

**A Comparative Study of Threshold Autoregressive, Smooth
Transition Regression and Markov Switching Autoregressive Models
on Stock Price Behaviour**

By

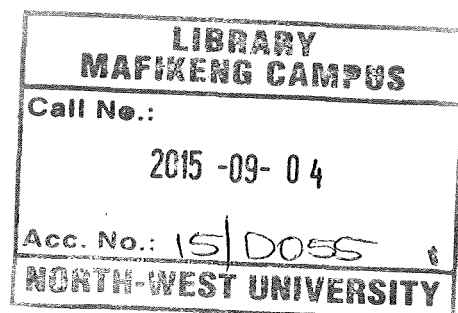
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**Dissertation submitted in fulfilment of the requirements for the
Masters' of Commerce in Operations Research at the Mafikeng
Campus of the North-West University**

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DECLARATION

I hereby declare that this submission is my own work towards the award of the M.Com degree and that, to the best of my knowledge, it contains no material previously published by another person nor material which had been accepted for the award of any other degree of a university, except where due acknowledgement had been made in the text.

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ACKNOWLEDGMENT

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DEDICATION

To my late grandmother and mother, Ms N. M. Xaba and Mrs M. F. Semelane for their care, support and love for the family.

ACRONYMS AND ABBREVIATIONS

ABSA	Absa Bank
ADF	Augmented Dickey-Fuller
ARCH	Autoregressive Conditional Heteroskedasticity
ARMA	Autoregressive Moving Average
BDS	Brock-Dechert-Scheinkman
B-NADF	Bierens Nonlinear Augmented Dickey-Fuller
CAPB	Capitec Bank
CUSUM	Cumulative Sum test
DM	Diebold Mariano test
DW	Durbin-Watson
FIRB	First Rand Bank
JSE	Johannesburg Stock Exchange
KSS	Kapetanois-Schmidt-Shin
KSS-NADF	Kapetanois-Schmidt-Shin Nonlinear Augmented Dickey-Fuller
LM	Lagrange Multiplier
LR	Likelihood Ratio
LSTR	Logistic Smooth Transition Regression
MA	Moving Average
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
ML	Maximum Likelihood
MS-AR	Markov Switching Autoregressive
MS-ARMA	Markov-Switching Autoregressive Moving Average
MSE	Mean Square Error
NEDB	Nedbank
NLS	Nonlinear Least Squares
OLS	Ordinary least square

RESET	Regression Specification Error
RMSE	Root Mean Square Error
RMSPE	Root Mean Square Prediction Error
SARB	South African Reserve Bank
SBC	Schwarz Bayesian Criterion
STDB	Standard Bank
STR	Smooth Transition Regression
TAR	Threshold Autoregressive
TARMA	Threshold Autoregressive Moving Average

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ABSTRACT

This study compared the in-sample forecasting accuracy of three forecasting nonlinear models namely: the Smooth Transition Regression (STR) model, the Threshold Autoregressive (TAR) model and the Markov-switching Autoregressive (MS-AR) model. Data used was daily close stock prices of five banks in the South African banking sector and was obtained from the Johannesburg Stock Exchange (JSE). It covered the period from 2010 to 2012 with a total of 563 observations. Nonlinearity and nonstationarity tests used confirmed the validity of the assumptions of the study. The study used model selection criteria, SBC to select the optimal lag order and for the selection of appropriate models. The Mean Square Error (MSE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) served as the error measures in evaluating the forecasting ability of the models. The MS-AR models proved to perform well with lower error measures as compared to LSTR and TAR models in most cases. The decision by error measures were supported by Diebold and Mariano test. The findings of the study revealed that the three nonlinear models and forecasting techniques are good but there is room for further improvement. More specifically, in the case of TAR and MS-AR, where autoregressive specifications were used, study recommended that the moving average (MA) and/or autoregressive moving average (ARMA) be used and results compared with the current results.

Chapter 1

Introduction

1.1 Background

In recent years, stock markets data analyses have become very important object of academic research. In the course of establishing deeper understanding of the financial crisis of 2007-2008, research findings revealed that standard time series models have several shortages in precision and robustness. The conventional methods often employed by data analysts to capture the dynamics and patterns in the most financial time series data have been based on the assumption of linearity, leading to most of the models failing to address the fundamentals of most financial data. Having discovered the glitch, various researchers and financial practitioners have shifted their attention to the use of nonlinear prediction methods. Statistical modelling and forecasting techniques fulfil many useful roles other than just being tools for producing future forecasts. The use of such statistical techniques in the field of finance reflects valid empirical and theoretical knowledge of how financial markets work much as they also help to explain their changes and the anticipation of any unexpected changes. Where linear methods fail to describe the dynamics of finance time series, nonlinear methods are the main alternatives. In the context of this study, the researcher examines the historical data of the closing stock prices of five major banks in South Africa.

1.2 Problem Statement

The literature highlights evidence of occasional sudden breaks in many financial and economic time series, especially stock market data, making it extremely difficulties for accurate prediction. These changes have been attributed to several reasons including changes in economic conditions, investor expectations, relative performance of other stock markets, responses to shocks from exogenous geopolitical events or financial crises, or disruptions due to weather related catastrophes, just to mention a few. This is supported by Vasanthi *et al.* (2010) who reiterated that prediction of financial market could be a complex task since the distribution of such data often changes over a period of time. Consequently, determining more effective and efficient ways of predicting the movement of stock market prices are important.

A number of nonlinear modelling techniques have been suggested in the literature to capture the suggested nonlinearities in economic and financial data. Commonly used among these models are the Smooth Transition Regressive (STR), Threshold Autoregressive (TAR) and Markov-Switching Autoregressive (MS-AR) models. These three modelling techniques differ from conventional linear econometric models by their assumption of existence of different segments or regimes, within which the time series may exhibit different behaviour. In the context of the current study, the statement of the problem is how these three methods do applied to model and forecast the five closing stock prices, and how the estimated models compare in terms of efficiency and performance.

1.3 Research Aim and Objectives

The aim of the study is to explore the possibility of developing empirical models capable of describing and forecasting each of the five South African major banks' closing stock prices. In addition, the study further investigates the question that although three different nonlinear univariate time series modelling and forecasting techniques are used for each of the five time series data being investigated in the study, one method particular may outperform others. More succinctly the objectives of this study are as follow:

- To investigating whether the underlying characteristics of the five closing prices being investigated in the study are nonlinear in nature.
- To model and forecast each of the five closing stock prices using three methods – STR, TAR, and MS-AR.
- To comparing the efficiency and performance of the three estimated models for each of the closing price of the banks stocks.
- To comparing the predictive power of the three estimated forecast models for each of the closing price of the banks stocks.

1.4 Methodology

A literature review has been undertaken as the foundation for the study. Different forecasting models for forecasting stock market pricing have been explored to determine the models which provide accurate predictions. Available secondary data was obtained from Johannesburg Stock Exchange (JSE) covering a period of two years from January 2010 to December 2012. TAR, STR and MS-AR were the main statistical methods used for the analysis. For model selection or model fit, the study used the Schwarz Bayesian Criterion

(SBC) by Schwarz (1978) to identify the best model. Forecasting efficiency was derived based on the following error measures: the Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Root Mean Square Prediction Error (RMSPE).

1.5 Significance of the Study

The study could empower stock market investors to make informed and accurate investment decisions. Again this will further boost the confidence of stakeholders in the financial industry to do more business with less risk exposure. Other beneficiaries of the study are investors, shareholders, directors, regulators and other financial institutions as well as researchers in the academia.

1.6 Novelty of the Study

This study employs a number of robust econometric techniques to investigate the dynamics of closing stock prices from the nonlinear perspective. Despite the abundance of studies on the behaviours of numerous economic and financial data from South Africa, nonlinearity has not been exploited to the fullest yet in the modelling and forecasting of such important variables. This study is an attempt to bridge this gap, specifically, as used in the investigation of the behaviours of the stock prices in South African banking. By using the three most powerful nonlinear modelling techniques, this study also provides a skilful guideline for modelling the different dynamic patterns of stock prices in general as well as the art involved in capturing the nonlinear attributes of stock prices. Overall, this study particularly intends to enhance the understanding of the patterns and movements in the closing stock prices of South Africa's five major banks as well as asymmetric regimes in stock prices in general.

1.7 Limitations and Problems

The scope is limited to the following:

- The study is limited to only the five largest banks in the South African banking sector because these are considered the systemically important banking institutions in the country.

- The study uses available data on closing stock prices collected over a period of two years from 2010 to 2012 consisting of 563 observations. The choice of this study period was based on the availability of data.
- There are several nonlinear methods according to literature. However, literature on only three (STR, TAR and MS-AR) is reviewed. These methods are used in this study for the purpose of comparative analyses. No other method may be considered.
- Due to limited available literature around the topic, the study may consult sources older than ten years.

1.7 Organisation of the Study

This study contains five chapters which follow a logical presentation to achieve the stated objectives of the study.

Chapter 2 delivers literature review of the methods used to forecast the stock market prices previously.

Chapter 3 provides a description of the research methodology. A detailed discussion of the research process and the theory of the statistical tests used in analysing and comparing the forecasting models are provided.

Chapter 4 gives a comprehensive report of the research results and an interpretation of the findings.

Chapter 5 provides summary of the finding of the study and recommendations for future research.

Chapter 2

Literature Review

2.1 Introduction

This chapter reviews literature on forecasting models dealing with stock market price behaviour. Different theories and arguments are explored and benefits and shortcomings of different methods for modelling stock market prices are identified. The chapter is organised as follows: Section 2.2 gives a general overview of the stock market and its role players. Section 2.3 presents the reason for forecasting stock market prices. Section 2.4 presents the forecasting methods. Section 2.5 presents the time series methods and Section 2.6 deals with the concluding remarks of the chapter.

2.2 The Stock Market and its Role Players

A stock market is a place where stocks, bonds, or other securities are bought and sold (American Dictionary, 2009). Preethi and Santhi (2012) explain a stock market as a public market for trading the company's stocks and derivatives at an approved stock price. Literature refers to shares as a stock. These terms will be used interchangeably in this study.

According De Cesari *et al.* (2010), many years ago, worldwide, participants (buyers and sellers) were individual retail investors and institutions such as banks, insurance companies and hedge funds, and also publicly traded corporations trading in their own shares. Investors such as wealthy businessmen were market participants. Previously, markets became more "institutionalized"; participants were institutions such as insurance companies, mutual funds, index funds, investor groups, banks and various other financial institutions.

Currently, participants in the stock market range from small individual stock investors to large hedge fund traders. Their orders usually end up with a professional at a stock exchange, who executes the order. Most stocks are traded on exchange, for example the JSE, which are places where buyers and sellers and decide on a price. The main objective of a stock exchange is to facilitate the exchange of securities between buyers and sellers, thus providing a marketplace.

2.3 The Reasons for Forecasting Stock Market Prices

There are many reasons for trying to forecast stock market prices, but the most basic one of these is financial gain. Any model that can be reliable in forecasting stock market prices would make the owner of the method very wealthy. Hence, many individuals, including academics, researchers, investment professionals and investors are searching for a superior method which will offer high returns (Dase *et al.*, 2011). According to Hemanth *et al.* (2012), the main objective of stock market forecasting is to determine the future price of a company stock or other financial instrument traded on a financial market exchange. The successful prediction of a stock's future price could help the buyer and seller to make good decisions. The investor may realize a significant profit by buying stock at its lowest price and sell when the price is at its highest level.

2.4 Forecasting Methods

Several forecasting methods in practice such as fundamental, technical and time series analysis are available. The popularity of one forecasting method as against another is solely based on their risk metrics. Forecasting is normally believed to be a very difficult task (e.g. see the study of (Idolor, 2010; Khan *et al.*, 2011; Vasanthi *et al.*, 2010). The use of raw data for stock market forecasting has been widely established using different methods such as data mining, Artificial Neural Network (ANN), hidden Markov chain, genetic algorithms and time series analysis amongst others. The study concentrates on the use of time series methods in forecasting future price movements of stocks in the financial industry.

2.4.1 Fundamental Analysis

Fundamental analysis involves the in-depth analysis of the changes in the stock prices in terms of outside macroeconomic variables. It assumes that the stock price depends on its intrinsic value and the expected return of the investors (Mendelsohn, 2000). According to Samarth *et al.* (2010), fundamental analysis studies the company's product sales, manpower, quality and infrastructure, among others, to understand its standing in the market and thereby its profitability as an investment. The data used to determine the intrinsic value of an asset and does not change on a daily basis. This makes it suitable for predicting the stock market on a long-term basis and not in the short term.

2.4.2 Technical Analysis

The technical analysis forecasts the suitable time to buy or sell a stock by utilising charts which contain raw data such as price, volume, highest and lowest prices per trading to forecast future stock price. These price charts are used to recognize trends of the stock price. To understand a company and its profitability through its stock prices in the market, these parameters can guide an investor towards making a careful decision. These parameters are termed indicators and oscillators (Samarth *et al.*, 2010). This is a very popular approach used to predict market movements. The problem of this method is that the extraction of trading rules from the study of charts is highly subjective, and as a result different analysts extract different trading rules when studying the same charts. This analysis can be used to predict the market price on a daily basis (Khan *et al.*, 2011).

The methods (fundamental and technical) discussed earlier are worthy but not applicable to the current study. The methods use opening price, volume, highest and lowest prices per trading to forecast future stock prices. Again they take into consideration the company's product sales, manpower, quality and infrastructure, among others, which are not relevant to the study. The interest in the study is on time series forecasting methods, which use the past data of the forecasted variable (closing stock price) and does not consider factors of the economy.

2.5 Time Series Methods

Apart from the commonly used methods of predicting stock market prices, namely fundamental and technical analysis, traditional time series forecasting methods are also used for the same purpose. The time series forecasting method uses past data of the forecast variable (such as stock price, interest rate, etc.) to analyse and model the patterns of the historic changes in the variable in order to forecast the future prices (Majumder & Hussain, 2010).

There are mainly two methods of time series modelling and forecasting which include linear and nonlinear methods. The linear methods include moving average, exponential smoothing, and time series regression among others. A well-known linear method is the autoregressive integrated moving average (ARIMA) model. ARIMA assumes a linear model but it is quite flexible as it can represent different types of time series, namely, the Autoregressive (AR),

moving average (MA) and the combination of AR and MA called ARMA series (Box & Jenkins, 1976).

2.5.1 Linear Methods

Linear methods have dominated forecasting in the past decades. Methods such as the MA and ARMA were quite successful in numerous applications. Their main advantage is that they are easy to develop and implement and simple to understand and interpret. However, these models have a shortcoming as they are unable to capture nonlinearity in data (Makridakis *et al.*, 1982). Linear methods are not capable of representing many nonlinear dynamic patterns such as asymmetry, amplitude dependence and volatility clustering.

Since linear models have a weakness in terms of capturing nonlinearity in data sets such as stock price inflation rate, interest rate and others, researchers have resorted to nonlinear methods such as the Smooth Transition Regressive (STR) model, the Threshold Autoregressive (TAR) model and the Markov switching autoregressive model (MS-AR) (Makridakis *et al.*, 1982).

2.5.2 Nonlinear Methods

There is not much evidence that the stock market prices are perfectly linear because it was noticed that the error between the predicted value and the actual value was quite high. The existence of the nonlinearity of the financial market was propounded by many researchers and financial analyst (Abhyankar *et al.*, 1997).

Some parametric nonlinear models such as the Autoregressive Conditional heteroskedasticity (ARCH) and general autoregressive conditional heteroskedasticity (GARCH), ANN, TAR, STAR and MS-AR models have been in use for forecasting over time. But most of the nonlinear statistical techniques require that the nonlinear model must be specified before the estimation of the parameters is done (Majumder & Hussain, 2010). The study concentrates on the use of three nonlinear time series methods (STR, TAR and MS-AR).

2.5.2.1 Smooth Transition Regression (STR) Models

STR models were originally developed as a generalization to models of two intersecting straight lines with an abrupt change from one linear regression to another at some unknown change point (Bacon & Watts, 1971). The method was generalized and used by Goldfeld and Quant (1972) in their so-called two-regime switching regression model. The STR model may be described as a generalization of the TAR model since it typically assumes a continuum of segments or states, bounded within a finite number of extreme regimes, where the behaviour of a particular time series is governed by the distance of the threshold variable to the regimes. This type of behaviour existing in the time series is captured via a continuous smooth transition function, hence the name.

In recent years, due to their flexibility, STR models are frequently used for modelling economic and financial data. While Goldfeld and Quandt (1972) and Chan and Tong (1986), resorted to modelling the transition between regimes using the cumulative distribution function of a standard normal variable as the transition function, Bacon and Watts (1971) employed the hyperbolic tangent as the transition function. In their paper, Luukkonen *et al.* (1988) used the logistic function, which has since become the most popular choice, as the transition function. The Logistic Smooth Regressive (LSTR) model has been applied to several economic and financial time series data by several authors including Teräsvirta and Anderson (1992) and Teräsvirta (1994), Teräsvirta (1998) and Potter (1999).

STR models have been applied to financial economics time series. For instance, Granger and Teräsvirta (1993) used the model to find whether there is any nonlinear relationship existing between United States (US) GNP growth and macroeconomics forces. Skalin and Teräsvirta (1999) also used TAR to study Swedish business cycles. The TAR method is a new application in other areas such as finance. McMillan (2001) found evidence of a nonlinear relationship among stock market returns and macroeconomic and financial variables in the United States. Using a two regime STAR model, the results show that while interest rates are important determinants in both regimes, the macroeconomic series (unemployment) only explains stock returns in one regime. Sarantis (2001) in his study found that STR was a suitable model to fit the data, as the changes in regime were smooth, rather than abrupt, in the stock markets.

Aslanidis (2002) demonstrated the use of STR models in UK stock market returns. The study used macroeconomic forces that influence UK stock returns such as GDP, interest rates, inflation rate, money supply and US stock prices. The study estimated TAR models where the linearity hypothesis was strongly rejected for at least one transition variable. The results revealed that non-linear models such as TAR describe the in-sample movements of the stock returns better than the linear models. Moreover, the US stock market appeared to play an important role in determining the UK stock market returns regime. Bredin *et al.* (2008) also demonstrated the ability of STR model in forecasting stock market indices of six developed countries. For each country, the study used the interest rates, dividend yield, inflation, exchange rate, industrial production and oil prices to forecast stock returns. The results of the study revealed that the STR model is superior to linear models in forecasting stock returns.

