dependent Variable: LOG(SOL)				
Method: Least Squares				
Sample(adjusted): 1982:02 2004:07				
Included observations: 270 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.385461	0.153005	9.055013	0.0000
LOG(SOL_EPS)	0.830390	0.097275	8.536502	0.0000
LOG(SOL_DPS)	0.313135	0.111566	2.806726	0.0054
RLRS	7.008143	0.766302	9.145400	0.0000
R-squared	0.955021	Mean dependent var	3.019166	
Adjusted R-squared	0.954514	S.D. dependent var	1.017724	
S.E. of regression	0.217055	Akaike info criterion	-0.202629	
Sum squared resid	12.53201	Schwarz criterion	-0.149320	
Log likelihood	31.35498	F-statistic	1882.630	
Durbin-Watson stat	0.282383	Prob(F-statistic)	0.000000	

Table 33: OLS Regression Results for dependent variable $\log(SOL)$ regressed on explanatory variables $\log(SOL_EPS)$, $\log(SOL_DPS)$ and RLRS

ADF Test Statistic	-4.128368	1% Critical Value	-4.64	
		5% Critical Value	-4.10	
		10% Critical Value	-3.81	
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RES)				
Method: Least Squares				
Sample(adjusted): 1982:04 2004:07				
Included observations: 268 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES(-1)	-0.134512	0.032582	-4.128368	0.0000
D(RES(-1))	-0.041909	0.061219	-0.684581	0.4942
R-squared	0.071348	Mean dependent var	0.001620	
Adjusted R-squared	0.067857	S.D. dependent var	0.114830	
S.E. of regression	0.110865	Akaike info criterion	-1.553570	
Sum squared resid	3.269427	Schwarz criterion	-1.526771	
Log likelihood	210.1784	Durbin-Watson stat	2.001629	

Table 34: Augmented Engle & Granger Unit Root Test Results on Residuals for Model 4. The τ statistic is greater in absolute value than the EG critical values at the 5% significance level thus the null of no co-integration is rejected.

ERROR CORRECTION MODELS for $\Delta \log(SOL)$

Dependent Variable: DLOG(SOL)				
Method: Least Squares				
Sample(adjusted): 1982:04 1999:12				
Included observations: 213 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012590	0.006398	1.967685	0.0504
RES(-1)	-0.092329	0.029070	-3.176103	0.0017
DLOG(SOL(-1))	0.121450	0.071264	1.704239	0.0898
D(RLRS(-1))	1.021016	1.065939	0.957856	0.3392
DLOG(SOL_EPS(-1))	0.115447	0.169433	0.681372	0.4964
R-squared	0.059966	Mean dependent var		0.012920
Adjusted R-squared	0.041888	S.D. dependent var		0.091682
S.E. of regression	0.089741	Akaike info criterion		-1.960573
Sum squared resid	1.675135	Schwarz criterion		-1.881669
Log likelihood	213.8010	F-statistic		3.317136
Durbin-Watson stat	2.038067	Prob(F-statistic)		0.011654

Table 35: ECM adding one lag of residual from co-integrating relationship and one lag of each dependent and independent variables

Dependent Variable: DLOG(SOL)				
Method: Least Squares				
Sample(adjusted): 1982:06 1999:12				
Included observations: 211 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.007727	0.006788	1.138269	0.2564
RES(-1)	-0.123178	0.030773	-4.002760	0.0001
DLOG(SOL(-1))	0.096639	0.072378	1.335187	0.1833
DLOG(SOL(-2))	0.083911	0.074027	1.133512	0.2584
DLOG(SOL(-3))	0.186788	0.073624	2.537063	0.0119
D(RLRS(-1))	0.424371	1.100775	0.385520	0.7003
D(RLRS(-2))	-0.173851	1.114681	-0.155965	0.8762
D(RLRS(-3))	-0.692935	1.074060	-0.645155	0.5196
DLOG(SOL_EPS(-1))	0.126900	0.169983	0.746543	0.4562
DLOG(SOL_EPS(-2))	0.204092	0.170697	1.195642	0.2333
DLOG(SOL_EPS(-3))	0.140054	0.169710	0.825253	0.4102
R-squared	0.119534	Mean dependent var		0.013374
Adjusted R-squared	0.075511	S.D. dependent var		0.091998
S.E. of regression	0.088456	Akaike info criterion		-1.961893
Sum squared resid	1.564902	Schwarz criterion		-1.787151
Log likelihood	217.9797	F-statistic		2.715254
Durbin-Watson stat	1.985415	Prob(F-statistic)		0.003791

Table 36: ECM adding one lag of residual from co-integrating relationship and three lags of each dependent and independent variables