Bonga-Bonga and Makakabule (2010) conducted a similar study to McMillan (2001) and Sarantis (2001). Their study tried to examine whether there is any relationship existing between stock returns and macroeconomic forces (variables) in SA. They applied the STR model to explain the smooth asymmetric response of stock returns from economic variables. The results of STR model were compared to OLS and random walk models. The STR model was found to be superior to OLS and Random Walk models in an out-of-sample forecast. Zhou (2010) conducted a study trying to find out whether the industrial production index data is nonlinear or not and then figure out whether the STAR model is sufficient to be used in modelling that type of data. The data used for the study was collected over a period of ten years from January 2000 to December 2010. The study determined that there was a structural break at time point December 2007, when the global financial crisis burst out first in the U.S and then spread to Europe. The study used STAR to model the industrial production index; adopted the procedures given by Teräsvirta (1994) to carry out the linearity test against the STAR model and then determined the delay parameter and to choose between the LSTAR model and the ESTAR model. The results of estimated model suggested that the ESTAR model outperformed the linear autoregressive model.

2.5.2.2 The Threshold Autoregressive (TAR) Models

TAR was proposed by Tong (1978) in time series modelling and further maturations were done by Tong and Lim (1980) and Tong (1983 and 1995). TAR is based on a couple of nonlinear features often experienced in practice such as asymmetry in decreasing and increasing patterns in a given time series. Typically, the TAR model can be described as a set

of different linear autoregressive (AR) models, with regime switches occurring due to the movement of threshold variable(s) with respect to fixed threshold(s). More specifically, in parts, the TAR model uses linear models to obtain a preferred approximation of the conditional mean. Although the TAR model is partially linear, the possibility of regime switching implies an overall nonlinear behaviour for a given time series.

The models of TAR have been applied more in the forecasting of economic variables. The common aim has been to compare the TAR forecasting performance with traditional linear models or other nonlinear models. In the early 90s, Cao and Tsay (1992) demonstrated the forecasting ability of TAR in forecasting United States (US) stock prices. The study applied various nonlinearity tests showed strong nonlinearity in US stock prices. The study used out-sample forecasting to compare TAR models and linear ARMA models. The results revealed that TAR models consistently outperform the linear ARMA models in multi-step ahead forecasts.

Boero (2003) in his study extended the TAR model to Self-Exciting Threshold Autoregressive (SETAR) forecast exchange rates. The SETAR models were specified with two and three regimes, and their performance assessed against that of a simple linear AR model and a GARCH model. Results showed that SETAR models outperformed other models. In their study, Hsu *et al.* (2010) in their study used nonlinear SETAR to forecast the Taiwan Stock Index. The aim of the study was to compare the ability of SETAR and linear ARIMA. The study compares the out-sample forecast performance of non-linear SETAR model with the linear ARIMA model. In terms of empirical results, the study found that the non-linear SETAR model has superior forecasting power to what the linear ARIMA model does in the Taiwan stock market.

Tan *et al.* (2010) applied TAR in their study to test the effectiveness of the Indian, Pakistani and Sri Lankan stock markets. The study applied various nonlinearity tests for nonlinearity and unit root test in stock prices of South Asian (India, Pakistan and Sri Lanka) stock markets. Tan *et al.* (2010) adopted the Caner and Hansen (2001) TAR model. The aim of the study was to find any potential of nonlinearity behaviour in stock prices. The study applied a TAR model to monthly stock prices for three South Asian countries over the period from January 1991 to September 2009. All the stock prices in their study showed a nonlinear behaviour.

2.5.2.3 Markov Switching Model (MSM) Models

MSM is a category of regime-switching methods built on the assumption that the regime existing at a particular time cannot be captured, since it is designated by an unobservable process. Developed by Hamilton (Hamilton, 1989), MSM assumes a first-order Markov process (that is, it depends only on the previous regime). For this particular study, an offshoot of the MSM is appealed to – the MS-AR model. Two important conceptual differences exist among TAR, STR, and MS-AR models. First, the MS-AR model uses less prior information than TAR and STR models. Second, while regime changes are predetermined in TAR and STR models by using the lagged values of the same time series, regime change in an MS-AR model is governed by an exogenous Markov process. Exogenous regime changes are extremely difficult to estimate in MS-AR models due to the presence of additional disturbances. Consequently, in the current study, no attempt is made to explain why regime changes occur and what the importance is of the timing of these regime switches in the current study.

MSM was applied to explain the specific features (inflation rate, interest rate, etc.) of macro-economic and financial time series by researchers (Hamilton 1989). Turner *et al.* (1989), Cecchetti *et al.* (1990) and Schaller and van Norden (1997) use MSM to model stock market return while Gray (1996), Hamilton (1988) and Ang and Bekaert (2002) employed the techniques to explain the behaviour of interest rates. The first application of MSM in financial econometrics was done by pioneers Turner *et al.* (1989) to capture the regime shifts behaviour in stock market returns using MS-AR. The study applied a Markov model of normal distribution to study the relationship between the market risk premium and variance of stock returns using monthly prices on the S & P 500. The study showed the usefulness of the Markov switching model allowing the regime shifts to happen in mean and variances and fitting the data effectively compared to other specifications of Markov regime switching models.

Chu *et al.* (1996) also carried out a study to examine the relationship between stock market returns and stock market volatility using the MS-AR model and concluded that there was a nonlinear and asymmetrical relationship between returns and volatility. The studies of Turner *et al.* (1989 and Chu *et al.* (1996) are not similar to the current study, Turner *et al.* (1989 and Chu *et al.* (1996) tried to examine the relationship between variables, while the current study

tries to find the best univariate MS-AR model that can be used to forecast the stock market prices.

In the late 1990s the study by Turner *et al.* (1989), namely the Markov model to intended to examine the stock market, the model was extended by Schaller and van Norden (1997) to include the price-dividend ratio as a determinant of both state-dependent expected returns and associated transition probabilities. The study reported a strong regime switching behaviour in the stock market returns. Lui (2011) carried out a study closest to the models considered by Turner *et al.* (1989) and Schaller and van Norden (1997). The model by Lui (2011) was extended their model by incorporating regressors in the state-dependent volatilities through a link function. The regressors were incorporated directly to assess sources of persistence on state-dependent volatilities. The model used succeeded to produce new evidence on the relationship between market volatility and expected returns. Specifically the author were studying the effect of two important volatility determinants of both price range and trade volume, thus assessing their importance in terms of both explanatory power and predictability for return volatility. The finding showed strong evidence of switching behaviour in the US stock market with equities switching between two states: low expected return and high volatility state.

Wasim and Bandi (2011) aimed to find the existence of bull and bear in the Indian stock market. The study used AIC, HQIC and SBC to determine the number of regimes. The study used two-state MS-AR (2) to identify bull and bear market regimes. The model selected predicted that the Indian stock market remained under a bull regime with very much higher probability than the bear regime. The study showed that the determination of the bull regime was more than a month in both the markets. The outcomes revealed that the bear phases occurred during all major global economic crises including recent US sub-prime (2008) and European debt crisis (2010).

Cruz and Mapa (2013) also contributed to the literature by developing an early warning system (EWS) for predicting the occurrence of high inflation in the Philippines. The aim of the study was to develop models that could help quantify the possibility of the future occurrence of high inflation. The prediction of MSM parameters was done using OxMetrics software and the inflation rate data was scaled, i.e. multiplied by 100. The study used four two-regime MSM, MS-AR (1) to MS-AR (4). The models were selected using the AIC and various diagnostic tests, including normality and linearity tests. The estimated parameters of

the MS-AR (2) were selected based on the AIC and tests. The results showed that Philippine inflation may be modelled by a two-state MS-AR (2), with the estimated average inflation rate. The empirical results suggest that it was more likely for the country to be in a low inflation rate framework than in a state of high inflation rate target framework of the BSP (Bangkok Sentraling Philippines).

2.6 Concluding Remarks

The literature study revealed the benefits and shortcomings of fundamental analysis, technical analysis and traditional time series on forecasting stock market prices. A number of studies using time series were reviewed and the linear and nonlinear approaches were found to be the relevant to the current study.

Chapter 3

Research Methodology

3.1 Introduction

Predictive modelling of stock markets in general, and in particular, performs many useful roles other than just being tools for producing forecasts. The use of such methods reflects valid empirical and theoretical knowledge of how stock markets work as well as helping to explain their dynamics and anticipate unexpected changes. The dual use of statistical and mathematical techniques in conventional time series econometrics has led to the design of more robust and effective tools for modelling and forecasting practices, although several of them break down when applied to time series with nonlinear structures. Although there are various nonlinear methods for modelling, and forecasting nonlinear time series, this study is restricted to the use of three important methods, namely TAR, STR and MS-AR modelling techniques.

3.2 Sampling Technique, Data Description and Source

There are 31 banks registered with the South African Reserve Bank (SARB). Twenty-one (21) of these banks are listed on the JSE. The study used the purposive sampling technique, due to limited time and responses obtained from all the twenty-one (21) banks listed on the JSE when a request was made to help provide data for the study. Of the 21 banks listed on the JSE, only five (5) responded by providing data for this study. The banks that responded were ABSA Bank (ABSA), Capitec Bank (CAPB), First National Bank (FIRB), Nedbank (NEDB) and Standard Bank (STDB). These banks were considered to be the sampling frame for the study. This scenario fits in with the purposive sampling since the intention had been to find readily available banks willing to provide data for the realization of the aims and objectives of the study. Coincidentally, these five banks constitute the five largest banks listed on the JSE.

For the purpose of addressing the research objectives, the study uses weekly historical data starting from the first week of January 2010 to the last week of December 2012, a total of 563 observations. Using the purposive sampling technique, five (5) banks from a population of twenty-one (21) banks were used. Based on this sample, a formal request was made to the

JSE for the weekly closing stock prices of the selected banks, a request that the JSE promptly responded to.

3.3 Preliminary Data Analysis

In statistics the norm is to perform preliminary data analysis in order to get the key features of the data and summarise the results. Before the main analysis of data, the study seeks to address important issues such as the normality of the actual data as suggested by Kline (2005) and Schumacker and Lomax (2004). Other descriptive statistics such as the mean, median and standard deviations of the variables are discussed. Furthermore, the skewness-kurtosis measures are estimated to check whether actual data is normal distributed, following the work of Joreskog (2000) and Cziraky *et al.* (2002).

3.4 Assessment of Data for Linearity

In order to apply the various methods needed to address the research aims and objectives of the current study, the data must first be tested for linearity and stationarity. Since nonlinearity in time series may occur in several ways, there exists no single test that dominates others in detecting nonlinearity. To test for nonlinearity in the data sets, the RESET (Regression Specification Error Test) and BDS (Brock-Dechert-Scheinkman) tests are used and the Cumulative Sum (CUSUM) test is used to investigate stability.

3.4.1 The RESET Test

According to Ramsey (1969) the RESET test is a specification test for linear regression analysis. In the context of the study, the commonly used linear regression model is the univariate autoregressive model of order p , denoted by $AR(p)$:

$$X_t = \beta_0 + \sum_{j=1}^p \beta_j X_{t-j} + \varepsilon_t, \quad (3.1)$$

where $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ are parameters and ε_t is independent and identically distributed random variable with mean 0 and variance σ_ε^2 . The AR order, p , is selected to minimize the error, ε_t . This is practically accomplished by selecting a value for p that minimizes an

information criterion, such as the SBC (Franses & van Dijk, 2000). If $\mathbf{X}_t = (1 \ X_{t-1} \ X_{t-2} \ \dots \ X_{t-p})'$, equation (3.1) becomes

$$X_t = \mathbf{X}'_{t-1}\beta + \varepsilon_t. \quad (3.2)$$

The RESET test involves, first, obtaining the OLS estimate, β , in equation (3.2), the residual $\hat{\varepsilon}_t = X_t - \hat{X}_t$, and the sum squared residuals

$$SSR_0 = \sum_{t=p+1}^n \hat{\varepsilon}_t^2. \quad (3.3)$$

- The second step involves estimating the regression

$$\hat{\varepsilon}_t = \mathbf{X}'_{t-1}\lambda_1 + \mathbf{M}'_{t-1}\lambda_2 + e_t, \quad (3.4)$$

where $\mathbf{M}'_{t-1} = (\hat{X}_t^2 \ X_t^3 \ \dots \ X_t^{s+1})$ for some $s \geq 1$, e_t is an independent and identically distributed random variable with mean 0 and variance σ_e^2 . From the estimated residuals $\hat{\varepsilon}_t = \hat{\varepsilon}_t - \hat{\varepsilon}_t$, the sum of squared residuals is computed as:

$$SSR_1 = \sum_{t=p+1}^n \hat{\varepsilon}_t^2. \quad (3.5)$$

- If the underlying AR (p) is adequate, the RESET test asserts that λ_1 and λ_2 are zero. Thus, the hypotheses to test are:

$$H_0 : \lambda_1 = \lambda_2 = 0 \quad (\text{Specification is indeed linear})$$

$$\text{vs.} \quad H_1 : \lambda_j \neq 0 \text{ for at least one } j \quad (\text{Specification is nonlinear})$$

The test statistic is the usual F-statistic of the equation given by

$$F^* = \frac{(SSR_0 - SSR_1)/r}{SSR_1/(n-p-r)} \sim F_{\alpha}(r, n-p-r) \quad (3.6)$$

where $r = s + p + 1$. At the α level, the null hypothesis of linearity is rejected in favour of the alternative hypothesis if

$$F^* > F_{\alpha}(r, n-p-r) \quad \text{or} \quad \text{prob}(F^*) < \alpha. \quad (3.7)$$

This means that the F test statistic is greater than the F critical value, and the study rejects the null hypothesis that the true specification is linear (which implies that the true specification is non-linear).

3.4.2 The Brock-Deckert-Schienkman (BDS) Test

If equation (3.1) is correctly specified, then under the null hypothesis of linearity, the residuals should be serially independent. This forms the basic idea behind various tests of nonlinearity. In practice, diagnostic tests of serial independence typically are based on certain aspects of the data such as the serial correlations or ARCH-type dependence while other tests explore dependence by testing the identical-and-independence-distributed (iid) condition of the residual term, which is sufficient for serial independence (Kuan, 2008; Kuan, 2009). One such test is the so-called Brock-Deckert-Schienkman (BDS) test - a form of portmanteau test. Portmanteau tests are residual-based tests in which the null hypotheses are well-stated but do not necessary have well-stated alternative hypotheses.

The BDS test can be applied to the estimated residuals from any time series process provided the time series process can be transformed into a form with iid errors. The BDS test, which focuses on the residual obtained after a linear structure has been removed from a process, tests the null hypothesis of linearity against a variety of alternative hypotheses. Under the null hypothesis of the BDS test, if the residuals are iid or follow a white noise process, then its m-lagged (also referred to as embedding dimension) correlation integral (also referred to as correlation function) is equal to the correlation integral of the (m-1)-lagged residuals. BDS test statistic is given by (Brock *et al.*, 1996) as:

$$BDS_{m,n} = \frac{\sqrt{n} [C_{m,n}(\epsilon) - C_{1,n}(\epsilon)^m]}{\sigma_m(\epsilon)} \quad (3.8)$$

where $C_{m,n}(\epsilon)$ is the correlation integral, $\sigma_m(\epsilon)$ is the asymptotic standard deviation of the numerator, and ϵ is the maximum difference between pairs of observations used in calculating the correlation integral. Brock *et al.* (1996) showed that, under the null hypothesis of the residuals being iid or following a white noise process,

$$BDS_{m,n} \sim N(0,1) . \quad (3.9)$$

The null hypothesis of iid residuals (whiteness or linearity) is rejected if the test statistic exceeds the critical value at the α -level of significance or if the p-value of $BDS_{m,n}$ is lower than α . Rejection of the null hypothesis is indicative of nonlinear dependence in time series data.

3.4.3 CUSUM Test

Stability is another aspect of nonlinearity in data. CUSUM examines data stability by testing for possible structural change in the data. On the one hand, if the model is stable, then β and the variance of the residuals do not change over time. In that case, the coefficients, $\hat{\beta} = (1 \ \beta_1 \ \beta_2 \ \dots \ \beta_p)'$, in equation (3.2) can be obtained from the matrix (Brown *et al.*, 1975):

$$\hat{\beta} = (\mathbf{X}'_{t-1} \mathbf{X}_{t-1})^{-1} \mathbf{X}'_{t-1} X_t \quad (3.10)$$

where X_t is the dependent variable in equation (3.1) and $\mathbf{X}_{t-1} = (1 \ X_{t-1} \ X_{t-2} \ \dots \ X_{t-p})'$ and $\varepsilon_t \sim \text{iid}(0, \sigma_\varepsilon^2)$. On the other hand, if the model is unstable, then β and the variance of the residuals possibly change over time. In that case, then β is replaced by b_t , say, and so

$$b_{t-1} = (\mathbf{X}'_{t-1} \mathbf{X}_{t-1})^{-1} \mathbf{X}'_{t-1} X_{t-1} \quad (3.11)$$

where $\mathbf{X}_{t-1} = (1 \ X_{t-1} \ X_{t-2} \ \dots \ X_{t-p})'$ and $\varepsilon_t \sim \text{iid}(0, \sigma_{t,\varepsilon}^2)$. If the AR(p) is stable, the parameters remain constant over time, suggesting the absence of any structural change in the data. Thus, the hypotheses to test are:

$$H_0 : \beta_1 = \beta_2 = \dots = \beta_p = \beta \quad (\text{say}) \quad (3.12)$$

$$\text{or} \quad H_0 : \sigma_{1,\varepsilon}^2 = \sigma_{2,\varepsilon}^2 = \dots = \sigma_{n,\varepsilon}^2 = \sigma_\varepsilon^2 \quad (\text{say})$$

Then, the variance of the recursive residuals is computed as:

$$\begin{aligned} \text{var}(\varepsilon_t) &= E(\varepsilon_t' \varepsilon_t) = \text{var}\{\varepsilon_t - \mathbf{X}'_t (\mathbf{b}_{t-1} - \beta)\} \\ &= \sigma_\varepsilon^2 + \mathbf{X}'_t \sigma_\varepsilon^2 (\mathbf{X}'_{t-1} \mathbf{X}_{t-1})^{-1} \mathbf{X}_t \end{aligned}$$

$$= \sigma_\varepsilon^2 \{1 + \mathbf{X}'_t (\mathbf{X}'_{t-1} \mathbf{X}_{t-1})^{-1} \mathbf{X}_t\} . \quad (3.13)$$

Define the scaled recursive residuals, ω_t , as

$$\omega_t = \frac{\varepsilon_t}{\sqrt{\{1 + \mathbf{X}'_t (\mathbf{X}'_{t-1} \mathbf{X}_{t-1})^{-1} \mathbf{X}_t\}}} = \frac{\varepsilon_t}{\sqrt{\text{var}(\varepsilon_t)}} = \frac{\varepsilon_t}{\text{s.e.}(\varepsilon_t)} = \frac{\varepsilon_t}{\sigma_\omega} , \quad (3.14)$$

then under constant parameters, $\omega_t \sim \text{iid}(0, \sigma_\omega^2)$. Then the CUSUM test statistic is given by:

$$W_t = \sum_{j=k+1}^t \omega_j , \quad t = k+1, k+2, \dots, n . \quad (3.15)$$

The cumulative sum of the square (CUSUMSQ) test statistic is given by:

$$S_t = \sum_{j=k+1}^t \omega_j^2 / \sum_{j=k+1}^n \omega_j^2 , \quad t = k+1, k+2, \dots, n . \quad (3.16)$$

These tests are performed by plotting W_t or S_t against time t . The confidence bounds are obtained by plotting the two lines that connect the points $[k, \pm a\sqrt{n-k}]$ and $[n, \pm 3a\sqrt{n-k}]$. At the 5% level (that is, 95% confidence interval) $a=0.948$ while at the 1% level (that is, 99% confidence interval) $a=1.143$. A test statistic meandering outside the confidence interval is indicative of a possible structural change, non-constancy in the parameters, and hence instability in the data, leading to the rejection of the null hypothesis of model stability.