Dependent Variable: DLOG(SOL)				
Method: Least Squares				
Sample(adjusted): 1982:09 1999:12				
Included observations: 208 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.005292	0.007517	0.704031	0.4823
RES(-1)	-0.127535	0.034817	-3.662988	0.0003
DLOG(SOL(-1))	0.077947	0.075971	1.026007	0.3062
DLOG(SOL(-2))	0.088057	0.074758	1.177894	0.2403
DLOG(SOL(-3))	0.193598	0.075179	2.575160	0.0108
DLOG(SOL(-4))	-0.052877	0.076716	-0.689260	0.4915
DLOG(SOL(-5))	-0.101194	0.077868	-1.299563	0.1953
DLOG(SOL(-6))	0.060573	0.078251	0.774091	0.4398
D(RLRS(-1))	0.551429	1.131354	0.487406	0.6265
D(RLRS(-2))	-0.197039	1.145377	-0.172030	0.8636
D(RLRS(-3))	-0.423628	1.116497	-0.379426	0.7048
D(RLRS(-4))	-0.996970	1.117823	-0.891885	0.3736
D(RLRS(-5))	-3.458522	1.119084	-3.090493	0.0023
D(RLRS(-6))	-0.258751	1.104757	-0.234216	0.8151
DLOG(SOL_EPS(-1))	0.125602	0.178615	0.703199	0.4828
DLOG(SOL_EPS(-2))	0.181629	0.176789	1.027380	0.3056
DLOG(SOL_EPS(-3))	0.100106	0.174706	0.572996	0.5673
DLOG(SOL_EPS(-4))	0.028050	0.175891	0.159473	0.8735
DLOG(SOL_EPS(-5))	0.309705	0.175816	1.761532	0.0798
DLOG(SOL_EPS(-6))	0.168530	0.174460	0.966005	0.3353
R-squared	0.181881	Mean dependent var	0.012987	
Adjusted R-squared	0.099199	S.D. dependent var	0.092377	
S.E. of regression	0.087675	Akaike info criterion	-1.939145	
Sum squared resid	1.445143	Schwarz criterion	-1.618228	
Log likelihood	221.6711	F-statistic	2.199760	
Durbin-Watson stat	1.983495	Prob(F-statistic)	0.003916	

Table 37: ECM adding one lag of residual from co-integrating relationship and six lags of each dependent and independent variables

FORECASTING PERFORMANCE OF ECM's

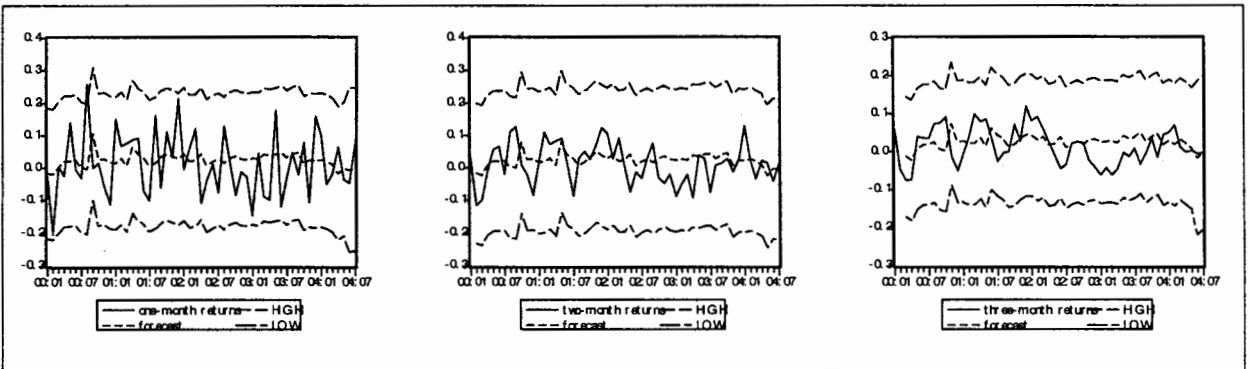


Figure 67: Forecasting performance of the ECM for $\Delta \log(\text{SOL})$ containing one lag of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

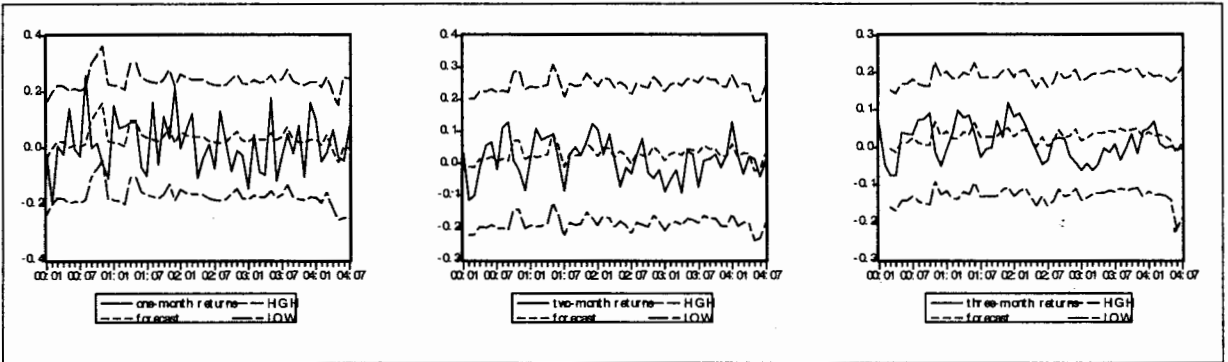


Figure 68: Forecasting performance of the ECM for $\Delta \log(\text{SOL})$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