Under the null hypothesis of model stability, Harvey and Collier (1977) developed a test with test statistic given by:

$$T^* = (n-1)^{1/2} S^{-1} \bar{W} \quad (3.17)$$

$$\text{where } \bar{W} = \frac{1}{n-k} \sum_{j=k+1}^n \omega_j \quad \text{and} \quad S^2 = \frac{1}{n-k-1} \sum_{j=k+1}^n (\omega_j - \bar{W})^2 .$$

The estimated T^* has a t-distribution with $(n-k-1)$ degree of freedom. The null hypothesis of model stability is rejected if T^* is greater than a critical value at the α -level or if the p-value of T^* is less than α , often 0.05.

3.4.4 ARCH Test

Under the null hypothesis of linearity, the residuals of a properly specified AR(p) model should be independent. Denote the autocorrelations of the residuals by $\rho_1, \rho_2, \dots, \rho_m$, where $m = n/4$ (n =sample size), then the independence of the residuals, ε_t , can be tested based on the hypotheses (Engle, 1982):

$$H_0 : \rho_1 = \rho_2 = \dots = \rho_m = 0 \quad (\text{Residuals are independent})$$

$$\text{vs.} \quad H_1 : \rho_j \neq 0 \text{ for at least one } j \quad (\text{Residuals are not independent})$$

The test statistic is the Q-statistic of squared residuals given by

$$Q(m) = n(n+2) \sum_{k=1}^m \frac{\rho_k^2}{n-k} \sim \chi_{\alpha}^2(m-p). \quad (3.18)$$

At the α level, the null hypothesis of linearity is rejected in favour of the alternative hypothesis if

$$Q(m) > \chi_{\alpha}^2(m-p) \quad \text{or} \quad \text{prob}[Q(m)] < \alpha. \quad (3.19)$$

This same test is particularly useful in detecting conditional heteroskedasticity in X_t . A closely related test to the Q-statistic test is the Lagrange test of Engle (1982) for autoregressive conditional heteroskedasticity (ARCH) test based on the linear regression:

$$\hat{\varepsilon}_t^2 = \eta_0 + \sum_{i=1}^m \eta_i \varepsilon_{t-i}^2 + v_t \quad (3.20)$$

where $\eta_0, \eta_1, \eta_2, \dots, \eta_m$ are parameters and v_t is independent and identically distributed random variable with mean 0 and variance σ_v^2 . Testing for heteroskedasticity involves testing the hypotheses:

$$H_0 : \eta_1 = \eta_2 = \dots = \eta_m = 0 \quad (\text{Homoskedasticity})$$

$$\text{vs.} \quad H_1 : \eta_j \neq 0 \text{ for at least one } j \quad (\text{Heteroskedasticity}).$$

The test statistic is the usual F-statistic:

$$F^* = \frac{R^2/m}{(1-R^2)/(n-m-1)} \sim F_{\alpha}(m, n-2m-1) \quad (3.21)$$

At the α level, the null hypothesis of linearity is rejected in favour of the alternative hypothesis if

$$F^* > F_{\alpha}(m, n-2m-1) \quad \text{or} \quad \text{prob}(F^*) < \alpha. \quad (3.22)$$

Asymptotically, $F^* \sim \chi_{\alpha}^2(m)$.

3.5 Nonlinear Tests of Stationarity

In order to apply the methods for modelling and forecasting, the five closing stock prices being used in the study must be investigated for the presence of stationarity. For the current study, nonlinear stationarity is tested using the Kapetanios-Shin-Snell Nonlinear Augmented Dickey-Fuller Unit (KSS-NADF) and Bierens Nonlinear Augmented Dickey-Fuller (B-NADF) unit root tests.

3.5.1 The KSS-NADF Unit Root Test

In the presence of nonlinearity in a time series data, the conventional unit root test, such as the ADF-GLS discussed above, may be inadequate for detection of stationarity in the data. In such a scenario it is therefore important that stationarity tests that accommodate nonlinearity, such as the KSS test, be used. The KSS test is a modification of the Augmented Dickey-Fuller (ADF), based on the following nonlinear model specification (Kapetanios *et al.*, 2003):

$$X_t = \beta X_{t-1} + \gamma X_{t-1}[1 - \exp(-\theta X_{t-d}^2)] + \varepsilon_t \quad (3.23)$$

which when parameterised yields:

$$\Delta X_t = \delta X_{t-1} + \gamma X_{t-1}[1 - \exp(-\theta X_{t-d}^2)] + \varepsilon_t \quad (3.24)$$

where $\delta = \beta - 1$, γ , θ are parameters that must be estimated and ε_t is the residual term. The KSS test sets $\delta = 0$ and the decay parameter, $d = 1$, so that the test is formally based on the following specification:

$$\Delta X_t = \gamma X_{t-1} [1 - \exp(-\theta X_{t-d}^2)] + \varepsilon_t \quad (3.25)$$

The KSS tests the null hypothesis of linear stationarity by setting $\theta = 0$ against the alternative that $\theta > 0$. However, Katepenios *et al.*, (2003) argue that it is impossible to directly test the null hypothesis since the speed of reversion, γ , is unknown. Using a first-order Taylor series approximation, Luukkonen *et al.* (1998) reformulated an estimable nonlinear specification for testing nonlinear stationarity in X_t as:

$$\Delta X_t = \xi \cdot X_{t-1}^3 + \varepsilon_t. \quad (3.26)$$

To account for the possibility of serial correlation in the error term, equation (3.26) is augmented with lags of the first-difference of X_t as:

$$\Delta X_t = \xi \cdot X_{t-1}^3 + \sum_{j=1}^p \delta_j \cdot \Delta X_{t-j} + \varepsilon_t \quad (3.27)$$

where ξ is the coefficient used to test the presence of a unit root. From the nonlinear stationarity specification, the KSS-NADF unit root test is based on the t-statistic:

$$\tau_{NL} = \frac{\hat{\xi}}{s.e.(\hat{\xi})} \quad (3.28)$$

where $s.e.(\hat{\xi})$ is the standard error of ξ . The following hypotheses are tested:

$$H_0 : \xi = 0 \quad (\text{Nonlinear nonstationarity})$$

$$\text{vs.} \quad H_1 : \xi < 0. \quad (\text{Nonlinear stationarity})$$

Three different asymptotic critical values are constructed with three different nonlinear model specifications - raw data, demeaned data, and de-trended data (Kapetanios *et al.*, 2003). The following scenarios prevail:

- If X_t has a zero mean, then the appropriate data to use is $Y_t = X_t$, the raw data.
- If X_t has a non-zero mean and zero trend, then the appropriate data to use is $Y_t = X_t - \bar{X}$, the demeaned data, where $\bar{X}$ is the mean of the data.
- If X_t has a non-zero mean and non-zero trend, then the appropriate data to use is $Y_t = X_t - (\alpha_0 + \alpha_1 t)$, the de-trended data, where $\alpha_0 + \alpha_1 t$ is the trendline obtained by regressing X_t on timepoint $t=1, 2, 3, \dots, n$ with an intercept term.

The KSS-NLADF test is sensitive to the choice of lag length, p . One prominent approach to select p is use of general-to-specific method suggested by Hall (1994). This involves setting up an upper bound, $p_{\max}$, suggested by Schwert (1989):

$$p_{\max} = \text{integer} \left[12. \left(\frac{n}{100} \right)^{1/4} \right] \quad (3.29)$$

where n is the sample size, estimating the test regression with $p = p_{\max}$. This study will, however, appeal to the lag length of 8 as recommended by Liew *et al.* (2004). At the 1%, 5% or 10% level, if the last included lag is significant, it is retained as the optimal lag and used in the KSS-NLADF unit root test. However, if the last included lag is not significant, p is reduced by one lag until last included lag is significant, and used as the optimal lag for the KSS-NLADF unit root test. The null hypothesis of the nonlinear unit root is rejected in favour of the alternative if the t-statistic is greater than the critical value at some α -level of significance. Table 3.1 presents asymptotic critical values at the 1%, 5% and 10% levels.

Table 3.1: Critical Values for KSS Nonlinear Unit Root Tests

Significance Level	Raw Data	De-Meaned Data	De-Trended Data
1	-2.82	-3.48	-3.93
5	-2.22	-2.93	-3.40
10	-1.92	-2.66	-3.13

Source: Kapetanios *et al.* (2003)

3.5.2 The B-NADF Unit Root Test

The Bierens Nonlinear ADF (B-NLADF) test is also a modification of the Augmented Dickey-Fuller (ADF) unit root test in which ADF auxiliary regression is further augmented with orthogonal Chebyshev polynomial. In the B-NLADF test, the null hypothesis of a unit root is tested against the alternative of nonlinear trend stationarity. The B-NLADF auxiliary regression is given by:

$$\Delta X_t = \xi \cdot X_{t-1} + \sum_{j=1}^p \delta_j \cdot \Delta X_{t-j} + \sum_{k=0}^m \theta_k C_{k,t} + \varepsilon_t \quad (3.30)$$

where $C_{1,t}$, $C_{2,t}$, ..., $C_{m,t}$ are Chebychev polynomials with $C_{0,t} = 1$, $C_{1,t}$ capturing a linear trend in the data, and $C_{2,t}$, ..., $C_{m,t}$ are cosine functions. The hypotheses to test are:

$$H_0 : \xi = 0 \quad (\text{Nonlinear unit root})$$

$$\text{vs.} \quad H_1 : \xi < 0. \quad (\text{No nonlinear unit root})$$

Three important tests - $t(m)$, $A(m)$ and $F(m)$ – are proposed by Bierens (1997) under the B-NLADF test. The $t(m)$ test is a t-test on the significance of the estimated coefficient, $\hat{\xi}$. Under the null hypothesis, the $F(m)$ test is a joint F-test that the estimated coefficient, $\hat{\xi}$, and the coefficients of the nonlinear Chebyshev polynomials are zero (not significant). The $A(m)$ test statistic given by

$$A(m) = \frac{n \cdot \hat{\xi}}{\left| 1 - \sum_{j=1}^p \hat{\delta}_j \right|} \quad (3.31)$$

where n is the sample size, is an alternative test for $t(m)$ test, and therefore can be used to check the robustness of results of the $t(m)$ test. As the tests are prone to size distortions, critical values used are based on the Monte Carlo simulations with 1000, 2000, 5000 or 10000 replications of a Gaussian AR(p) process for the first-difference data, ΔX_t , where p is determined by an information criterion such as AIC, SBC, BIC and HQC. As argued in

Bierens (1997), there is not a unique way of choosing m as a low value may be insufficient to detect nonlinearity under the alternative hypothesis and a too high value may result in lack of power. For this reason, this study considers different values of m with the optimal order, p , determined by the SBC criterion. Decisions about nonlinear stationarity or otherwise, will be made based on comparisons of test statistics with asymptotic critical values. The null hypothesis of a nonlinear unit root is rejected if a test statistic is less than its associated critical value at the 1%, 5% or 10% level.

3.6 Modelling and Forecasting Methods

This section presents an overview of the three nonlinear time series modelling and forecasting methods which include the STR model, TAR model and MS-AR model.

3.6.2 Smooth Transition Regression Models

Smooth Transition Regression models are a set of nonlinear models that incorporates both the deterministic changes in parameters over time and the regime switching behaviour within the time series data (van Dijk, Teräsvirta & Franses, 2002). The general STR model for a time series $\{X_t : t=1,2,3,\dots,n\}$ is:

$$X_t = \left(\alpha_0 + \sum_{i=1}^p \alpha_i X_{t-i} \right) + \left(\beta_0 + \sum_{i=1}^p \beta_i X_{t-i} \right) G(S_{t-d}, \gamma, c) + \varepsilon_t, \quad (3.32)$$

where $G(S_{t-d}, \gamma, c)$ is the transition function with S_{t-d} as the transition variable which determines the switching point, d is the decay parameter, γ is the smoothing parameter that determines the smoothness of the transition variable, c is the threshold parameter, $\alpha_0, \alpha_1, \alpha_2, \dots, \alpha_p$ and $\beta_0, \beta_1, \beta_2, \dots, \beta_p$ are the parameters of the two autoregressive components of the model with optimal lag length p , and ε_t is an error term. The two most popular transition functions are the logistic smooth and exponential functions given, respectively, by:

$$\begin{aligned} \text{Logistic Function:} \quad G(S_{t-d}, \gamma, c) &= \frac{1}{1 + \exp\{-\gamma(S_{t-d} - c)\}}, \quad \gamma > 0 \\ \text{Exponential Function:} \quad G(S_{t-d}, \gamma, c) &= \frac{1}{1 + \exp\{-\gamma(S_{t-d} - c)^2\}}, \quad \gamma > 0. \end{aligned} \quad (3.33)$$

The optimal lag length, p , of the autoregressive components is selected using automatic selectors based on information criteria. Using the appropriate transition function and transition variable, the STR model can be estimated using nonlinear least squares (NLS). The estimated parameters are obtained by minimizing the sum of squared residuals:

$$RSS(\Psi) = \sum_{t=1}^n \varepsilon_t^2 \quad (3.34)$$

where $\Psi = (\alpha', \beta', \gamma, c)$ with $\alpha = (\alpha_0 \ \alpha_1 \ \alpha_2 \ \dots \ \alpha_p)'$ and $\beta = (\beta_0 \ \beta_1 \ \beta_2 \ \dots \ \beta_p)'$. Using nonlinear optimization algorithm, a two-dimensional grid search is conducted over γ and c , allowing the selection of the pair that gives the smallest estimator for the residual variance, $\sigma_\varepsilon^2(\gamma, c)$.

3.6.1 Threshold Autoregressive Model

The TAR model is basically an extension of the Autoregressive model, which allows for the parameters to change in the model according to the number of segments (breaks), m , deemed to exist within the data. If the time series, $\{X_t : t=1, 2, 3, \dots, n\}$, changes structurally with m break points, then there are $w = m + 1$ segments or regimes with a TAR model representation given by (Tong, 1978):

$$X_t = \begin{cases} \alpha_{1,0} + \phi_{1,1}X_{1,t-1} + \phi_{1,2}X_{1,t-2} + \phi_{1,3}X_{1,t-3} + \dots + \phi_{1,p_1}X_{1,t-p_1} + \varepsilon_{1,t} & , \quad t=1, 2, \dots, n_1 \\ \alpha_{2,0} + \phi_{2,1}X_{2,t-1} + \phi_{2,2}X_{2,t-2} + \phi_{2,3}X_{2,t-3} + \dots + \phi_{2,p_2}X_{2,t-p_2} + \varepsilon_{2,t} & , \quad t=n_1+1, n_1+2, \dots, n_2 \\ \vdots & \\ \vdots & \\ \alpha_{w,0} + \phi_{w,1}X_{w,t-1} + \phi_{w,2}X_{w,t-2} + \phi_{w,3}X_{w,t-3} + \dots + \phi_{w,p_w}X_{w,t-p_w} + \varepsilon_{w,t} & , \quad t=n_w, n_w+1, \dots, n \end{cases} \quad (3.35)$$

where $\varepsilon_{j,t}$ ($j=1, 2, \dots, w$) are iid error term and $n_1, n_2, \dots, n_m$ (where $n_1 < n_2 < \dots < n_w$) are respectively the sample sizes of segment 1, segment 2, ..., and segment w . The TAR model in equation (3.32) allows different variances for all w segments (regimes). In order to stabilize the variance over different segments (regimes), restriction of the form is applied:

$$X_t = I_1 \left[\alpha_{1,0} + \sum_{i=1}^{p_1} \phi_{1,i} X_{1,t-i} \right] + I_2 \left[\alpha_{2,0} + \sum_{i=1}^{p_2} \phi_{2,i} X_{2,t-i} \right] + \dots + I_w \left[\alpha_{w,0} + \sum_{i=1}^{p_w} \phi_{w,i} X_{w,t-i} \right] + e_t \quad (3.36)$$

where I_t is the indicator function such that $I_t = 1$ when it correspond to segment j and $I_t = 0$, if otherwise. Each of the m segments can easily be estimated using OLS while the TAR model in equation (3.33) can be estimated using Nonlinear Least Squares (NLS), however, boundaries for the segments need to be determined. One possible approach to determining boundaries for the segments is by possible locating structural breaks. The existence of at least structural break in a time series is indicative that the data is nonlinear.