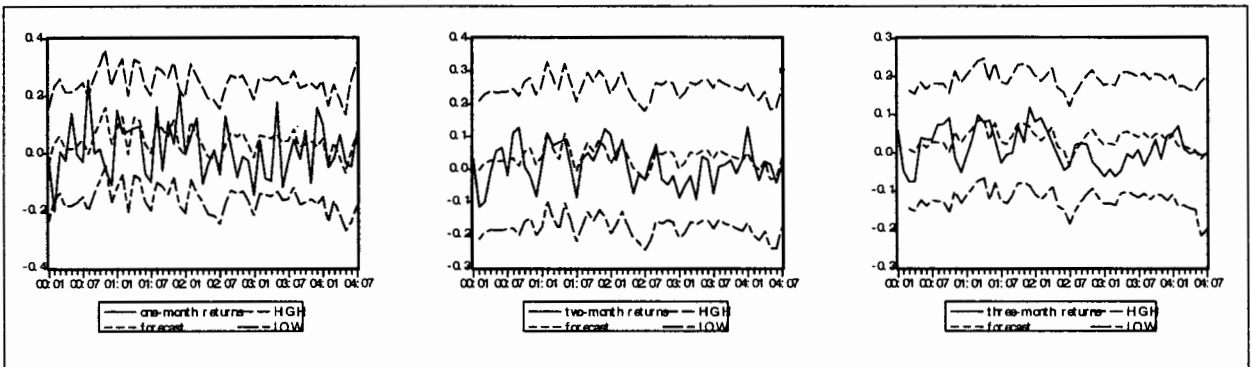


Figure 69: Forecasting performance of the ECM for $\Delta \log(\text{SOL})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

9.5. MODEL 5 – $\Delta\log(SAP)$

Dependent Variable: LOG(SAP)				
Method: Least Squares				
Sample(adjusted): 1996:10 2004:07				
Included observations: 94 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	3.845335	0.285496	13.46895	0.0000
PXPULP	0.000510	0.000279	1.829546	0.0707
SAP_EPS	-0.002005	0.008888	-0.225558	0.8221
SAP_DPS	0.465457	0.037037	12.56721	0.0000
RLRS	-6.088709	1.284317	-4.740816	0.0000
R-squared	0.882591	Mean dependent var	4.063327	
Adjusted R-squared	0.877315	S.D. dependent var	0.569026	
S.E. of regression	0.199310	Akaike info criterion	-0.336188	
Sum squared resid	3.535471	Schwarz criterion	-0.200907	
Log likelihood	20.80085	F-statistic	167.2591	
Durbin-Watson stat	0.641995	Prob(F-statistic)	0.000000	

Table 38: OLS Regression Results for dependent variable $\log(SAP)$ regressed on explanatory variables PXPULP, SAP_EPS, SAP_DPS and RLRS

ADF Test Statistic	-4.479323	1% Critical Value	-4.96	
		5% Critical Value	-4.42	
		10% Critical Value	-4.13	
Augmented Dickey-Fuller Test Equation				
Dependent Variable: D(RES)				
Method: Least Squares				
Sample(adjusted): 1996:12 2004:07				
Included observations: 92 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
RES(-1)	-0.374596	0.083628	-4.479323	0.0000
D(RES(-1))	0.122810	0.103548	1.186022	0.2387
R-squared	0.184897	Mean dependent var	0.003419	
Adjusted R-squared	0.175840	S.D. dependent var	0.157860	
S.E. of regression	0.143310	Akaike info criterion	-1.026113	
Sum squared resid	1.848400	Schwarz criterion	-0.971291	
Log likelihood	49.20118	Durbin-Watson stat	1.986080	

Table 39: Augmented Engle & Granger Unit Root Test Results on Residuals for Model 5. The τ statistic is greater in absolute value than the EG critical values at the 5% significance level thus the null of no co-integration is rejected.

ERROR CORRECTION MODELS for $\Delta \log(\text{SAP})$

Dependent Variable: DLOG(SAP)				
Method: Least Squares				
Sample(adjusted): 1996:12 2002:01				
Included observations: 62 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016361	0.018022	0.907883	0.3678
RES(-1)	-0.240484	0.089652	-2.682404	0.0096
DLOG(SAP(-1))	0.033619	0.136467	0.246351	0.8063
D(PXPULP(-1))	0.000656	0.000921	0.712417	0.4792
D(RLRS(-1))	-2.318546	2.488411	-0.931738	0.3555
D(SAP_EPS(-1))	-0.016029	0.018979	-0.844566	0.4019
R-squared	0.154273	Mean dependent var		0.019069
Adjusted R-squared	0.078762	S.D. dependent var		0.145905
S.E. of regression	0.140041	Akaike info criterion		-1.001991
Sum squared resid	1.098250	Schwarz criterion		-0.796139
Log likelihood	37.06173	F-statistic		2.043049
Durbin-Watson stat	1.904978	Prob(F-statistic)		0.086470

Table 40: ECM adding one lag of residual from co-integrating relationship and one lag of each dependent and independent variables

Dependent Variable: DLOG(SAP)				
Method: Least Squares				
Sample(adjusted): 1997:02 2002:01				
Included observations: 60 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.018754	0.018842	0.995356	0.3248
RES(-1)	-0.288709	0.095867	-3.011565	0.0042
DLOG(SAP(-1))	0.100267	0.143535	0.698554	0.4883
DLOG(SAP(-2))	0.095747	0.151304	0.632811	0.5300
DLOG(SAP(-3))	0.240026	0.146270	1.640974	0.1076
D(PXPULP(-1))	0.002271	0.001251	1.815045	0.0760
D(PXPULP(-2))	-0.003360	0.001570	-2.140301	0.0377
D(PXPULP(-3))	0.001369	0.001340	1.021717	0.3123
D(RLRS(-1))	-2.367823	2.714293	-0.872353	0.3875
D(RLRS(-2))	3.414298	2.677173	1.275337	0.2086
D(RLRS(-3))	2.310587	2.660816	0.868375	0.3897
D(SAP_EPS(-1))	-0.035912	0.025838	-1.389886	0.1713
D(SAP_EPS(-2))	0.015089	0.018763	0.804207	0.4254
D(SAP_EPS(-3))	0.017444	0.019795	0.881234	0.3828
R-squared	0.333330	Mean dependent var		0.019234
Adjusted R-squared	0.144923	S.D. dependent var		0.148236
S.E. of regression	0.137075	Akaike info criterion		-0.935616
Sum squared resid	0.864317	Schwarz criterion		-0.446936
Log likelihood	42.06849	F-statistic		1.769202
Durbin-Watson stat	2.079256	Prob(F-statistic)		0.077988

Table 41: ECM adding one lag of residual from co-integrating relationship and three lags of each dependent and independent variables

Dependent Variable: DLOG(SAP)				
Method: Least Squares				
Sample(adjusted): 1997:05 2002:01				
Included observations: 57 after adjusting endpoints				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.012442	0.022542	0.551971	0.5849
RES(-1)	-0.368888	0.121443	-3.037556	0.0048
DLOG(SAP(-1))	0.055298	0.165068	0.334999	0.7399
DLOG(SAP(-2))	0.041346	0.170392	0.242650	0.8099
DLOG(SAP(-3))	0.220696	0.171892	1.283919	0.2087
DLOG(SAP(-4))	0.085905	0.171368	0.501292	0.6197
DLOG(SAP(-5))	0.004578	0.171103	0.026757	0.9788
DLOG(SAP(-6))	0.174144	0.167343	1.040641	0.3061
D(PXPULP(-1))	0.003350	0.001500	2.233874	0.0328
D(PXPULP(-2))	-0.003519	0.001714	-2.053252	0.0486
D(PXPULP(-3))	0.002167	0.001777	1.219422	0.2319
D(PXPULP(-4))	-0.001679	0.001847	-0.909307	0.3702
D(PXPULP(-5))	0.001209	0.001897	0.637282	0.5286
D(PXPULP(-6))	-0.000899	0.001726	-0.520891	0.6061
D(RLRS(-1))	-3.856027	3.329361	-1.158188	0.2556
D(RLRS(-2))	2.938459	3.011720	0.975675	0.3368
D(RLRS(-3))	1.798010	3.064854	0.586654	0.5617
D(RLRS(-4))	4.046781	3.232643	1.251849	0.2200
D(RLRS(-5))	-1.560152	2.860857	-0.545344	0.5894
D(RLRS(-6))	-4.246233	2.729583	-1.555634	0.1299
D(SAP_EPS(-1))	-0.035647	0.029121	-1.224092	0.2301
D(SAP_EPS(-2))	-0.007003	0.028823	-0.242971	0.8096
D(SAP_EPS(-3))	0.007790	0.031323	0.248698	0.8052
D(SAP_EPS(-4))	0.031619	0.033669	0.939111	0.3549
D(SAP_EPS(-5))	0.037684	0.021496	1.753099	0.0895
D(SAP_EPS(-6))	0.012423	0.022248	0.558364	0.5806
R-squared	0.521494	Mean dependent var	0.021365	
Adjusted R-squared	0.135601	S.D. dependent var	0.149987	
S.E. of regression	0.139447	Akaike info criterion	-0.799046	
Sum squared resid	0.602811	Schwarz criterion	0.132872	
Log likelihood	48.77280	F-statistic	1.351396	
Durbin-Watson stat	2.324607	Prob(F-statistic)	0.211428	

Table 42: ECM adding one lag of residual from co-integrating relationship and six lags of each dependent and independent variables

FORECASTING PERFORMANCE OF ECM's

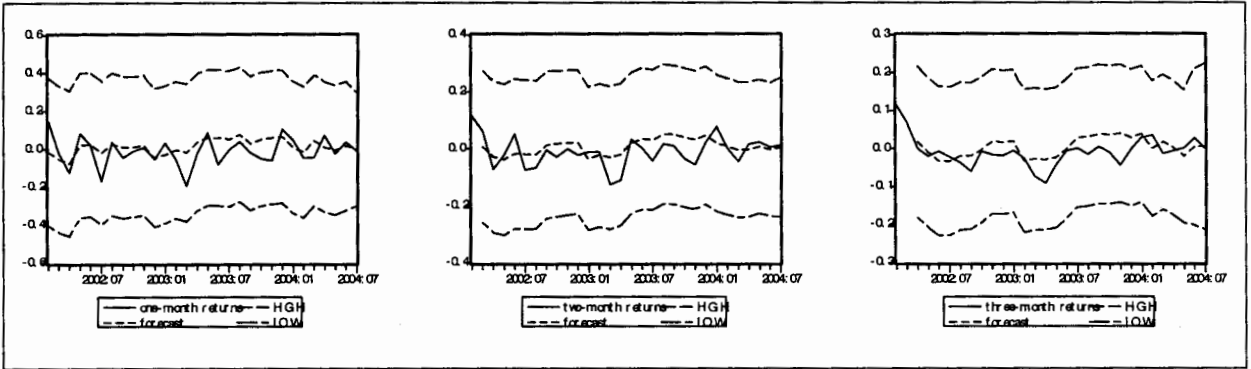


Figure 70: Forecasting performance of the ECM for $\Delta\log(\text{SAP})$ containing one lag of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