To test for structural change due to the presence of one break point, the Chow test is widely used. However, for multiple break points the Bai-Perron test is usually applied. The Bai-Perron test assumes the following vector-form multiple-structural-break model with m breaks (w segments/ regimes):

$$X_t = \begin{cases} \mathbf{X}'_{t-1}\boldsymbol{\beta} + \mathbf{Z}'_t\delta_1 + \varepsilon_{1,t} & , \quad t = 1, 2, \dots, n_1 \\ \mathbf{X}'_{t-1}\boldsymbol{\beta} + \mathbf{Z}'_t\delta_2 + \varepsilon_{2,t} & , \quad t = n_1 + 1, n_1 + 2, \dots, n_2 \\ \vdots & \\ \mathbf{X}'_{t-1}\boldsymbol{\beta} + \mathbf{Z}'_t\delta_{m+1} + \varepsilon_{m+1,t} & , \quad t = n_m + 1, n_m + 2, \dots, n \end{cases} \quad (3.37)$$

where is $\mathbf{X}_{j,t-1} = (1 \ X_{j,t-1} \ X_{j,t-2} \ \dots \ X_{j,t-p_j})'$ is the column vector of with $j=1,2,\dots,m+1$ at time t whose effects are invariant with time and $\mathbf{Z}_t$ is a column vector of the explanatory variables at time t whose effects vary over time, and $\varepsilon_{j,t}$ are the error terms. The break points, $n_1, n_2, \dots, n_m$, are treated as unknowns and are estimated together with the unknown coefficients, $\boldsymbol{\beta}$ and δ_j are coefficients, when n observations available. A structural change in a given time series means $\boldsymbol{\beta} = 0$. Using the OLS principle, the Bai-Perron test involves sequentially estimating the regression coefficients of the $m+1$ data segments/regimes along with the break points in the sample of n observations. Bai and Perron (2003) discussed three types of test – a test of no break vs. a fixed number of breaks, a double maximum test, and a sequential test – notable among them is the sequential test. The sequential test involves the following steps:

- Using the full sample, a test of parameter constancy with unknown break is conducted. If the test rejects the null hypothesis of constancy, the breakpoint

associated with this result is estimated and noted as the first breakpoint. A test statistic called the Fisher statistic associated with the first breakpoint is then obtained.

- If the Fisher statistic associated with the first breakpoint is greater than the critical value, this first breakpoint is then used to divide the sample into two samples. For each of the two sub-samples, a single unknown breakpoint test is conducted in each subsample. If the Fisher statistic is greater than the critical value for each of the two samples, the date corresponding to the higher value is chosen as the second breakpoint.
- Sequentially, this procedure is repeated until all of the subsamples do not reject the null hypothesis of constancy (that is, no further breakpoints are left).

3.6.3 Markov Switching Autoregressive Models

The underlying principle of Markov Switching Models is to decompose nonlinear time series into a finite sequence of distinct stochastic processes, states or regimes, whereby the parameters are allowed to take on different values with regard to the state/regime prevailing at time t . Switches between states/regimes arise from the outcome of an unobservable regime variable, S_t , which is assumed to evolve according to a Markov Chain. One particular type of MSM is the Markov Switching Autoregressive (MS-AR) model. Given the time series $\{X_t : t = 1, 2, 3, \dots, n\}$, the MS-AR model assumes the representation (Hamilton, 1989):

$$X_t - \mu(S_t) = \phi_1[X_{t-1} - \mu(S_{t-1})] + \phi_2[X_{t-2} - \mu(S_{t-2})] + \dots + \phi_p[X_{t-p} - \mu(S_{t-p})] + \varepsilon_t$$

which, when re-parameterised yields:

$$X_t = c + \phi_1 X_{t-1} + \phi_2 + \dots + \phi_p X_{t-p} + \varepsilon_t$$

$$\text{or} \quad X_t = \sum_{i=1}^p \phi_i X_{t-i} + \varepsilon_t \quad (3.38)$$

where $\phi_1, \phi_2, \dots, \phi_p$ represent the coefficients of the AR(p) process, $\varepsilon_t \sim \text{iid}(0, \sigma_\varepsilon^2)$ and $\mu(S_t)$ are constants that are dependent on the states/regimes S_t and represent μ_1 if the process is in state/ regime 1 ($S_t = 1$), μ_2 if the process in state/regime 2 ($S_t = 2$), ..., and μ_R if the process

is in state/regime R ($S_t = R$, the last state/regime). The change from one state to another is governed by the R-state first-order Markov Chain with transition probabilities, expressed as:

$$p_{ij} = P(S_t = j | S_{t-1} = i), \quad i, j = 1, 2 \quad (3.39)$$

where p_{ij} is the probability of moving from state i at time $t-1$ to state j at time t . Using the fact that:

$$p_{1i} + p_{2i} + \dots + p_{Ri} = 1, \quad (3.40)$$

the probability of state i being followed by state j (also known as the transition matrix) is given by:

$$P = \begin{pmatrix} p_{11} & p_{21} & \dots & p_{R1} \\ p_{12} & p_{22} & \dots & p_{R2} \\ . & & & \\ . & & & \\ p_{1R} & p_{2R} & \dots & p_{RR} \end{pmatrix} \quad (3.41)$$

In the current study, two states or regimes assumed that $R=2$ and the underlying MS-AR (p) model is given by:

$$X_t = \begin{cases} c_1 + \sum_{i=1}^p \phi_{1,i} X_{t-i} + \varepsilon_{1,t}, & \text{if } S_t = 1 \\ c_2 + \sum_{i=1}^p \phi_{2,i} X_{t-i} + \varepsilon_{2,t}, & \text{if } S_t = 2 \end{cases} \quad (3.42)$$

The transition matrix is, thus, given by:

$$P = \begin{pmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \end{pmatrix} \quad (3.43)$$

so that $p_{11} + p_{12} = 1$ and $p_{21} + p_{22} = 1$. P represents the probability of change in regime. For this two-regime MS-AR model, there are four transition probabilities given by:

$$P(S_t = 1 | S_{t-1} = 1) = p_{11}$$

$$P(S_t = 2 | S_{t-1} = 1) = p_{12} = 1 - p_{11} \quad (3.44)$$

$$P(S_t = 2 | S_{t-1} = 2) = p_{22}$$

$$P(S_t = 1 | S_{t-1} = 2) = p_{21} = 1 - p_{22}$$

The MS-AR allows one to make inferences about the value of the observed regime, S_t , through the observed behaviour of X_t . This inference takes the form of probabilities called ‘filtered probabilities’, which are estimated using a simple iterative algorithm that computes both the likelihood function recursively and $P(S_t = i | \Omega_t)$, the filtered probability conditional on the set of observations, $\Omega_t = (X_t, X_{t-1}, X_{t-2}, \dots, X_1, X_0)$ up to time t . If the whole data set is used, the probabilities obtained are called the ‘smoothed probabilities’ which is estimated conditional on all the n available observations, $\Omega_n = (X_t, X_{t-1}, X_{t-2}, \dots, X_1, X_0)$. An important result that can be derived from the transition matrix is the expected duration (or average duration) of regime i as well as the average duration of regime i . The expected duration of regime i is given by:

$$E[D(S_t = i)] = \bar{D}(S_t = i) = 1/(1 - p_{ii}) = 1/p_{ij} . \quad (3.45)$$

A small value of p_{ij} ($i \neq j$) is an indication that the model tends to stay longer in state i while its reciprocal $1/p_{ij}$ describes the expected duration of the process to stay in state i .

3.7 Model Evaluation

Just as in the case of linear models, evaluation of nonlinear models is necessary. The evaluation of nonlinear models is based on the properties of resulting residuals. Using the residuals, various tests for misspecification, including non-normality, parameter non-constancy and autocorrelation.

3.7.1 Graphical Method for Assessing Univariate Normality

Assessing the assumption of normality is required by most statistical procedures. Parametric statistical analysis assumes a certain distribution of the data, usually the normal distribution. If the assumption of normality is violated, interpretation and inference may not be reliable or valid. Therefore it is significant to test this assumption before forecasting with the estimated model. Basically, there are three common ways to check the normality assumption. The

easiest way is by using graphical methods. The common used graphical methods are histogram, P-P plots and Q-Q plots. The current study uses histograms and Q-Q plots to assess normality (Razali & Wah, 2011).

3.7.2 Parameter Constancy Tests

The test parameter constancy is based on the notion that the parameters of an estimated nonlinear model are constant over time. The test is conducted to test the null hypothesis is the parameters are constant over time against the alternative that the parameters change smoothly and continuously over time. The test statistic has an asymptotic chi-square distribution. The null hypothesis of parameter constancy is rejected in favour of the alternative if the test statistic exceeds a critical value or the probability of the test statistic is less than the 0.05 level. Here again, there is an F-statistic version of the test based on the scaled residuals which can also be used (Luukkonen *et al.*, 1988).

3.7.3 Autocorrelation Tests

Once a model has been estimated, the residual term, ε_t , may be subjected to autocorrelation. A number of tests for autocorrelation are discussed in the literature, including the Durbin-Watson test and the Breusch-Godfrey test.

Durbin-Watson Test

A simple test commonly used to detect autocorrelation of residuals at two time points, t and $t-1$, is the Durbin-Watson (DW) statistic. The residuals, ε_t , assume the AR(1) representation:

$$\varepsilon_t = \rho \cdot \varepsilon_{t-1} + v_t, \quad \text{where} \quad v_t \sim \text{iid}(0, \sigma_v^2). \quad (3.46)$$

In the absence of autocorrelation in $\rho = 0$. Hence, the hypotheses usually considered in the Durbin-Watson test are:

$$H_0 : \rho = 0$$

$$H_1 : \rho \neq 0$$

The test statistic is:

$$DW = \frac{\sum_{t=2}^n (\varepsilon_t - \varepsilon_{t-1})^2}{\sum_{t=1}^n \varepsilon_t^2} \quad (3.47)$$

where $\varepsilon_t = y_t - \hat{y}_t$ and y_t and $\hat{y}_t$ are, respectively, the observed and predicted values of the response variable. Upper and lower critical values, d_U and d_L have been tabulated for different values of k (the number of explanatory variables) and n . Based on the estimated DW, the following decisions suffice:

- H_0 is rejected if $DW < d_{L,\alpha/2}$ or if $(4 - DW) < d_{L,\alpha/2}$,
- H_0 is not rejected if $DW > d_{U,\alpha/2}$ or if $(4 - DW) > d_{U,\alpha/2}$,
- Inconclusive if $d_{L,\alpha/2} \leq DW \leq d_{U,\alpha/2}$ and if $d_{L,\alpha/2} \leq (4 - DW) \leq d_{U,\alpha/2}$.

Breusch-Godfrey Test

One method that overcomes the shortcomings of the Durbin-Watson test statistic is the Breusch-Godfrey (BG) test (Gujarati, 2003). The BG test involves running the regression model, storing the residual, ε_t , and running the AR(m) auxiliary regression:

$$\varepsilon_t = \rho_1 \varepsilon_{t-1} + \rho_2 \varepsilon_{t-2} + \dots + \rho_m \varepsilon_{t-m} + v_t, \quad (3.48)$$

where $v_t \sim \text{iid}(0, \sigma_v^2)$ is a white noise disturbance term with zero mean and constant variance.

The null hypothesis of no autocorrelation is that:

$$\begin{aligned} H_0 : \rho_1 = \rho_2 = \dots = \rho_m = 0 \\ H_1 : \rho_i \neq 0 \text{ for at least one } i \end{aligned}$$

The test statistic is the joint F-test for the significance of the residuals $\varepsilon_{t-1}, \varepsilon_{t-2}, \dots, \varepsilon_{t-m}$,

$$F^* = \frac{\sum_{t=1}^n (\hat{\varepsilon}_t - \bar{\varepsilon}) / (m-1)}{\sum_{t=1}^n (\varepsilon_t - \hat{\varepsilon}_t) / (n-m)} \sim F_{\alpha}(m-1, (n-m)). \quad (3.49)$$

The null hypothesis m-order autocorrelation for ε_t is rejected if $F^* > F_{\alpha}(m-1, (n-m))$.

3.8 Model Selection Criteria

Schwarz Bayesian Criterion (SBC) developed by Schwarz (1978) was derived from a Bayesian modification of the AIC criterion. The idea of SBC is to select the model that has a minimise value. SBC is a function of the number of observation n , the SSE, the number of independent variables $p \leq m + 1$ where p includes the intercept, as shown in equation (3.50).

$$SBC = n \ln \left(\frac{SSE}{n} \right) + p \ln(n) \quad (3.50)$$

The penalty term for SBC is similar to AIC, but uses a multiplier of $\ln n$ for p instead of a constant by incorporating the sample size n .

3.9 Comparison of Model Performance

On the basis of reliability, validity and wide use, the following performance (error) measuring metrics are recommended for evaluating models. In order to select the appropriate models for each of the five closing stock prices among the three nonlinear modelling techniques which include SETAR, STR and MS-AR, four error metrics, RMSE, MAE, MAPE, and RSMPE, are appealed to. Given the time series, X_t and estimated series, $\hat{X}_t$, the four error metrics are defined below:

- $RMSE = \sqrt{\frac{\sum_{t=1}^n (X_t - \hat{X}_t)^2}{n}} \quad (3.51)$

- $MAE = \frac{1}{n} \sum_{t=1}^n |X_t - \hat{X}_t| \quad (3.52)$

- $MAPE = \frac{1}{n} \sum_{t=1}^n \left| \frac{X_t - \hat{X}_t}{X_t} \right| * 100\% \quad (3.53)$

- $RMSPE = \sqrt{\frac{1}{n} \sum_{t=1}^n \left(\frac{X_t - \hat{X}_t}{X_t} \right)^2} \quad (3.54)$

3.10 Diebold-Mariano (DM) Test of Comparing Model Forecasting Accuracy

Comparing forecasting ability of competing models built for a given data is very important. Although the lower the forecast measure, the better the forecasting performance, it does not

necessarily imply superior forecasting ability since the difference between error measures from competing models may not be significantly different from zero. One simple approach to compare the forecast accuracy of competing models is the DM test, which tests the equality of forecast accuracy of pairs of competing models built for a particular data. If the pair of forecast errors, $\varepsilon_{1,t}$ and $\varepsilon_{2,t}$ have equal forecasting accuracy, then the expected square differences (mean of the square differences),

$$\bar{d} = E(d_t) = E(\varepsilon_{1,t}^2 - \varepsilon_{2,t}^2) \quad (3.55)$$

should be approximately zero, that is $\bar{d} = \frac{1}{n} \sum_{t=1}^n d_t \approx 0$. The Diebold-Mariano test, thus, formulates the following hypotheses to be tested:

$$H_0: \bar{d} = 0 \quad (\text{Forecasting accuracy of pair of models is equal})$$

$$\text{vs. } H_1: \bar{d} \neq 0 \quad (\text{Forecasting accuracy of pair of models is not equal})$$

With h -step ahead forecasts are generated from a model, the Diebold-Mariano test statistic, S , is given by:

$$S = \frac{\bar{d}}{\sqrt{\text{var}(\bar{d})}} \sim N(0,1) \quad (3.56)$$

where $\text{var}(\bar{d}) = \frac{1}{n} \left[\gamma_0 + 2 \sum_{k=1}^{h-1} \gamma_k \right]$ is the asymptotic variance of $\bar{d}$. The term, γ_0 , is the variance of the loss differential, d_t , while γ_k , the k -th auto-covariance of d_t at time t , is given by:

$$\hat{\gamma}_k = \frac{1}{n} \sum_{t=k+1}^n (d_t - \bar{d})(d_{t-k} - \bar{d}). \quad (3.57)$$

The null hypothesis of Model 1 having equal forecasting accuracy as Model 2 is rejected if the test statistic, S , is greater than critical value or the p -value of S is less than the 1%, 5% or 10% level. In case the null hypothesis is rejected, a higher positive t -statistic for Model 1 than Model 2 suggests that Model 2 is more accurate than Model 1.

3.11 Concluding Remarks

This chapter has presented an overview of various statistical tests and forecasting methods to be used in analysing the closing stock prices of the five banks. Criteria used to identifying appropriate forecasting models for each of the closing stock prices are also discussed. These tests and methods are used in the next chapter.

Chapter 4

Empirical Analysis and Results

4.1 Introduction

In this chapter, results from the empirical analysis of data are presented and discussed in light of the study aim and objectives outlined in Chapter 3. The results are summarised in tables and some are presented as figures.

4.2 Preliminary Data Analyses Results

In this section, a preliminary analysis of data is conducted with the aim to identify the broad characteristics of the measured variables used in the study. This covers includes type of data, graphical method of analysis, and other basic descriptive statistics such as mean, median, standard deviation, skewness and kurtosis. Furthermore, the study conducts as test of nonlinearity and a nonlinear unit root test.

4.2.1 Descriptive Statistics Results

Table 4.1: Descriptive Statistics of Closing Stock Prices

Variable	ABSA	CAPB	FIRB	NEDB	STDB
Mean	14074.067	18611.456	2276.195	15322.052	10473.478
Median	13801.000	18450.000	2089.000	14600.000	10505.000
StdDev	870.926	2194.105	364.299	1921.300	665.826
Skewness	-0.001	0.000	0.000	0.000	0.000
Z-Score	-0.014	-0.001	-0.002	-0.002	0.000
P-Value	0.989	0.999	0.999	0.999	1.000
Kurtosis	-0.015	-0.008	-0.008	-0.007	-0.007
Z-Score	0.025	0.056	0.059	0.061	0.063
P-Value	0.980	0.955	0.953	0.952	0.949
Skewness-Kurtosis					
Chi-Sq.	0.001	0.003	0.003	0.004	0.004
P-Value	1.000	0.998	0.998	0.998	0.998

Prior to executing the main analysis of data, the study addresses a few very important issues such as the normality of the actual data as suggested by (Schumacker and Lomax, 2004 and Kline, 2005). Other descriptive statistics such as the mean and standard deviations of the variables are discussed. The results of these measures are summarised in Table 4.1. The

observed means of the five variables are explained by a symmetrical distribution. This is due to the closeness of the median and the mean values displayed by the variables. Upon observation, CAPB, NEDB and ABSA have the highest mean and median scores on the closing stock price respectively. Furthermore, the skewness and kurtosis measures are estimated by a normal distribution. This is proven by the associated observed probability values of these measures and is in accordance with (Joreskog *et al.*, 2000 and Cziraky *et al.*, 2002).

The general impression given by the results is that the five closing stock prices differ from one another with some banks having more stocks than others. Measures of normality in the raw data proved that the data is approximated by a normal distribution allowing the analysis to be proceeded with further with the said data. The results are in line with the study by (Schumacker and Lomax, 2004 and Kline, 2005). Next, the study presents the results of time series plot of the five closing stock prices given as a combination of Figure 4.1. This is aimed at identifying the broad characteristics of the variables used in this study.