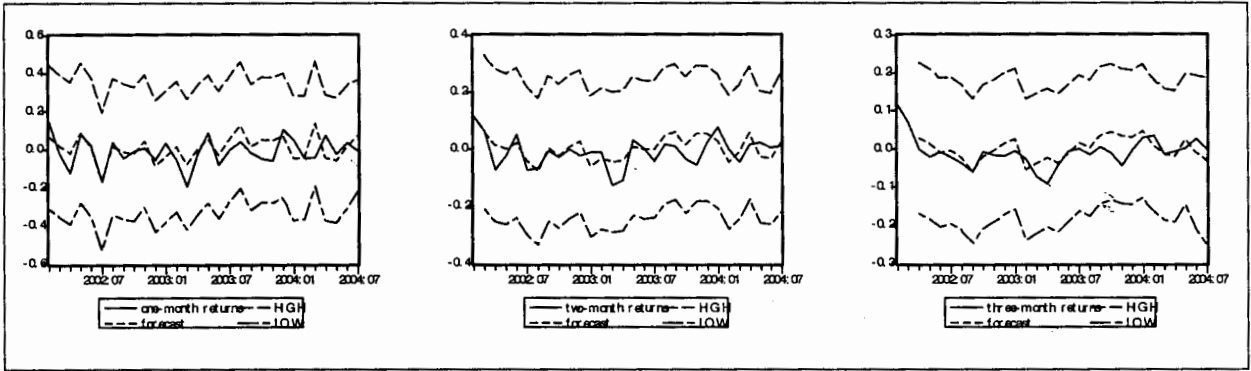


Figure 71: Forecasting performance of the ECM for $\Delta\log(\text{SAP})$ containing three lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

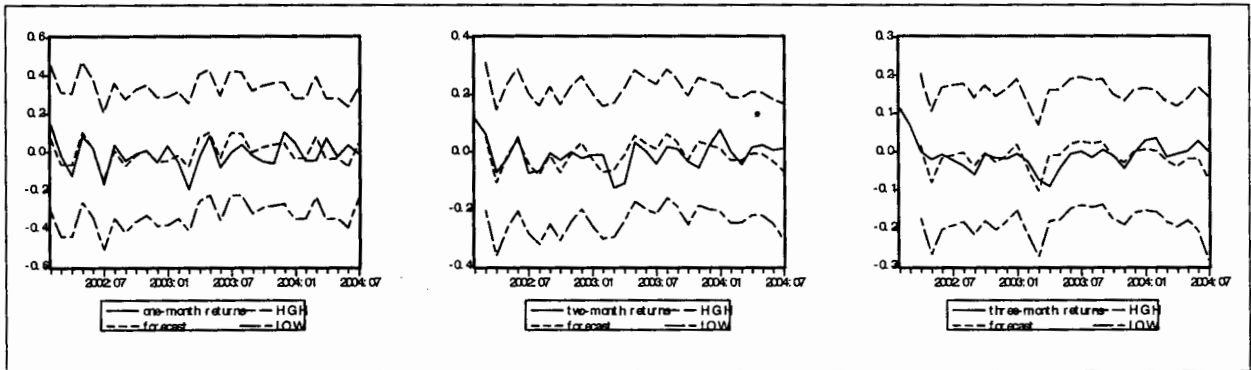


Figure 72: Forecasting performance of the ECM for $\Delta\log(\text{SAP})$ containing six lags of each of the dependent and explanatory variables. The diagrams depict the forecasts for one, two and three month average log returns respectively. The High and Low series are the 95% confidence interval associated with the forecast.

10. APPENDIX D

EVIEWS sample program for constructing and evaluating forecasts for $\Delta \log(\text{IMP})$ using the ECM containing one lag of the residual and one lag of each of the dependent and explanatory variables

```
delete s1 s2

sample s1 1971:04 1999:12          ' Estimation Period
sample s2 2000:01 2004:07        ' Forecast Evaluation Period

%d1 = "1971:04"                   ' start date of estimation period
%d2 = "1999:12"                   ' end date of estimation period
%d3 = "2000:01"                   ' start date of evaluation period
%d4 = "2004:07"                   ' end date of evaluation period

'Forecast Evaluation Criteria
matrix(3,3) adj_r2
matrix(3,3) aic
matrix(3,3) ic
matrix(3,3) rmse
matrix(3,3) sign

scalar rmse_f1 = 0
scalar rmse_f2 = 0
scalar rmse_f3 = 0
scalar z
scalar count

'Generate two series for the average log return of IMP over 2 and 3 months respectively
smpl @all
genr dlog2_imp = (dlog(imp) + dlog(imp(+1)))/2
genr dlog3_imp = (dlog(imp) + dlog(imp(+1)) + dlog(imp(+2)))/3

!n = @dtoo(%d2) - @dtoo(%d1)      ' no. of months in estimation period
!m = @dtoo(%d4) - @dtoo(%d3)      ' no. of months in evaluation period

' Estimate the ECM for log return of IMP share price in the estimation period s1
' ECM using one lag of residual, one lag of each dependent and explanatory variables
smpl s1
equation ec1_1.ls dlog(imp) c res(-1) dlog(imp(-1)) dlog(platpm(-1)) d(rlrs(-1)) dlog(imp_eps(-1))

'Now need to test the model's forecasting performance using a one-month rolling window approach
'Forecast one, two and three month average log return of IMP in forecast evaluation period s2

'FORECAST FOR ONE-MONTH RETURNS
'forecast of dlog(imp(n+h+1)) made at n+h for h = 0,1,2, ... (m-1)
'At each point add one month to the sample and reestimate the parameters using all n+h+1 observations h =
0,1,2, ... (m-1)

rmse_f1 = 0
count=0

for !h = 0 to (!m-1)

    'Reestimate parameters
    equation ec1_2.ls dlog(imp) c res(-1) dlog(imp(-1)) dlog(platpm(-1)) d(rlrs(-1)) dlog(imp_eps(-1))
    ec1_2.rls(r,s)

    'Add one month to the sample
    smpl 1971:04 1999:12+(!h+1)
```

```

'One-month-ahead forecast
gener dlimp_f1(!n+!h+1) = c(1) + c(2)*res(!n+!h) + c(3)*dlog(imp(!n+!h)) + c(4)*dlog(platpm(!n+!h)) +
c(5)*d(rlrs(!n+!h)) + c(6)*dlog(imp_eps(!n+!h))

'Compute forecast error associated with forecast of (n+h+1) made at (n+h)
gener f1_err(!n+!h+1) = dlog(imp(!n+!h+1)) - dlimp_f1(!n+!h+1)

'Compute 95% forecast interval
gener stderr_f1_err(!n+!h+1) = sqrt((r_resse(!n+!h+1))^2 + @se^2)
gener f1_high(!n+!h+1) = dlimp_f1(!n+!h+1) + 1.96*stderr_f1_err(!n+!h+1)
gener f1_low(!n+!h+1) = dlimp_f1(!n+!h+1) - 1.96*stderr_f1_err(!n+!h+1)

'Compute part of Root mean squared error (RMSE)
if f1_err(!n+!h+1) = NA then
    rmse_f1 = 0 + rmse_f1
else
    rmse_f1 = (f1_err(!n+!h+1))^2 + rmse_f1
endif

'Compute part of % correct sign predictions
gener test1(!n+!h+1) = dlog(imp(!n+!h+1))*dlimp_f1(!n+!h+1)
if test1(!n+!h+1) > 0 then
    z = 1
else
    z = 0
endif
count = count + z

next

'Compute end of Root mean squared error (RMSE)
rmse_f1 = sqrt(1/(!m)*rmse_f1)

'Compute Forecast Evaluation Criterion
adj_r2(1,1) = @rbar2
aic(1,1) = @aic
ic(1,1) = sqrt(@r2)
rmse(1,1) = rmse_f1
sign(1,1) = (1/!m)*count

'Plot forecast, actual series and 95% confidence interval
smpl s2
graph g1_f1.plot dlog(imp) dlimp_f1 f1_high f1_low

'FORECAST FOR TWO-MONTH AVERAGE RETURNS
'Forecast of [dlog(imp(n+h+1)) + dlog(imp(n+h+2))]/2 or equivalently dlog2_imp(+1) made at n+h for h =
0,1,2, ... (m-2)
'First forecast is made for n+2
'At each point add one month to the sample and reestimate the parameters using all n+h+2 observations h =
0,1,2, ... (m-2)

smpl s1
rmse_f1 = 0
count=0

for !h = 0 to (!m-2)

    'Estimate parameters
    equation ec1_2.ls dlog2_imp c res(-1) dlog(imp(-1)) dlog(platpm(-1)) d(rlrs(-1)) dlog(imp_eps(-1))
    ec1_2.rls(r,s)

```

```

'Add one month to the sample starting at n+2
  smpl 1971:04 1999:12+(!h+2)

  'Two-month-ahead forecast
  genr dlimp_f1_2(!n+!h+2) = c(1) + c(2)*res(!n+!h) + c(3)*dlog(imp(!n+!h)) + c(4)*dlog(platpm(!n+!h)) +
  c(5)*d(rirs(!n+!h))+ c(6)*dlog(imp_eps(!n+!h))

  'Compute forecast error associated with forecast of (n+h+2) made at (n+h)
  genr f1_2_err(!n+!h+2) = dlog2_imp(!n+!h+1) - dlimp_f1_2(!n+!h+2)

  'Compute 95% forecast interval
  genr stderr_f1_2_err(!n+!h+2) = sqrt((r_resse(!n+!h+2))^2 + @se^2)
  genr f1_2_high(!n+!h+2) = dlimp_f1_2(!n+!h+2) + 1.96*stderr_f1_2_err(!n+!h+2)
  genr f1_2_low(!n+!h+2) = dlimp_f1_2(!n+!h+2) - 1.96*stderr_f1_2_err(!n+!h+2)

  'Compute part of Root mean squared error (RMSE)
  if f1_2_err(!n+!h+2) = NA then
    rmse_f1 = 0 + rmse_f1
  else
    rmse_f1 = (f1_2_err(!n+!h+2))^2 + rmse_f1
  endif

  'Compute part of % correct sign predictions
  genr test1(!n+!h+2) = dlog2_imp(!n+!h+1)*dlimp_f1_2(!n+!h+2)
  if test1(!n+!h+2) > 0 then
    z = 1
  else
    z = 0
  endif
  count = count + z

  next

'Compute end of Root mean squared error (RMSE)
rmse_f1 = sqrt(1/(!m-1)*rmse_f1)

'Compute Forecast Evaluation Criterion
adj_r2(2,1) = @rbar2
aic(2,1) = @aic
ic(2,1) = sqrt(@r2)
rmse(2,1) = rmse_f1
sign(2,1) = (1/(!m-1))*count

'Plot forecast, actual series and 95% confidence interval
  smpl s2
  graph g2_f1.plot dlog2_imp(-1) dlimp_f1_2 f1_2_high f1_2_low

'FORECAST FOR THREE-MONTH AVERAGE RETURNS
'Forecast of [dlog(imp(n+h+1)) + dlog(imp(n+h+2)) + dlog(imp(n+h+3))]/3 or equivalently dlog3_imp(+1)
made at n+h for h = 0,1,2, ... (m-3)
'First forecast is made for n+3
'At each point add one month to the sample and reestimate the parameters using all n+h+3 observations h =
0,1,2, ... (m-3)

  smpl s1
  rmse_f1 = 0
  count=0

  for !h = 0 to (!m-3)

    'Reestimate parameters
    equation ec1_2.ls dlog3_imp c res(-1) dlog(imp(-1)) dlog(platpm(-1)) d(rirs(-1)) dlog(imp_eps(-1))