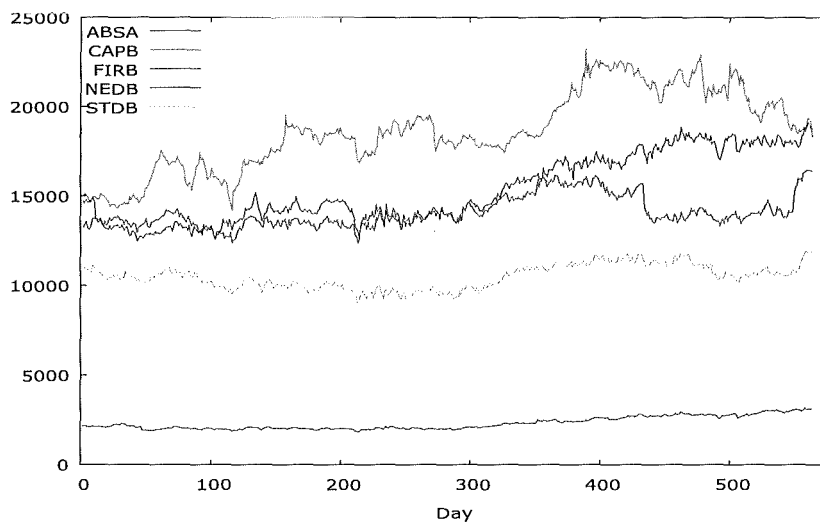


Figure 4.1: Graphical Representation of the Five Closing Stock Prices

A visual examination of the plot reveals different kinds of patterns as which are also explained by the descriptive statistics. FIRB has the lowest stock prices and is estimated by an upward sloping trend. Stock prices of other banks are explained by irregular increasing patterns with ABSA and NEDB showing convergence at several stages. Given this movements by the stock prices, the data is not stationary at all levels. Further empirical analysis is continued by employing the nonlinear unit root test.

4.2.2 Tests of Nonlinearity Results

Having established that all the series are normally distributed, it is equally important to investigate whether the series are independent identical distributed (*iid*) (no structural changes). Failure to reject the hypothesis that increments of stock price time series are *iid* cannot be sustained in situations of structural changes in time series. The RESET, CUSUM, ARCH and BDS tests proposed by Brock *et al.* (1996) are used. The results are presented in Appendix A. As observed from the results, the SBC selected optimal lag length 2 for ABSA and NEDB and lag 1 was chosen for CAPB, FIRB, and STDB. This information was incorporated to compute the test statistics summarised in Table 4.2.

Table 4.2: Estimated AR Models with Nonlinearity Tests

		ABSA	CAPB	FIRB	NEDB	STDB
Parameter Estimate	α_0	263.614 (1.8731) [0.0616]	197.824 (2.001) [0.0459]	2.9902 (0.3089) [0.7575]	47.3057 (0.6324) [0.5274]	182.023 (2.013) [0.0446]
	α_1	0.862676 (20.5228) [0.0000]	0.9897 (187.60) [0.0000]	0.9995 (237.80) [0.0000]	0.8596 (20.51) [0.0000]	0.9828 (114.0) [0.0000]
	α_2	0.119039 (2.8155) [0.0050]			0.1379 (3.279) [0.0011]	
RESET Test for Specification	Test Statistic	4.00483 [0.0188]	3.4352 [0.0329]	3.6984 [0.0254]	4.9172 [0.0076]	8.7728 [0.0002]
CUSUM Test for Parameter Stability	Test Statistic (Harvey-Collier)	2.58915 [0.0099]	0.6004 [0.5485]	1.7090 [0.0880]	2.6447 [0.0084]	0.2375 [0.8123]
Test for ARCH Effects	LM	3.1967 [0.07379]	71.2252 [0.0000]	3.0925 [0.0787]	5.9051 [0.0151]	12.1992 [0.0022]

Figures in (•) are t-statistics while figures in [•] are p-values

The RESET tests reveal significant results at the three significance levels, suggesting that the null hypothesis that linear least square regression analysis for the five variables is inappropriate. Using the three levels of significance, the null hypothesis that there is no ARCH structure in the residuals from the respective AR models is also rejected. Based on these findings, it has been proved, statistically, that there is some nonlinear behaviour in all the five variables, hence the use of nonlinear modelling and forecasting methods. The three test statistics are significant at the three significance levels providing evidence that the parameters of the models cannot be estimated linearly. Though nonlinear at the 10%

significance level, the ARCH test corresponding to ABSA and FIRB is not significant at small significance levels.

Table 4.3: BDS Tests of Independence

Variable	Dimension	BDS Statistic	z-Statistic	Prob.
ABSA	2	0.178630	52.27131	0.0000
	3	0.303560	55.98916	0.0000
	4	0.388503	60.28004	0.0000
	5	0.445491	66.43633	0.0000
	6	0.482768	74.78954	0.0000
CAPB	2	0.185976	82.93639	0.0000
	3	0.316507	89.49905	0.0000
	4	0.405443	97.06684	0.0000
	5	0.464713	107.6417	0.0000
	6	0.503433	121.9538	0.0000
FIRB	2	0.193361	76.47148	0.0000
	3	0.328641	82.09922	0.0000
	4	0.423591	89.24088	0.0000
	5	0.489871	99.45601	0.0000
	6	0.535997	113.3531	0.0000
NEDB	2	0.188697	94.53704	0.0000
	3	0.321515	102.2553	0.0000
	4	0.414213	111.6740	0.0000
	5	0.478582	124.9957	0.0000
	6	0.523133	143.0782	0.0000
STDB	2	0.170253	89.35494	0.0000
	3	0.288450	95.71337	0.0000
	4	0.369022	103.3819	0.0000
	5	0.422702	114.2590	0.0000
	6	0.457039	128.8516	0.0000

Table 4.3 above reports the BDS test results. Based on the results, the BDS statistics reject the null hypothesis of no structural change at the 1%, 5% and 10% levels of significance. Furthermore, the results suggest that the variables are nonlinear according to the LM test. The associated p-values are greater than the 1%, 5% and 10% significance levels.

4.2.3 Nonlinear Unit Root Test Result

As a starting point for the KSS-NLADF, various regression analyses were conducted to examine whether the raw (zero-mean), de-meaned (single-mean) or de-trended data be used in conducting the KSS-NLADF test. The results, reported in Appendix B and C, show the intercept term, c , and trend variable, t , being significant at the 5% level for all five variables, thus suggesting that de-trended variables be used in the KSS-NLADF unit root tests. Upon using the SBC for selection of the optimal lags associated with closing stock for the five banks, the KSS NLADF unit root test was computed and Table 4.4 gives summary results of this test. At the 0.05 level, the null hypothesis of a nonlinear unit root in ABSA, CAPB, FIRB and NEDB is rejected since the KSS test statistics are all greater than the critical values of -3.13, -3.40 and -3.93 at 1%, 5% and 10% significance levels, respectively. This means that ABSA, CAPB, FIRB and NEDB exhibit asymmetric and nonlinear stationarity. The results, however, indicate that the null hypothesis of nonlinear unit root in STDB cannot be rejected, indicating that STDB has a unit root.

Table 4.4: KSS Nonlinear Unit Root Test

Bank	Optimal Lag, P	Estimate	Std. Err	t-Value	p-Value	KSS
ABSA	1	-.000000020	7.487E-9	-2.68	0.0077	-2.67664
CAPB	2	-.000000005	1.9813E-9	-2.70	0.0071	-2.70126
FIRB	3	-.000000206	8.7758E-8	-2.35	0.0193	-2.34622
NEDB	1	-.000000015	4.3729E-9	-3.32	0.0010	-3.32274
STDB	0	-.000000060	1.2588E-8	-4.77	0.0001	-4.76565

Critical values of the KSS-NLADF test with constant and trend at the 10%, 5% and 1% significant levels are -3.13, -3.40 and -3.93, respectively.

Table 4.5: Bierens Nonlinear Unit Root Test Results

Bank	m	t-Test		Am		F-Test	
		Statistic	5% Critical Value	Statistic	5% Critical Value	Statistic	5% Critical Value
ABSA	2	-2.8556	-3.97	-20.6715	-27.2	3.1916	1.08
	5	-4.4372	-5.16	-43.3766	-48.7	4.0562	1.83
	10	-6.8818	-6.67	-89.6121	-80.3	4.8848	2.15
	15	-7.3307	-7.89	-103.0385	-112.4	3.9183	2.36
	20	-8.6817	-9.00	-137.5241	-145.7	4.0834	2.52
CAPB	2	-2.2387	-3.97	-12.6037	-27.2	2.2546	1.08
	5	-4.1939	-5.16	-33.9801	-48.7	3.6163	1.83
	10	-4.4909	-6.67	-41.3511	-80.3	2.5293	2.15
	15	-7.2159	-7.89	-97.3750	-112.4	4.1744	2.36
	20	-7.4247	-9.00	-104.5964	-145.7	3.3754	2.52
FIRB	2	-2.6593	-3.97	-12.7934	-27.2	2.9569	1.08
	5	-5.2442	-5.16	-54.5963	-48.7	4.9939	1.83
	10	-6.2399	-6.67	75.2555	-80.3	3.8577	2.15
	15	-7.4658	-7.89	-104.1044	-112.4	3.7836	2.36
	20	-7.8911	-9.00	-113.3282	-145.7	3.3911	2.52
NEDB	2	-4.2306	-3.97	-30.0178	-27.2	6.3504	1.08
	5	-6.0093	-5.16	-67.1012	-48.7	79.0804	1.83
	10	-7.4250	-6.67	-103.2396	-80.3	5.5080	2.15
	15	-8.4151	-7.89	-130.5011	-112.4	4.5205	2.36
	20	-9.3462	-9.00	-158.2898	-145.7	4.5205	2.52
STDB	2	-3.0172	-3.97	-19.7936	-27.2	3.4409	1.08
	5	-5.0136	-5.16	-54.3884	-48.7	5.0826	1.83
	10	-6.2232	-6.67	-75.9670	-80.3	4.1588	2.15
	15	-7.0899	-7.89	-97.6555	-112.4	3.6429	2.36
	20	-8.4819	-9.00	-135.2659	-145.7	3.9220	2.52

Table 4.5 presents the results of the B-NLADF unit root tests for various Chebyshev polynomial orders. The optimal lag length for each variable was chosen using the SBC while the test statistics were obtained using based on 2000 replications of a Gaussian AR (m) process. The results show that null hypothesis of nonlinear unit root cannot be rejected at the conventional level of 0.05 for all the five variables. The t-test, Am and F test statistics are all greater than their corresponding critical values. In conclusion, all five variables are non-stationary at levels.

4.3 Model Estimation and Diagnostic Results

This section provides the results of the STR, TAR and MS-AR models according to the methodology in Chapter 3.

4.3.1 Smooth Transition Regression Analysis

This section provides the results for the STR modelling technique. Also shown are the forecasts of the model for the five variables. As a starting point, AR models up to lag five (5) were estimated with each of the five variables in order to determine the appropriate lag order, p , for the estimation of the STR models. Appendix D displays the results from SBC.

Table 4.6: Linearity Test and Model Suggestions

Dependent variable	Variables in AR Part	Variable	F	F4	F3	F2	Model Suggested
ABSA(t)	CONST	ABSA(t-1)*	0.0007339	0.008896	0.01972	0.03130	LSTR1
	ABSA(t-1)	TREND	0.0343700	0.459430	0.47523	0.00501	LSTR1
CAPB(t)	CONST	CAPB(t-1)*	0.0022413	0.0142900	0.01856	0.25802	LSTR1
	CAPB(t-1)	TREND	0.0172160	0.0054638	0.09258	0.34243	LSTR1
FIRB(t)	CONST	FIRB(t-1)*	0.0072062	0.03012	0.00696	0.80962	LSTR1
	FIRB(t-1)	TREND	0.0000774	0.993850	0.00011	0.00574	LSTR1
NEDB(t)	CONST	NEDB(t-1)*	0.0210190	- 0.2238e-	0.00045	0.87273	LSTR1
	NEDB(t-1)	TREND	0.00000461	02	0.01945	0.00011	LSTR1
STDB(t)	CONST	STDB(t-1)*	0.0000000	0.0000000	0.00006	0.31605	LSTR1
	STDB(t-1)	TREND	0.0205700	0.0270450	0.27182	0.07704	LSTR1

F-statistics of null hypotheses, H_{04} , H_{03} , H_{02} are F4, F3, F2, respectively

Having identified the optimal lag orders to be used as endogenous variables in STR model estimations, tests of linearity against the alternative hypotheses of nonlinearity were performed and the results summarized in Table 4.6. From the results, the null hypothesis of linearity is rejected in favour of the alternative hypothesis of nonlinearity for each of the five variables. This is due to the p-values of the F statistics which are all less than 5% level of significance. In addition, at the optimal lag length of 1, the p-values of the F4, F3 and F2 test statistics suggest the LSTR1 model type with trend as the transition variable. Therefore, the closing stock price of the five biggest banks in South Africa can be modelled via LSTR1 with nonlinear dynamic processes governed by their respective first lags. Once the suggested STR models have been specified, the nonlinear least squares (NLS) method was used to estimate models and the results are summarised in Table 4.7.

Table 4.7: Estimated LSTR Models

Dep. Var.	Variable	Estimate	t-Stat	p-Value	R-Square	Adj. R-Square
ABSA(t)	----- Linear Part -----				0.94704	0.9471
	CONST	1407.01652	4.4602	0.0000		
	ABSA(t-1)	0.89731	38.7516	0.0000		
	---- Nonlinear Part ----					
	ABSA(t-1)	0.01213	3.8226	0.0001		
	Gamma	14.19718	0.7681	0.4427		
C1	14598.19084	138.9240	0.0000			
CAPB(t)	----- Linear Part -----				0.98467	0.9847
	CONST	244.32152	2.3887	0.0172		
	CAPB(t-1)	0.98762	177.9250	0.0000		
	---- Nonlinear Part ----					
	CONST	-244.32152	-2.3887	0.0172		
	Gamma	17.97761	1.2362	0.2169		
C1	22476.78769	94.3540	0.0000			
FIRB(t)	----- Linear Part -----				0.99051	0.9905
	CONST	239.56090	3.8898	0.0001		
	FIRB(t-1)	0.87937	28.3434	0.0000		
	---- Nonlinear Part ----					
	CONST	-206.50774	-3.1367	0.0018		
	FIRB(t-1)	0.10941	3.3907	0.0007		
Gamma	800.73372	0.1317	0.8953			
C1	2132.44609	347.5154	0.0000			
NEDB(t)	----- Linear Part -----				0.98693	0.9870
	NEDB(t-1)	1.00023	1121.5372	0.0000		
	---- Nonlinear Part ----					
	CONST	813.8	2.2596	0.0242		
	NEDB(t-1)	-0.0	-2.246	0.0251		
	Gamma	14.1	0.756	0.4498		
C1	15526.9	30.4711	0.0000			
STDB(t)	----- Linear Part -----				0.96003	0.9601
	CONST	268.61160	1.8589	0.0636		
	STDB(t-1)	0.99933	95.3909	0.0000		
	---- Nonlinear Part ----					
	CONST	-266.0	-2.2890	0.0225		
	Gamma	7.2	1.9281	0.0544		
C1	9284.20	98.9096	0.0000			

Once the suggested STR models have been specified, the nonlinear least squares (NLS) method was used to estimate them and the results are summarised in Table 4.7. As revealed by the results, all five variables have been found to be autoregressive processes since their

lags are significant in both the linear and nonlinear parts. Time series plots of the linear and nonlinear parts of the LSTR1 models are displayed in Appendix E. By observation the estimated models seem good judging from the high R^2 and R^2_{adj} values. Again, the transition values (C1), for ABSA, CAPB, NEDB, and STDB suggest that closing stock price of these banks switch between two regimes. In fact, a closing stock price less than transition values 14598.19 for ABSA, 22476.79 for CAPB, 2132.45 for FIRB, 15526.88 for NEDB, and 9284.20 for STDB are regarded as low stock yield periods for these banks. Closing stock price larger than these values implies even higher stock prices. From the results in Table 4.7, the LSTR1 models estimated for ABSA, CAPB, FIRB, NEDB and STDB, by nonlinear least square are as follows:

$$ABSA_t = 1407.0165 + 0.8973 * ABSA_{t-1} + (0.0121 * ABSA_{t-1}) * \left[\frac{1}{1 + \exp\{-14.1972 * (ABSA_{t-1} - 14598.1908)\}} \right]$$

$$CAPB_t = 244.3215 + 0.9876 * CAPB_{t-1} - 244.3215 * \left[\frac{1}{1 + \exp\{-17.9776 * (CAPB_{t-1} - 22476.7877)\}} \right]$$

$$FIRB_t = 239.5609 + 0.8794 * FIRB_{t-1} + (-206.5077 + 0.1094 * FIRB_{t-1}) * \left[\frac{1}{1 + \exp\{-800.7337 * (FIRB_{t-1} - 2132.4461)\}} \right]$$

$$NEDB_t = 1.0002 + (813.7908 - 0.0462 * NEDB_{t-1}) * \left[\frac{1}{1 + \exp\{-14.1209 * (NEDB_{t-1} - 15526.8778)\}} \right]$$

$$STDB_t = 268.6116 + 0.9993 * STDB_{t-1} - 266.0423 * \left[\frac{1}{1 + \exp\{-7.2914 * (STDB_{t-1} - 9284.1958)\}} \right]$$

Appendix F depicts the transition functions of the LSTR models for the closing stock prices over time, revealing high stock yield periods for the five banks. Appendix F particularly reveals ABSA recording high stock yields during the second and third day of September 2011, the second day of December 2011, the first half of 2012, the second day of November 2012, and the last three days of December 2012. As regards Capitec Bank, the bank recorded high stock yields during the third day of April 2012 and the third day of June 2012, during the third day of August 2012 and the last day of August 2012, and on the single day 28 September 2012. First Rand Bank, on the other hand, recorded two stock yield periods during the first and second days of November 2010 and during the whole year 2012. Nedbank

recorded high stock yields during the second day of January 2012 to the last day of December 2012. Standard Bank recorded high yields from the first day of October 2010 to the last day of August 2011 and throughout almost the whole year 2012.

Appendix F also displays the plots of the Logistic Transition Functions (LTF) with 1 Location parameter (LTF1), which is the plot of transition function against transition variable for the five stock prices. In particular, when the transition variable for ABSA is less (higher) than 14598.1094, and thus the transition function is less (higher) than 0.5, ABSA stock closes in low-yield (high-yield) regime. Similar, when the transition variables for CAPB, FIRB, NEDB and STDB are, respectively, less (higher) than 22476.78769, 2132.44609, 15526.87781 and 9284.19582, and thus the respective transition functions are less (higher) than 0.5, CAPB, FIRB, NEDB and STDB stocks, respectively, close in low-yield (high-yield) regimes.