```

```
ec1_2.rls(r,s)
```

```
'Add one month to the sample starting at n+3  
smpl 1971:04 1999:12+(!h+3)
```

```
'Three-month-ahead forecast
```

```
gener dlimp_f1_3(!n+!h+3) = c(1) + c(2)*res(!n+!h) + c(3)*dlog(imp(!n+!h)) + c(4)*dlog(platpm(!n+!h)) +  
c(5)*d(rlrs(!n+!h))+ c(6)*dlog(imp_eps(!n+!h))
```

```
'Compute forecast error associated with forecast of (n+h+3) made at (n+h)
```

```
gener f1_3_err(!n+!h+3) = dlog3_imp(!n+!h+1) - dlimp_f1_3(!n+!h+3)
```

```
'Compute 95% forecast interval
```

```
gener stderr_f1_3_err(!n+!h+3) = sqrt((r_resse(!n+!h+3))^2 + @se^2)  
gener f1_3_high(!n+!h+3) = dlimp_f1_3(!n+!h+3) + 1.96*stderr_f1_3_err(!n+!h+3)  
gener f1_3_low(!n+!h+3) = dlimp_f1_3(!n+!h+3) - 1.96*stderr_f1_3_err(!n+!h+3)
```

```
'Compute part of Root mean squared error (RMSE)
```

```
if f1_3_err(!n+!h+3) = NA then  
    rmse_f1 = 0 + rmse_f1  
else  
    rmse_f1 = (f1_3_err(!n+!h+3))^2 + rmse_f1  
endif
```

```
'Compute part of % correct sign predictions
```

```
gener test1(!n+!h+3) = dlog3_imp(!n+!h+1)*dlimp_f1_3(!n+!h+3)  
if test1(!n+!h+3) > 0 then  
    z = 1  
else  
    z = 0  
endif  
count = count + z
```

```
next
```

```
'Compute end of Root mean squared error (RMSE)
```

```
rmse_f1 = sqrt(1/(!m-2)*rmse_f1)
```

```
'Compute Forecast Evaluation Criterion
```

```
adj_r2(3,1) = @rbar2  
aic(3,1) = @aic  
ic(3,1) = sqrt(@r2)  
rmse(3,1) = rmse_f1  
sign(3,1) = (1/(!m-2))*count
```

```
'Plot forecast, actual series and 95% confidence interval
```

```
smpl s2  
graph g3_f1.plot dlog3_imp(-2) dlimp_f1_3 f1_3_high f1_3_low
```

Eviews Program Explanation

Sequence of steps executed by Eviews program forecasting future log returns of imp [$\Delta\log(\text{imp})$] over one, two and three months respectively:

Forecasting future ONE MONTH returns using a one-month rolling window approach (roll window forward by h at each step):

START: Estimate model in In-Sample Estimation Period (use set of coefficients to determine the 1 st one-month-ahead forecast)		
Time (n+h)	Obs. (n+h+1)	Action
n+0	n+1	Determine forecast for $\Delta\log(\text{imp}(n+1))$ at time n: $f_{n,1} = E[\Delta\log(\text{imp}(n+1))]$
n+1	n+2	Expand window by one observation and re-estimate model using all (n+1) observations Determine forecast for $\Delta\log(\text{imp}(n+2))$ at time n+1: $f_{n+1,1} = E[\Delta\log(\text{imp}(n+2))]$
n+2	n+3	Expand window by one observation and re-estimate model using all (n+2) observations Determine forecast for $\Delta\log(\text{imp}(n+3))$ at time n+2: $f_{n+2,1} = E[\Delta\log(\text{imp}(n+3))]$
...
n+m-1	n+m	Expand window by one observation and re-estimate model using all (n+m-1) observations Determine forecast for $\Delta\log(\text{imp}(n+m))$ at time n+m-1: $f_{n+m-1,1} = E[\Delta\log(\text{imp}(n+m))]$

Forecasting future TWO MONTH AVERAGE returns using a one-month rolling window approach (roll window forward by h at each step starting at (n+2)):

Generate a series that equals the two month average returns for log(IMP):

$$\Delta \log 2_imp = \frac{(\Delta \log(imp) + \Delta \log(imp(+1)))}{2}$$

$$\Rightarrow \Delta \log 2_imp(+1) = \frac{(\Delta \log(imp(+1)) + \Delta \log(imp(+2)))}{2}$$

\Rightarrow etc.