Table 4.8: Test of No Error Auto-correlation

LSTR Model	Lag	F-Value	df1	df2	p-Value
ABSA	1	4.6760	1	555	0.0310
	2	2.4112	2	553	0.0907
	3	1.6351	3	551	0.1802
	4	1.1997	4	549	0.3099
	5	1.0443	5	547	0.3907
CAPB	1	0.2244	1	556	0.6359
	2	1.8534	2	554	0.1577
	3	2.1050	3	552	0.0985
	4	1.5771	4	550	0.1789
	5	1.3294	5	548	0.2501
FIRB	1	0.0790	1	554	0.7787
	2	1.5033	2	552	0.2233
	3	2.5754	3	550	0.0531
	4	2.2432	4	548	0.0632
	5	1.7809	5	546	0.1149
NEDB	1	8.3502	1	555	0.0140
	2	5.2707	2	553	0.0154
	3	4.1135	3	551	0.0167
	4	3.0820	4	549	0.0158
	5	2.5393	5	547	0.0276
STDB	1	2.9260	1	555	0.0877
	2	3.2175	2	553	0.0408
	3	2.4330	3	551	0.0641
	4	1.8546	4	549	0.1170
	5	1.4715	5	547	0.1973

Having estimated the nonlinear LSTR models for the five closing stock prices, diagnostic tests were conducted to evaluate their appropriateness. The test results summarised in Table 4.8 show that the residuals from all the five LSTR models are not autocorrelated (since the p-values of the F-statistics are all greater than 1%). In addition, the Durbin-Watson and Breusch-Godfrey tests of the residuals from the LSTR models reported in Table 4.9 reveal that p-values are greater than the 1%, 5% or 10% conventional levels, supporting the claim that the residuals are not autocorrelated.

Table 4.9: Durbin-Watson and Breusch-Godfrey test Residual from LSTR Models

Residual Variable	Autocorrelation Tests of Residuals						
	Durbin-Watson Test				Breusch-Godfrey Test		
	Order	DW	Pr < DW	Pr > DW	Alternative	LM	Pr > LM
ABSA	1	2.1702	0.9784	0.0216	AR(1)	4.0879	0.0432
	2	1.9926	0.4817	0.5183	AR(2)	4.0974	0.1289
	3	1.9658	0.3740	0.6260	AR(3)	4.2426	0.2364
	4	1.9482	0.3131	0.6869	AR(4)	4.5967	0.3312
	5	1.9478	0.3265	0.6735	AR(5)	4.9689	0.4197
CAPB	1	1.9942	0.4725	0.5275	AR(1)	0.0230	0.8795
	2	1.8073	0.0123	0.9877	AR(2)	4.3505	0.1136
	3	2.1215	0.9366	0.0634	AR(3)	7.1169	0.0683
	4	1.9824	0.4674	0.5326	AR(4)	7.1744	0.1270
	5	1.9415	0.3000	0.7000	AR(5)	7.5866	0.1805
FIRB	1	2.0236	0.6100	0.3900	AR(1)	0.0829	0.7734
	2	2.1386	0.9542	0.0458	AR(2)	2.8769	0.2373
	3	2.1593	0.9759	0.0241	AR(3)	6.8041	0.0784
	4	1.8682	0.0753	0.9247	AR(4)	8.5970	0.0720
	5	1.9530	0.3490	0.6510	AR(5)	8.6364	0.1245
NEDB	1	2.0171	0.5801	0.4199	AR(1)	2.6238	0.1053
	2	2.1471	0.9632	0.0368	AR(2)	4.4045	0.1106
	3	2.0884	0.8715	0.1285	AR(3)	4.4047	0.2209
	4	1.9750	0.4328	0.5672	AR(4)	4.8952	0.2982
	5	2.0549	0.7939	0.2061	AR(5)	6.9184	0.2268
STDB	1	2.1364	0.9473	0.0527	AR(1)	2.6186	0.1056
	2	2.1281	0.9410	0.0590	AR(2)	5.3803	0.0679
	3	1.8763	0.0832	0.9168	AR(3)	6.7759	0.0794
	4	1.9591	0.3602	0.6398	AR(4)	7.0012	0.1358
	5	2.0163	0.6414	0.3586	AR(5)	7.0034	0.2204

Furthermore, the histograms of the residuals from the LSTR models displayed in Appendix G are roughly symmetrical, suggesting that the five residuals follow a normal distribution. Lastly, the plots of the residuals from the LSTR models against time also supported in Appendix G reveal points roughly evenly distributed around the horizontal line, suggesting that the residuals have constant variance. At the 1% level of significance, the parameter

consistency test results in Table 4.10 fail to reject the null hypothesis that the parameters in the estimated LSTR models are constant since the p-values of the F-statistics are all greater than 0.01.

Table 4.10: Parameter Constancy Test

Dependent Variable	Transition				
	Function	F-value	df ₁	df ₂	p-Value
ABSA	H1	4.4875	3.0000	552.0000	0.0140
	H2	2.7519	6.0000	549.0000	0.0121
	H3	4.7828	9.0000	546.0000	0.0101
CAPB	H1	4.5697	3.0000	552.0000	0.0136
	H2	5.1352	6.0000	549.0000	0.0107
	H3	5.0077	9.0000	546.0000	0.0109
FIRB	H1	2.9711	4.0000	550.0000	0.0191
	H2	3.0994	8.0000	546.0000	0.0120
	H3	2.5749	12.0000	542.0000	0.0125
NEDB	H1	11.8379	3.0000	552.0000	0.0110
	H2	7.5028	6.0000	549.0000	0.0105
	H3	5.4845	9.0000	546.0000	0.0103
STDB	H1	0.8115	3.0000	552.0000	0.4878
	H2	1.5186	6.0000	549.0000	0.1697
	H3	1.9846	9.0000	546.0000	0.0390

Lastly, the results from the tests of no remaining nonlinearity reported in Table 4.11 show that the null hypothesis of no remaining nonlinearity (in all the five estimated LSTR models), H_{04} , cannot be rejected since the F-statistics, F_4 , are all greater than 0.10. The estimated LSTR models appear to predict very well the actual closing stock prices judging from the overlay plots of the actual series and estimated LSTR models in Appendix H.

Table 4.11: Test of No Remaining Nonlinearity

Dependent Variable	Transition				
	Variable	F	F4	F3	F2
ABSA	ABSA(t-1)	0.90441	0.48557	0.91977	0.79473
CAPB	CAPB(t-1)	0.25915	0.43220	0.28495	0.13239
FIRB	FIRB(t-1)	0.88020	0.93597	0.42488	0.86961
NEDB	NEDB(t-1)	0.69127	0.55794	0.19111	0.66476
STDB	STDB(t-1)	0.14612	0.41011	0.71324	0.32509

F-statistics of null hypotheses, H_{04} , H_{03} , H_{02} are F_4 , F_3 , F_2 , respectively

4.3.2 Threshold Autoregressive Models for Closing Stock Price

Table 4.12: Bai-Perron Multiple Breakpoint Tests

Variable	Breaks	Estimated break dates	SBC
ABSA	0	*	13.54859
	1	294	12.94868
	2	317, 434	12.51355
	3	227, 321, 434	12.40560
	4	85, 227, 321, 434	12.38961
	5	85, 169, 256, 341, 434	12.45489
CAPB	0	*	15.39653
	1	361	14.41423
	2	140, 364	13.67083
	3	140, 369, 480	13.44908
	4	124, 229, 373, 480	13.44289
	5	124, 208, 292, 376, 480	13.51731
FIRB	0	*	11.80542
	1	352	10.06853
	2	325, 420	9.323394
	3	311, 395, 479	9.275323
	4	85, 311, 395, 479	9.244522
	5	85, 227, 311, 395, 479	9.251088
NEDB	0	*	15.13099
	1	334	13.24736
	2	324, 422	12.72723
	3	125, 325, 422	12.37323
	4	125, 209, 325, 422	12.33640
	5	125, 209, 312, 396, 480	12.56978
STDB	0	*	13.01153
	1	327	12.13189
	2	101, 326	11.67100
	3	101, 326, 480	11.50525
	4	93, 205, 326, 480	11.40993
	5	93, 205, 312, 396, 480	11.46288

As indicated in Chapter 3, switches between one regime and another depend on a threshold variable and threshold value. As discussed in Chapter 3, this study follows the Hsu *et al.* (2010) structural break concept in selecting the thresholds. In particular, assuming that the numbers thresholds are unknown, the Bai-Perron multiple breakpoint method was applied. Table 4.12 presents the Bai-Perron multiple breakpoint test results. From these results, the SBC selects the optimal breakpoint of 4 for all the five variables, suggesting that each variable can be represented by five (5) regimes. Plots of the estimated Bai-Perron models depicting the five regimes are displayed in Appendix I and the QQ-plots of the respective

residuals. As also shown in Table 4.13, the selected breakpoints for each of the five variables are all significant at the 1% significance level according to the observed probabilities.

Table 4.13: Tests of Significance of Breakpoints

Variable	Regime	Range	N	Variable	Estimate	t-Statistic	p-Value
ABSA	1	1 - 84	84	C	13604.43	136.0729	0.0000
	2	85 - 226	142	C	13302.07	140.2041	0.0000
	3	227 - 320	94	C	13932.65	191.7661	0.0000
	4	321 - 433	113	C	15394.75	109.2226	0.0000
	5	434 - 563	130	C	14170.06	227.8273	0.0000
CAPB	1	1 - 123	123	C	15631.84	44.15701	0.0000
	2	124 - 228	105	C	17891.78	68.92769	0.0000
	3	229 - 372	144	C	18487.52	143.6898	0.0000
	4	373 - 479	107	C	21688.14	108.9249	0.0000
	5	480 - 563	84	C	20146.56	44.39768	0.0000
FIRB	1	1 - 84	84	C	2041.976	55.22180	0.0000
	2	85 - 310	226	C	1971.880	199.1651	0.0000
	3	311 - 394	84	C	2320.373	48.99916	0.0000
	4	395 - 478	84	C	2684.783	61.66100	0.0000
	5	479 - 563	85	C	2865.329	44.54210	0.0000
NEDB	1	1 - 124	124	C	13269.96	80.32833	0.0000
	2	125 - 208	84	C	14353.71	226.9175	0.0000
	3	209 - 324	116	C	13960.73	98.30849	0.0000
	4	325 - 421	97	C	16470.11	72.54039	0.0000
	5	422 - 563	142	C	17999.34	198.1990	0.0000
STDB	1	1 - 92	92	C	10584.35	2049.757	0.0000
	2	93 - 204	112	C	9988.739	1355.522	0.0000
	3	205 - 325	121	C	9657.092	311.1253	0.0000
	4	326 - 479	154	C	11229.57	186.2747	0.0000
	5	480 - 563	84	C	10785.71	240.3055	0.0000

This section focuses on estimating TAR models on the basis that each stock price is a linear AR within a regime of that particular variable. First, for each regime of a particular variable, an AR model was run by allowing maximum five (5) lags and their respective SBC reported in Appendix J. With ABSA and STDB, the SBC selects an optimal lag length one (1) for all five (5) regimes while the SBC selects lag length 1 for Segment 1, 2, 3 and 5, and lag length 3 for Segment 4. Regarding FIRB, the SBC selects lag length 1 for Segments 1, 2, 4 and 5, and lag 5 for Segment 3. In the case of NEDB, the SBC selects lag length 1 for Segments 1, 3 and 5, and lag 3 for Segments 2 and 4. Using these optimal lag lengths, the AR models were estimated for each segment of each of the five variables. At the 5% level, the final estimated AR models were obtained by eliminating the insignificant lags (Table 4.14). The final estimated TAR models are reported in Table 4.16. As observed from these results, all AR

lags are significant at the 1%, 5% or 10% levels. From the histogram and QQ-plot shown in Appendix K, the residuals from the various TAR models are normally distributed. Furthermore, the plots of the residuals against time reported in Appendix L suggest that the residuals from the estimated TAR models have constant variances.

Table 4.14: Estimated AR Models for Various Regimes

Dep. Var.	Regime	Obs. Used	Indept. Var.	Estimate	t-Stats	p-Value
ABSA	1	84	c ABSA_1	2372.968 0.825795	2.862639 13.55567	0.0053 0.0000
	2	42	c ABSA_1	2361.677 0.822431	3.677453 17.04073	0.0003 0.0000
	3	94	c ABSA_1	3362.194 0.759203	3.416943 10.75278	0.0009 0.0000
	4	113	c ABSA_1	1727.536 0.888305	2.687830 21.28440	0.0083 0.0000
	5	130	ABSA_1	1.001126	845.8643	0.0000
CAPB	1	1-123	CAPB_1	1.000359	786.0314	0.0000
	2	124-228	c CAPB_1	1091.422 0.939456	1.952541 30.09464	0.0536 0.0000
	3	229-372	CAPB_1	1.000429	1187.378	0.0000
	4	373-479	c CAPB_1 CAPB_2 CAPB_3	3348.876 0.712308 0.372501 -0.238626	3.139218 7.024210 3.198823 -2.358417	0.0022 0.0000 0.0018 0.0203
	5	480-563	CAPB_1	0.998432	516.4120	0.0000
FIRB	1	1-84	FIRB_1	0.998951	517.1496	0.0000
	2	85-310	c FIRB_1	356.0919 0.819699	4.598306 20.88000	0.0000 0.0000
	3	311-394	FIRB_1	1.002070	610.7966	0.0000
	4	395-478	FIRB_1	1.000966	655.1065	0.0000
	5	479-563	FIRB_1	1.001150	590.6781	0.0000
NEDB	1	1-124	c NEDB_1	1247.460 0.905337	2.988265 28.80007	0.0034 0.0000
	2	125-208	c NEDB_1 NEDB_3	3616.177 0.987213 -0.238960	3.934625 13.27187 -3.229563	0.0002 0.0000 0.0018
	3	209-324	c NEDB_1	1674.865 0.880819	2.390493 17.56034	0.0185 0.0000
	4	325-421	NEDB_1 NEDB_3	0.690000 0.311491	8.645537 3.895387	0.0000 0.0002
	5	422-563	c NEDB_1	3044.447 0.831404	3.558600 17.49098	0.0005 0.0000
STDB	1	1-92	c STDB_1	1485.843 0.859032	2.587903 15.83980	0.0113 0.0000
	2	93-204	c STDB_1	1483.653 0.851225	2.952541 16.92481	0.0039 0.0000
	3	205-325	c STDB_1	1747.010 0.819622	3.160950 14.32614	0.0020 0.0000
	4	326-479	c STDB_1	1296.731 0.884897	3.322421 25.46883	0.0011 0.0000
	5	480-563	STDB_1	1.001027	728.1717	0.0000

Table 4.15: Durbin-Watson and Breusch-Godfrey Tests of Residuals from TAR Models

Autocorrelation Tests of Residuals							
Residual Variable	Durbin-Watson Test				Breusch-Godfrey Test		
	Order	DW	Pr < DW	Pr > DW	Alternative	LM	Pr > LM
ABSA	1	2.1082	0.9005	0.0995	AR(1)	1.6564	0.1981
	2	1.9490	0.2869	0.7131	AR(2)	1.9327	0.3805
	3	1.9514	0.3113	0.6887	AR(3)	2.3216	0.5084
	4	1.9390	0.2756	0.7244	AR(4)	2.8054	0.5909
	5	1.9514	0.3421	0.6579	AR(5)	3.0804	0.6876
CAPB	1	1.8981	0.1136	0.8864	AR(1)	1.0117	0.3145
	2	1.9542	0.3088	0.6912	AR(2)	1.0953	0.5783
	3	2.0920	0.8800	0.1200	AR(3)	2.9127	0.4053
	4	2.0543	0.7792	0.2208	AR(4)	3.5436	0.4713
	5	1.9588	0.3752	0.6248	AR(5)	3.6014	0.6081
FIRB	1	2.0219	0.6027	0.3973	AR(1)	0.0684	0.7937
	2	2.1443	0.9605	0.0395	AR(2)	3.0335	0.2194
	3	2.1626	0.9781	0.0219	AR(3)	7.0232	0.0712
	4	1.8579	0.0594	0.9406	AR(4)	9.1788	0.0568
	5	1.9368	0.2809	0.7191	AR(5)	9.3263	0.0967
NEDB	1	2.1374	0.9482	0.0518	AR(1)	2.7399	0.0979
	2	1.9907	0.4730	0.5270	AR(2)	2.7412	0.2540
	3	2.0454	0.7332	0.2668	AR(3)	3.0955	0.3771
	4	1.9112	0.1776	0.8224	AR(4)	3.7921	0.4349
	5	2.0100	0.6131	0.3869	AR(5)	3.8260	0.5747
STDB	1	2.0716	0.8021	0.1979	AR(1)	0.7317	0.3923
	2	2.0704	0.8100	0.1900	AR(2)	1.5746	0.4551
	3	1.8522	0.0475	0.9525	AR(3)	4.1620	0.2445
	4	1.9150	0.1891	0.8109	AR(4)	5.1518	0.2721
	5	2.0070	0.5997	0.4003	AR(5)	5.1518	0.3976

The Durbin-Watson and Breusch-Godfrey values of the residuals from the estimated TAR models reported in Table 4.15 show that the p-values are all greater than the 1%, 5% or 10% levels, suggesting the residuals are not autocorrelated. Appendix L also displays the overlay plots of the five actual stock price series and their predicted series. A visual examination of the overlay plots in Appendix L suggests the estimated TAR models are reasonable.

Table 4.16: Estimated TAR Models

MODEL 1

Dependent Variable: ABSA

$$\text{ABSA} = \text{I1} * (\text{C}(1) + \text{C}(2) * \text{ABSA_1}) + \text{I2} * (\text{C}(3) + \text{C}(4) * \text{ABSA_1}) + \text{I3} * (\text{C}(5) + \text{C}(6) * \text{ABSA_1}) + \text{I4} * (\text{C}(7) + \text{C}(8) * \text{ABSA_1}) + \text{I5} * (\text{C}(9) * \text{ABSA_1})$$

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	2372.968	1048.480	2.263247	0.0240
C(2)	0.825795	0.077052	10.71732	0.0000
C(3)	2386.699	650.5343	3.668829	0.0003
C(4)	0.820463	0.048884	16.78401	0.0000
C(5)	3733.219	874.7009	4.267995	0.0000
C(6)	0.732856	0.062796	11.67038	0.0000
C(7)	1840.186	692.9351	2.655640	0.0081
C(8)	0.881074	0.045018	19.57142	0.0000
C(9)	1.000339	0.001225	816.4269	0.0000
R-squared	0.948991	Schwarz criterion		13.50103
Adjusted R-squared	0.948254	Durbin-Watson stat		2.108242

MODEL 2

Dependent Variable: CAPB

$$\text{CAPB} = \text{I1} * (\text{C}(1) * \text{CAPB_1}) + \text{I2} * (\text{C}(2) + \text{C}(3) * \text{CAPB_1}) + \text{I3} * (\text{C}(4) * \text{CAPB_1}) + \text{I4} * (\text{C}(5) + \text{C}(6) * \text{CAPB_1} + \text{C}(7) * \text{CAPB}(-2) + \text{C}(8) * \text{CAPB}(-3)) + \text{I5} * (\text{C}(9) * \text{CAPB_1})$$

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1.000446	0.001563	640.0509	0.0000
C(2)	1441.481	636.0464	2.266315	0.0238
C(3)	0.920211	0.035552	25.88318	0.0000
C(4)	1.000821	0.001209	827.7597	0.0000
C(5)	2983.457	824.0883	3.620313	0.0003
C(6)	0.716250	0.084546	8.471738	0.0000
C(7)	0.374637	0.097122	3.857384	0.0001
C(8)	-0.228059	0.084111	-2.711422	0.0069
C(9)	0.997983	0.001449	688.9222	0.0000
R-squared	0.985124	Schwarz criterion		14.10767
Adjusted R-squared	0.984908	Durbin-Watson stat		1.898038

MODEL 3

Dependent Variable: FIRB

$$\text{FIRB} = \text{I1} * (\text{C}(1) * \text{FIRB_1}) + \text{I2} * (\text{C}(2) + \text{C}(3) * \text{FIRB_1}) + \text{I3} * (\text{C}(4) * \text{FIRB_1}) + \text{I4} * (\text{C}(5) * \text{FIRB_1}) + \text{I5} * (\text{C}(6) * \text{FIRB_1})$$

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	0.998951	0.001915	521.5750	0.0000
C(2)	355.5556	87.66296	4.055939	0.0001
C(3)	0.819949	0.044442	18.44991	0.0000
C(4)	1.002188	0.001678	597.3176	0.0000
C(5)	1.001118	0.001450	690.4768	0.0000
C(6)	1.001137	0.001350	741.3204	0.0000
R-squared	0.990508	Schwarz criterion		10.04377
Adjusted R-squared	0.990422	Durbin-Watson stat		2.021898

Table 4.16 continued: Estimated TAR Models

MODEL 4

Dependent Variable: NEDB

$$\text{NEDB} = I_1 * (C(1) + C(2) * \text{NEDB}_{-1}) + I_2 * (C(3) + C(4) * \text{NEDB}_{-1} + (5) * \text{NEDB}(-3)) + I_3 * (C(6) + C(7) * \text{NEDB}_{-1}) + I_4 * (C(8) * \text{NEDB}_{-1} + C(9) * \text{NEDB}(-3)) + I_5 * (C(10) + C(11) * \text{NEDB}_{-1})$$

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1414.938	1354.395	1.044701	0.2966
C(2)	0.892528	0.102173	8.735495	0.0000
C(3)	-20560.01	2762.216	-7.443303	0.0000
C(4)	-2.562839	0.192509	-13.31283	0.0000
C(6)	1726.918	1550.095	1.114073	0.2657
C(7)	0.876889	0.110954	7.903171	0.0000
C(8)	0.717100	0.191316	3.748249	0.0002
C(9)	0.284765	0.191779	1.484858	0.1382
C(10)	3017.190	1984.132	1.520660	0.1289
C(11)	0.832901	0.110275	7.552972	0.0000
R-squared	0.921947	Schwarz criterion		15.52496
Adjusted R-squared	0.920670	Durbin-Watson stat		0.791968

MODEL 5

Dependent Variable: STDB

$$\text{STDB} = I_1 * (C(1) + C(2) * \text{STDB}_{-1}) + I_2 * (C(3) + C(4) * \text{STDB}_{-1}) + I_3 * (C(5) + C(6) * \text{STDB}_{-1}) + I_4 * (C(7) + C(8) * \text{STDB}_{-1}) + I_5 * (C(9) * \text{STDB}_{-1})$$

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1485.843	643.2156	2.310023	0.0213
C(2)	0.859032	0.060756	14.13897	0.0000
C(3)	1557.045	564.5780	2.757892	0.0060
C(4)	0.843761	0.056492	14.93596	0.0000
C(5)	1771.688	462.4663	3.830956	0.0001
C(6)	0.816977	0.047865	17.06845	0.0000
C(7)	1384.418	396.2032	3.494212	0.0005
C(8)	0.877154	0.035288	24.85710	0.0000
C(9)	1.000742	0.001336	748.8949	0.0000
R-squared	0.961252	Schwarz criterion		12.69002
Adjusted R-squared	0.960692	Durbin-Watson stat		2.071583

Based on the results in Table 4.16, the estimated TAR models for the closing stock prices,

ABSA, CAPB, FIRB, NEDB and STDB are, respectively:

$$\text{ABSA}_t = I_1 * (2372.97 + 0.8258 * \text{ABSA}_{t-1}) + I_2 * (2386.70 + 0.8205 * \text{ABSA}_{t-1}) + I_3 * (3733.22 + 0.7329 * \text{ABSA}_{t-1}) + I_4 * (1840.19 + 0.8811 * \text{ABSA}_{t-1}) + I_5 * (1.0003 * \text{ABSA}_{t-1})$$

$$\text{CAPB}_t = I_1 * (1.0005 * \text{CAPB}_{t-1}) + I_2 * (1441.48 + 0.9202 * \text{CAPB}_{t-1}) + I_3 * (1.0008 * \text{CAPB}_{t-1}) + I_4 * (2983.46 + 0.7163 * \text{CAPB}_{t-1} + 0.3746 * \text{CAPB}_{t-2} - 0.2281 * \text{CAPB}_{t-3}) + I_5 * (0.9980 * \text{CAPB}_{t-1})$$

$$\text{FIRB}_t = I_1 * (0.9990 * \text{FIRB}_{t-1}) + (355.556 + 0.8199 * \text{FIRB}_{t-1}) + I_3 * (1.0022 * \text{FIRB}_{t-1}) + I_4 * (1.00112 * \text{FIRB}_{t-1}) + I_6 * (1.00114 * \text{FIRB}_{t-1})$$

$$\begin{aligned} NEDB_t = & I_1 * (1414.94 + 0.8925 * NEDB_{t-1}) + I_2 * (3785.64 + 0.9518 * NEDB_{t-1} - 0.2153 * NEDB_{t-3}) \\ & + I_3 * (1726.92 + 0.8769 * NEDB_{t-1}) + I_4 * (0.7171 * NEDB_{t-1} + 0.2848 * NEDB_{t-3}) \\ & + I_5 * (3017.19 + 0.8329 * NEDB_{t-1}) \end{aligned}$$

$$\begin{aligned} STDB_t = & I_1 * (1485.84 + 0.8590 * STDB_{t-1}) + I_2 * (1557.05 + 0.8438 * STDB_{t-1}) + I_3 * (1771.69 + 0.8170 * STDB_{t-1}) \\ & + I_4 * (1384.42 + 0.8772 * STDB_{t-1}) + I_5 * (1.0007 * STDB_{t-1}) \end{aligned}$$

where

$$I_k = \begin{cases} 1 & \text{regime } k \\ 0 & \text{otherwise} \end{cases}$$

4.3.3 Markov-Switching AR Models for Stock Prices

First, in order to ascertain the possibility of using two-regime switching models for the variables, linearity likelihood ratio (LR) tests were conducted and the regime results reported in Table 4.17. Findings from the linearity LR results suggest that the null hypothesis of no regime switching is rejected in favour of the existence of two regimes since the p-value of the chi-square statistics for all the five variables are less than the 10%, 5% or 1% level. Therefore, the LR test results support a two-state regime for all the five variables. Similar results were reported by Ismail and Isa (2007), Psaradakis *et al.* (2009), Wasin and Bandi (2011) and Yarmohammadi *et al.* (2012).

Table 4.17: Linearity LR Test of Two-Regime Switch

Variable	Chi-Square Test Statistic	P-value
ABSA	53.794	0.0000
CAPB	100.100	0.0000
FIRB	21.788	0.0006
NEDB	11.296	0.0796
STDB	12.042	0.0610

In order to find the optimal lag length for the estimation of the univariate MS-AR (p) model, different AR models were estimated with up to five (5) and their SBC reported in Appendix M. From these results, an optimal lag length one (1) is deemed appropriate for each of the five two-regime MS-AR (p) models. Results for the estimated MS-AR (1) models are shown in Table 4.18. As observed from these results, with ABSA, CAPB and FIRB, the variances of Regime 2, $\sigma^2(s_t=2)$, is greater than the variance of Regime 1, $\sigma^2(s_t=1)$, suggesting that for these three closing stock prices, Regime 2 is more volatile than Regime 1. In other words,

Regime 2 captures the behaviours in ABSA, CAPB and FIRB in an unstable manner while Regime 1 captures the behaviours of the three stock prices in a stable manner. The opposite happens in the case of NEDB and STDB since the variances of Regime 1, $\sigma^2(s_t = 1)$, is greater than the variance of Regime 2, $\sigma^2(s_t = 2)$. It is also observed that, for ABSA, FIRB, NEDB and STDB, the estimated regime-dependent intercepts (expected daily increments in closing stock prices) are higher in Regime 1 than in Regime 2 (that is, $\mu(s_t = 1) > \mu(s_t = 2)$ for ABSA, FIRB, NEDB and STDB) while the opposite holds in the case of CAPB. In other words, changes in ABSA, FIRB, NEDB and STDB closing stock prices increased in a stable state while opposite holds for CAPB.

Table 4.18: Two-Regime MS-AR Modelling Results

	ABSA	CAPB	FIRB	NEDB	STDB
$\mu(s_t = 1)$	13749.6	17853.9	2276.56	15390.1	10507.0
$\mu(s_t = 2)$	13642.6	18761.8	2194.16	14488.6	10457.0
$\phi_1(s_t = 1)$	0.996758	1.00108	0.998810	0.994343	0.973702
$\phi_1(s_t = 2)$	0.531652	0.945820	1.259510	1.000960	1.180030
$\sigma^2(s_t = 1)$	178.457	201.356	34.4960	241.296	137.350
$\sigma^2(s_t = 2)$	241.037	331.188	116.217	190.232	18.7274
p_{11}	0.989355	0.98621	0.995928	0.995980	0.94730
p_{12}	0.061359	0.041621	0.999979	0.004151	0.69051
p_{21}	0.010645	0.013793	0.0040724	0.004019	0.052702
p_{22}	0.938640	0.958380	0.0000212	0.995850	0.309490
$E[D(s_t = 1)]$	16.2975	24.0263	1.0000	240.8884	1.4482
$E[D(s_t = 2)]$	93.9408	72.5005	245.5554	248.8181	18.9746

Furthermore, the probabilities of a closing stock price remaining in Regime 1, p_{11} , are smaller than the probability of a closing stock price staying in Regime 2, p_{22} , for all the five closing stock prices. In fact, the probabilities of a closing stock price staying in Regime 1 lie in the range of 0.947 to 0.996 with an expected duration, $E[D(s_t = 1)]$, of 1 to 241 days. Similarly, the probabilities of a stock price staying in Regime 2 lie in the range 0.000 to 0.958 with an expected duration, $E[D(s_t = 2)]$, of 19 to 249 days. In other words, closing stock prices can stay slightly longer in Regime 2 than in Regime 1. Appendix N displays the smoothed probability plots for the two-regime MS-AR models fitted to the five closing stock prices, ABSA, CAPB, FIRB, NEDB and STDB. Having a close look at the smoothed probabilities of Regime 1 and

Regime 2, it appears that there is a correlation between the two regimes. This is because when the probability of Regime 1 is close to one, the probability of Regime 2 is close to zero, and vice versa. This finding suggests that the estimated MS-AR models perform very well in getting the direction of change of a series from Regime 1 to Regime 2 or from Regime 2 to Regime 1.

Table 4.19: Durbin-Watson and Breusch-Godfrey Tests of Residuals from MS-AR Models

Autocorrelation Tests of Residuals							
Residual Variable	Durbin-Watson Test				Breusch-Godfrey Test		
	Order	DW	Pr < DW	Pr > DW	Alternative	LM	Pr > LM
ABSA	1	2.2164	0.9950	0.0050	AR(1)	6.5863	0.0103
	2	2.0236	0.6262	0.3738	AR(2)	6.9170	0.0315
	3	1.9552	0.3277	0.6723	AR(3)	7.0898	0.0691
	4	1.9656	0.3893	0.6107	AR(4)	7.2620	0.1227
	5	1.9946	0.5419	0.4581	AR(5)	7.2658	0.2016
CAPB	1	1.8644	0.0537	0.9463	AR(1)	2.4202	0.1198
	2	1.8338	0.0267	0.9733	AR(2)	5.7201	0.0573
	3	2.0462	0.7364	0.2636	AR(3)	6.4492	0.0917
	4	1.9734	0.4251	0.5749	AR(4)	6.4748	0.1664
	5	2.0071	0.6000	0.4000	AR(5)	6.4860	0.2618
FIRB	1	2.0739	0.8096	0.1904	AR(1)	0.7684	0.3807
	2	2.2016	0.9926	0.0074	AR(2)	6.6655	0.0357
	3	2.1766	0.9855	0.0145	AR(3)	12.0590	0.0072
	4	1.9171	0.1958	0.8042	AR(4)	12.2991	0.0153
	5	1.9712	0.4314	0.5686	AR(5)	12.3304	0.0305
NEDB	1	2.0216	0.6012	0.3988	AR(1)	3.7097	0.0541
	2	2.1727	0.9819	0.0181	AR(2)	5.7199	0.0573
	3	2.0847	0.8620	0.1380	AR(3)	5.7823	0.1227
	4	1.9458	0.3028	0.6972	AR(4)	5.8780	0.2084
	5	2.0223	0.6679	0.3321	AR(5)	7.2371	0.2036
STDB	1	2.1703	0.9785	0.0215	AR(1)	4.0822	0.0433
	2	2.1492	0.9652	0.0348	AR(2)	7.9635	0.0187
	3	1.9396	0.2636	0.7364	AR(3)	8.0898	0.0442
	4	1.9712	0.4151	0.5849	AR(4)	8.1527	0.0861
	5	2.0337	0.7152	0.2848	AR(5)	8.2477	0.1431

Next, the study assesses the estimated MS-AR models for the five closing stock prices – ABSA, CAPB, FIRB, NEDB and STDB by performing a number of residual analyses. The histograms of the residuals from the estimated MS-AR models displayed in Appendix K are roughly bell-shaped and the near diagonal nature of the QQ-plots suggests that the residuals are normally distributed. Results from the autocorrelation analysis of the residuals reported in

Table 4.19 show that the p-values of the Durbin-Watson and Breusch-Godfrey test statistics are greater than the 1%, 5% or 1% levels, suggesting that the residuals are not autocorrelated. The residual plots reported in Appendix O show that points are roughly evenly distributed about the horizontal line, suggesting that the estimated residuals are not autocorrelated. This finding is supported by the Portmanteau test results reported in Table 4.20 (that is, the p-values of the chi-square test statistics are greater than 1%, 5% or 10% levels).

Table 4.20: Portmanteau Test of Scaled Residuals from MASR Models

Variable	Chi-Square Statistic	p-Value
ABSA	33.701	0.0696
CAPB	33.602	0.0711
FIRB	34.233	0.0619
NEDB	27.410	0.2389
STDB	25.251	0.3375

Appendix P also displays the overlay plots of the actual series and predicted series from the various MS-AR(1) models. The estimated MS-AR(1) models appear to predict the actual series well, suggesting that the MS-AR models have performed relatively well in tracking the behaviours of the five closing stock price. Based on the smoothed probabilities of the various MS-AR(1) models, closing stock yields were classified into one of the two regimes – stable regime (Regime 1) and volatile regime (Regime 2) – as reported in Table 4.21. The classification results show FIRB closing stock prices having the longest period of stability (560 days or 99.64% stability of the time) with an average duration of 186.67 days, while NEDB closing stock prices have the shortest period of stability (290 days or 51.60% stability of the time) with an average duration of 290days.

Table 4.21: Regime Classification Based on Smoothed Probabilities

Stock Price	Regime 1 (Stable State)			Regime 2 (Volatile State)		
	Range	Days	Avg. Prob.	Range	Days	Avg. Prob.
ABSA	2 - 149	148	0.945	150 - 162	13	0.667
	163 - 212	50	0.968	213 - 258	46	0.914
	259 - 286	28	0.822	287 - 294	8	0.674
	295 - 432	138	0.998	433 - 442	10	0.817
	443 - 563	121	0.943			
	Total Days: 485 (86.30%) Avg. Duration: 97.00 Days			Total Days: 77 (13.70%) Avg. Duration: 19.25 Days		
CAPB	2 - 116	115	0.969	117 - 125	9	0.999
	126 - 156	31	0.994	157 - 157	1	1.000
	158 - 228	71	0.997	229 - 272	44	0.985
	273 - 388	116	1.000	389 - 389	1	1.000
	390 - 390	1	0.535	391 - 391	1	0.888
	392 - 476	85	0.978	477 - 562	86	0.940
	563 - 563	1	0.641			
	Total Days: 420 (74.73%) Avg. Duration: 60.00 Days			Total Days 142 (25.27%) Avg. Duration: 23.67 Days		
FIRB	2 - 46	45	0.999	47 - 47	1	1.000
	48 - 350	303	0.999	351 - 351	1	0.802
	352 - 563	212	1.000			
	Total Days: 560 (99.64%) Avg. Duration: 186.67 Days			Total Days: 2 (0.36%) Avg. Duration: 1.00 Day		
NEDB	215 - 504	290	0.964	2 - 214	213	0.993
				505 - 563	59	0.977
	Total Days: 290 (51.60%) Avg. Duration: 290.00 Days			Total Days: 272 (48.40%) Avg. Duration: 136.00 Days		
STDB	2 - 7	6	0.938	8 - 8	1	0.582
	9 - 37	29	0.917	38 - 39	2	0.688
	40 - 170	131	0.943	171 - 172	2	0.599
	173 - 284	112	0.950	285 - 286	2	0.546
	287 - 362	76	0.968	363 - 365	3	0.743
	366 - 374	9	0.952	375 - 376	2	0.702
	377 - 394	18	0.948	395 - 395	1	0.527
	396 - 399	4	0.997	400 - 400	1	0.631
	401 - 452	52	0.973	453 - 453	1	0.517
	454 - 498	45	0.953	499 - 500	2	0.682
	501 - 541	41	0.926	542 - 543	2	0.637
	544 - 563	20	0.924			
	Total Days: 543 (96.62%) Avg. Duration: 45.25 Days			Total Days: 19 (3.38%) Avg. Duration: 1.73 Days		

4.4 Model Comparison and Forecast Accuracy

One other objective of the current study has been to compare the forecast ability among three nonlinear forecasting methods: STR, TAR, and MS-AR. Forecast future values are of great importance for decision-making and policy formulation. All three model(s) meet the requirements in terms of assumptions. The models are deemed accurate and are used in the forecasting process. The four criteria MAE, RMSE, MAPE, and RMSPE as discussed in chapter 3 are used to measure forecast accuracy by the models. Table 4.22 summarizes the results of the in-sample forecast accuracy measures of the three models for the five closing stock price.