START: Estimate model in In-Sample Estimation Period (use set of coefficients to determine the 1 st two-month-ahead forecast at time n+2)		
Time n+h	Obs. (n+h+2)	Action
n+0	n+2	Determine forecast for $\Delta \log 2_imp(n+1)$ at time n: $f_{n,2} = E[\Delta \log 2_imp(n+1)] = E\left[\frac{(\Delta \log(imp(n+1)) + \Delta \log(imp(n+2)))}{2}\right]$
n+1	n+3	Expand window by one observation and re-estimate model using all (n+2) observations Determine forecast for $\Delta \log 2_imp(n+2)$ at time n+1: $f_{n+1,2} = E[\Delta \log 2_imp(n+2)] = E\left[\frac{(\Delta \log(imp(n+2)) + \Delta \log(imp(n+3)))}{2}\right]$
n+2	n+4	Expand window by one observation and re-estimate model using all (n+3) observations Determine forecast for $\Delta \log 2_imp(n+3)$ at time n+2: $f_{n+2,1} = E[\Delta \log 2_imp(n+3)] = E\left[\frac{(\Delta \log(imp(n+3)) + \Delta \log(imp(n+4)))}{2}\right]$
...
n+m-2	n+m	Expand window by one observation and re-estimate model using all (n+m-2) observations Determine forecast for $\Delta \log 2_imp(n+m-1)$ at time n+m-2: $f_{n+m-2,2} = E[\Delta \log 2_imp(n+m-1)] = E\left[\frac{(\Delta \log(imp(n+m-1)) + \Delta \log(imp(n+m)))}{2}\right]$

Forecasting future THREE MONTH AVERAGE returns using a one-month rolling window approach (roll window forward by h at each step starting at (n+3)):

Generate a series that equals the two month average returns for log(IMP):

$$\Delta \log 3_imp = \frac{(\Delta \log(imp) + \Delta \log(imp(+1)) + \Delta \log(imp(+2)))}{3}$$

$$\Rightarrow \Delta \log 3_imp(+1) = \frac{(\Delta \log(imp(+1)) + \Delta \log(imp(+2)) + \Delta \log(imp(+3)))}{3}$$

\Rightarrow etc.

START: Estimate model in In-Sample Estimation Period (use set of coefficients to determine the 1 st three-month-ahead forecast at time n+3)		
Time n+h	Obs. (n+h+3)	Action
n+0	n+3	Determine forecast for $\Delta \log 3_imp(n+1)$ at time n: $f_{n,3} = E[\Delta \log 3_imp(n+1)]$ $= E\left[\frac{(\Delta \log(imp(n+1)) + \Delta \log(imp(n+2)) + \Delta \log(imp(n+3)))}{3}\right]$
n+1	n+4	Expand window by one observation and re-estimate model using all (n+3) observations Determine forecast for $\Delta \log 3_imp(n+2)$ at time n+1: $f_{n+1,3} = E[\Delta \log 3_imp(n+2)]$ $= E\left[\frac{(\Delta \log(imp(n+2)) + \Delta \log(imp(n+3)) + \Delta \log(imp(n+4)))}{3}\right]$
n+2	n+5	Expand window by one observation and re-estimate model using all (n+4) observations Determine forecast for $\Delta \log 3_imp(n+3)$ at time n+2: $f_{n+2,3} = E[\Delta \log 3_imp(n+3)]$ $= E\left[\frac{(\Delta \log(imp(n+3)) + \Delta \log(imp(n+4)) + \Delta \log(imp(n+5)))}{3}\right]$
...
n+m-3	n+m	Expand window by one observation and re-estimate model using all (n+m-1) observations Determine forecast for $\Delta \log 3_imp(n+m-2)$ at time n+m-3: $f_{n+m-3,3} = E[\Delta \log 3_imp(n+m-2)]$ $= E\left[\frac{(\Delta \log(imp(n+m-2)) + \Delta \log(imp(n+m-1)) + \Delta \log(imp(n+m)))}{3}\right]$

11. References

1. Barr, G. and Kantor, B., (2002) *The South African Economy and its Asset Markets – An integrated Approach*, University of Cape Town.
2. Chatfield, C., (2001) *Time Series Forecasting*, Chapman & Hall/CRC.
3. Davidson, R. and MacKinnon, J.G., (1993) *Estimation and Inference in Econometrics*, Oxford University Press, New York.
4. Engle, R.F. and Granger, C.W.J., (1987) *Co-integration and Error Correction: Representation, Estimation, and Testing*, *Econometrica*, 55(2), 251-276.
5. EViews 3 & 4 Help Manual.
6. Granger, C. W. J. and Morgenstern, O., (1970) *Predictability of Stock Market Prices*, D. C. Heath and Company, Lexington, Massachusetts.
7. Gujarati, N. D., (1995) *Basic Econometrics*, 3rd Edition, McGraw-Hill, Inc.
8. Hendry, D.F. and Ericsson, N.R., (2001) *Understanding Economic Forecasts*, Massachusetts Institute of Technology.
9. Ross, S., Westerfield, R.W., Jordan, B.D., and Fifer, C., (2001) *Fundamentals of Corporate Finance, 2nd South African Edition*, McGraw-Hill, Inc.
10. Swanson, N.R., (1998) *Money and output viewed through a rolling window*, *Journal of Monetary Economics* 41, 455-473.
11. Wooldridge, J. M., (2003) *Introductory Econometrics: A Modern Approach, 2e*, Thomson South-Western.