Table 4.22: Forecast Comparison among LSTR, TAR and MS-AR Models

Measure	Method	ABSA	Capitec	FRIB	NEDB	STDB
RMSE	LSTR	200.2572	270.9698	35.48659	219.5906	133.0790
	TAR	196.5424	266.1471	35.48629	210.4875	131.0235
	MS-AR	186.7458	217.5940	35.32322	213.6210	129.6859
MAE	LSTR	148.9902	189.5397	27.03180	167.8142	103.7846
	TAR	147.2353	186.6499	26.93976	162.2681	101.3549
	MS-AR	143.0377	160.6033	27.34744	165.5507	97.6963
MAPE	LSTR	0.010624	0.010107	0.011973	0.011023	0.009965
	TAR	0.010502	0.009945	0.011929	0.010653	0.009735
	MS-AR	0.010188	0.008587	0.012121	0.010863	0.009400
RMSPE	LSTR	0.251849	0.239601	0.283848	0.261327	0.236247
	TAR	0.248965	0.235339	0.282786	0.252104	0.230791
	MS-AR	0.241512	0.203568	0.287354	0.257530	0.222846

According to the results, the four performance-selection criteria select the MS-AR(1) model for ABSA, CAPB and STDB, and TAR model for NEDB accordingly. MAE, MAPE and RMSPE select the TAR model for FIRB, RMSE selects the MS-AR(1) model for FIRB. Based on the findings by Dacco and Satchell (1999), the FIRB is also best modelled by the MS-AR(1) model.

4.5 Comparing Predictive Accuracy of Models

As indicated earlier, a lower MSE, RMSPE or MAPE does not necessarily suggest a superior forecasting ability of a model since the difference between error metrics, say MSEs, for two

different models may not be significantly different from zero (Harris & Sollis, 2003). Consequently, in order to assess the predictive accuracy of the three estimated models, DM tests for pairs of models for each of the five stock prices were performed using the absolute error loss differential and the results summarized in Table 4.23.

Table 4.23: Comparison of Model Accuracy: Diebold-Mariano Absolute Error Test

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed bandwidth = 6.0000)			
Absolute Error Loss Differential		t-Statistic	Prob.
Bank	Hypothesis		
ABSA	LSTR vs. TAR	1.014665	0.3107
	LSTR vs. MS-AR	2.179559	0.0297
	TAR vs. MS-AR	1.349791	0.1776
CAPB	LSTR vs. TAR	1.123201	0.2618
	LSTR vs. MS-AR	5.373818	0.0000
	TAR vs. MS-AR	5.244782	0.0000
FIRB	LSTR vs. TAR	9.402805	0.0000
	LSTR vs. MS-AR	11.93061	0.0000
	TAR vs. MS-AR	12.86748	0.0000
NEDB	LSTR vs. TAR	2.472060	0.0137
	LSTR vs. MS-AR	1.112818	0.2663
	TAR vs. MS-AR	-1.113170	0.2661
STDB	LSTR vs. TAR	2.052297	0.0406
	LSTR vs. MS-AR	4.499932	0.0000
	TAR vs. MS-AR	2.354316	0.0189

According to these results, the null hypothesis of the pair models LSTR-TAR and LSTR-MS-AR for ABSA having equal predictive accuracy and cannot be rejected since their respective p-values (0.3107 and 0.1776) of the test statistics are greater than 5%. However, the null hypothesis that the paired model LSTR-MS-AR for ABSA having the same predictive accuracy is rejected since the p-value (0.0297) of the test statistic is less than 5%. In that case, since the t-statistic (2.179559) is positive, it can be concluded that the estimated MS-AR model for ABSA is more accurate than the estimated LSTR model for ABSA. Similarly, the null hypothesis of the pair model LSTR-TAR for CAPB having equal predictive accuracy and cannot be rejected since the p-value (0.2618) of the test statistic is greater than 0.05. However, the null hypothesis that the pair models LSTR-MS-AR and TAR-MS-AR for CAPB having the same predictive accuracy is rejected since their respective p-values (0.0000 and 0.0000) of the test statistics are less than 0.05. In that case, since their respective t-statistics (5.373818 and 5.244782) are positive, it can be concluded that the estimated MS-AR model for CAPB is more accurate than the estimated LSTR and TAR model for CAPB.

Regarding the predictive accuracies of the estimated models for FIRB, the null hypothesis of the paired models LSTR-TAR, LSTR-MS-AR and TAR-MS-AR for FIRB having equal predictive accuracy is rejected since their respective p-values (0.0000, 0.0000 and 0.0000) of the test statistics are less than 0.05. In that case, since their respective t-statistics (9.402805, 11.93061 and 12.86748) are positive, it can be concluded that while the estimated TAR and MS-AR models for FIRB are more accurate than their LSTR counterpart, the estimated MS-AR model for FIRB is more accurate than its LSTR and TAR counterparts. According to the NEDB results, the null hypothesis of the paired models LSTR-MS-AR and TAR-MS-AR for NEDB having equal predictive accuracy cannot be rejected since their respective p-values (0.2663 and 0.2661) of the test statistics are greater than 0.05. However, the null hypothesis that the paired model LSTR-TAR for NEDB having the same predictive accuracy is rejected since the p-value (0.0137) is less than 0.05. In that case, since the t-statistic (2.472060) is positive, it can be concluded that the estimated TAR model for NEDB is more accurate than its LSTR counterpart.

Lastly, the null hypothesis of the paired models LSTR-TAR, LSTR-MS-AR, and TAR-MS-AR for STDB having equal predictive accuracy is rejected since their respective p-values (0.0406, 0.0000 and 0.0189) of the test statistics are less than 0.05. In that case, since their respective t-statistics (2.052297, 4.499932 and 2.35316) are positive, it can be concluded that while the estimated TAR and MS-AR models for STDB are more accurate than their LSTR counterpart, the estimated MS-AR model for STDB is more accurate than its LSTR and TAR counterpart models for STDB. These findings that while the estimated respective LSTR and TAR models for the closing stock prices seem equally accurate, the MS-AR models are largely found to be more accurate than the LSTR and TAR models.

4.6 Concluding Remarks

This chapter presented an empirical analysis of the five closing stock prices under investigation. The analysis addressed the research objectives of the study outlined in chapter one. The results reveal the character of the stock prices and provided the best nonlinear model in terms of forecasting closing stock prices. A summary of findings and recommendations for future research are presented in the next chapter.

Chapter Five

Conclusions and Future Work

5.1 Introduction

The primary objective of the current dissertation has been to develop predictive models for forecasting closing stock prices of five prominent banks in South Africa using nonlinear methods. The use of the nonlinear methods is informed by the fact that the usual assumption of time series data being modelled as linear could be flawed, especially in situations where the data is, in fact, nonlinear in nature. This chapter presents a summary of the key findings as well as the concluding remarks. Some directions for future research are also proposed.

5.2 Summary of Findings

As a step in analysing the data, exploratory analyses were conducted to examine the nature of the data in question. Descriptive analyses were conducted which showed Capitec (CAPB), Nedbank (NEDB) and ABSA as having the highest mean and median scores. The first objective of the study was to provide evidence that the underlying characteristics of the five variables used in the study were nonlinear in nature. To address this objective, various tests, including the RESET, ARCH and BDS, were conducted. Results from the RESET tests of the five variables suggested that the use of a linear regression modelling technique was inappropriate. In addition, the residuals from various autoregressive (AR) models fitted to the data were found to have ARCH structures, further supporting the use of nonlinear modelling methods. To further examine the existence or otherwise of any structural change in the data, BDS tests were conducted and the results revealed no structural change in the data while Lagrange Multiplier (LM) tests also suggested that the five variables were nonlinear in nature. Using the KSS and Bierens nonlinear unit root tests, the results indicated the nonlinear stationarity among the variables.

The second objective of the study was to use three nonlinear modelling techniques, namely, Smooth Transition Regression (STR), Threshold Autoregressive (TAR), and Markov Switching Autoregressive (MS-AR) models, to model each of the five variables separately. The STR technique suggested LSTR1 models for all five variables, while the TAR modelling technique involved a maximum lag of three in coming up with suitable TAR models for the

five variables, and the MS-AR modelling technique allowed up to a maximum lag of one in determining the appropriate MS-AR models for the five variables. As the third objective sought to compare the efficiency and the performance of the three estimated models for each of the variables, error measures including RMSE, MAE, MAPE and RMSPE were employed. The results showed that while ABSA, CAPB, FIRB and STDB are best modelled by MS-AR(1), NEDB is best modelled by TAR. The fourth objective sought to compare the predictive powers of competing models based on the notion that a lower RMSE, MAE, MAPE or RMSPE does not necessarily translate to a superior forecasting ability. Using the Diebold-Mariano test, the results proved that the MS-AR modelling technique performed better in most cases compared to the LSTR and TAR modelling techniques. From the discussions of the results, the following conclusions can be drawn:

- All five closing stock prices are nonlinear in nature.
- All five closing stock prices do not change structurally.
- The almost negligible error measures suggest that the various estimated predictive models for the five closing stock prices are robust, efficient and reliable for purposes of forecasting.

5.3 Recommendations for Future Research

The preceding section presented a summary of the results obtained in the study. Although the three nonlinear modelling and forecasting techniques proved to be good, there is room for further improvement. More specifically, in the case of TAR and MS-AR, where autoregressive specifications were used, it is recommended that the moving average (MA) and/or autoregressive moving average (ARMA) be used and results compared with the current results. Consequently, the use of Threshold Moving Average (TMA), Threshold Autoregressive Moving Average (TARMA), Markov-Switching Moving Average (MS-MA) and Markov-Switching Autoregressive Moving Average (MS-ARMA) modelling techniques is highly recommended. Banking and other financial institutions are encouraged to refer to the results of this study when embarking on investment and savings policies. This may save these institutions time and energy as they will know exactly what areas to focus on first.

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APPENDICES

APPENDIX A

Optimal Lag Selection for AR Specification

Variable	Lag	SBC
ABSA(t)	1	13.48991
	2	13.48883
	3	13.49927
	4	13.51109
CAPB(t)	1	14.08583
	2	14.09767
	3	14.1038
	4	14.11012
FIRB(t)	1	10.03122
	2	10.04261
	3	10.04663
	4	10.04781
NEDB(t)	1	13.65478
	2	13.64814
	3	13.65515
	4	13.66344
STDB(t)	1	12.67503
	2	12.67884
	3	12.68246
	4	12.69517

APPENDIX B

Optimal Lag Length Selection for KSS Unit Root Tests

B1: KSS Auxiliary Equations for ABSA

Dependent Variable d_DETABSA NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.921E-8	7.8318E-9	-2.45	0.0145
d_DETABSA_1	1	-0.1244	0.0431	-2.88	0.0041
d_DETABSA_2	1	-0.0392	0.0433	-0.90	0.3662
d_DETABSA_3	1	-0.0162	0.0434	-0.37	0.7096
d_DETABSA_4	1	-0.008128	0.0434	-0.19	0.8514
d_DETABSA_5	1	-0.001844	0.0433	-0.04	0.9660
d_DETABSA_6	1	0.0276	0.0431	0.64	0.5224
d_DETABSA_7	1	0.006028	0.0430	0.14	0.8885
d_DETABSA_8	1	0.0119	0.0428	0.28	0.7810

Dependent Variable d_DETABSA NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.902E-8	7.7961E-9	-2.44	0.0150
d_DETABSA_1	1	-0.1221	0.0431	-2.83	0.0048
d_DETABSA_2	1	-0.0377	0.0434	-0.87	0.3853
d_DETABSA_3	1	-0.0182	0.0434	-0.42	0.6746
d_DETABSA_4	1	-0.0132	0.0433	-0.30	0.7611
d_DETABSA_5	1	-0.000936	0.0432	-0.02	0.9827
d_DETABSA_6	1	0.0291	0.0430	0.68	0.4984
d_DETABSA_7	1	0.004185	0.0425	0.10	0.9216

Dependent Variable d_DETABSA NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.894E-8	7.7577E-9	-2.44	0.0150
d_DETABSA_1	1	-0.1215	0.0431	-2.82	0.0050
d_DETABSA_2	1	-0.0388	0.0433	-0.90	0.3707
d_DETABSA_3	1	-0.0209	0.0433	-0.48	0.6299
d_DETABSA_4	1	-0.0126	0.0432	-0.29	0.7698
d_DETABSA_5	1	-0.000020	0.0431	-0.00	0.9996
d_DETABSA_6	1	0.0285	0.0425	0.67	0.5029

Dependent Variable d_DETABSA NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.845E-8	7.7161E-9	-2.39	0.0171
d_DETABSA_1	1	-0.1229	0.0430	-2.86	0.0044
d_DETABSA_2	1	-0.0410	0.0431	-0.95	0.3417
d_DETABSA_3	1	-0.0220	0.0431	-0.51	0.6101
d_DETABSA_4	1	-0.0141	0.0430	-0.33	0.7423
d_DETABSA_5	1	-0.004323	0.0425	-0.10	0.9191

B1 continued

Dependent Variable d_DETABSA					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.856E-8	7.6539E-9	-2.42	0.0156
d_DETABSA_1	1	-0.1209	0.0428	-2.82	0.0049
d_DETABSA_2	1	-0.0414	0.0430	-0.96	0.3360
d_DETABSA_3	1	-0.0226	0.0429	-0.53	0.5984
d_DETABSA_4	1	-0.0135	0.0425	-0.32	0.7511

Dependent Variable d_DETABSA					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.876E-8	7.6045E-9	-2.47	0.0139
d_DETABSA_1	1	-0.1222	0.0427	-2.86	0.0044
d_DETABSA_2	1	-0.0429	0.0429	-1.00	0.3178
d_DETABSA_3	1	-0.0208	0.0425	-0.49	0.6251

Dependent Variable d_DETABSA					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-1.923E-8	7.5402E-9	-2.55	0.0110
d_DETABSA_1	1	-0.1197	0.0426	-2.81	0.0051
d_DETABSA_2	1	-0.0397	0.0423	-0.94	0.3487

Dependent Variable d_DETABSA					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETABSA3_1	1	-2.004E-8	7.487E-9	-2.68	0.0077
d_DETABSA_1	1	-0.1140	0.0421	-2.71	0.0069

B2: KSS Auxiliary Equations for CAPB

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-4.852E-9	2.0575E-9	-2.36	0.0187
d_DETCAPB_1	1	-0.0147	0.0437	-0.34	0.7369
d_DETCAPB_2	1	0.0887	0.0431	2.06	0.0401
d_DETCAPB_3	1	-0.0768	0.0433	-1.77	0.0767
d_DETCAPB_4	1	-0.0204	0.0435	-0.47	0.6389
d_DETCAPB_5	1	0.0220	0.0436	0.50	0.6141
d_DETCAPB_6	1	-0.0263	0.0434	-0.60	0.5458
d_DETCAPB_7	1	-0.0357	0.0434	-0.82	0.4110
d_DETCAPB_8	1	0.0301	0.0434	0.69	0.4879

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-4.704E-9	2.0444E-9	-2.30	0.0218
d_DETCAPB_1	1	-0.0165	0.0435	-0.38	0.7050
d_DETCAPB_2	1	0.0872	0.0430	2.03	0.0431
d_DETCAPB_3	1	-0.0776	0.0432	-1.80	0.0732
d_DETCAPB_4	1	-0.0220	0.0435	-0.51	0.6134
d_DETCAPB_5	1	0.0188	0.0434	0.43	0.6656
d_DETCAPB_6	1	-0.0239	0.0433	-0.55	0.5817
d_DETCAPB_7	1	-0.0369	0.0433	-0.85	0.3950

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-4.884E-9	2.0312E-9	-2.40	0.0165
d_DETCAPB_1	1	-0.0148	0.0434	-0.34	0.7339
d_DETCAPB_2	1	0.0875	0.0429	2.04	0.0421
d_DETCAPB_3	1	-0.0766	0.0432	-1.77	0.0767
d_DETCAPB_4	1	-0.0186	0.0432	-0.43	0.6673
d_DETCAPB_5	1	0.0163	0.0432	0.38	0.7063
d_DETCAPB_6	1	-0.0223	0.0432	-0.52	0.6053

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-4.985E-9	2.0187E-9	-2.47	0.0138
d_DETCAPB_1	1	-0.0142	0.0433	-0.33	0.7441
d_DETCAPB_2	1	0.0884	0.0429	2.06	0.0397
d_DETCAPB_3	1	-0.0744	0.0429	-1.73	0.0835
d_DETCAPB_4	1	-0.0203	0.0430	-0.47	0.6378
d_DETCAPB_5	1	0.0172	0.0431	0.40	0.6906

B2 continued

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-4.901E-9	2.0047E-9	-2.44	0.0148
d_DETCAPB_1	1	-0.0144	0.0432	-0.33	0.7392
d_DETCAPB_2	1	0.0873	0.0426	2.05	0.0410
d_DETCAPB_3	1	-0.0736	0.0428	-1.72	0.0858
d_DETCAPB_4	1	-0.0212	0.0429	-0.49	0.6210

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-5.011E-9	1.9896E-9	-2.52	0.0121
d_DETCAPB_1	1	-0.0120	0.0430	-0.28	0.7794
d_DETCAPB_2	1	0.0856	0.0425	2.02	0.0442
d_DETCAPB_3	1	-0.0729	0.0427	-1.71	0.0883

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-5.352E-9	1.9813E-9	-2.70	0.0071
d_DETCAPB_1	1	-0.0168	0.0429	-0.39	0.6954
d_DETCAPB_2	1	0.0888	0.0425	2.09	0.0370

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-5.055E-9	1.9806E-9	-2.55	0.0110
d_DETCAPB_1	1	-0.0214	0.0430	-0.50	0.6186

Dependent Variable d_DETCAPB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates

Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETCAPB3_1	1	-5.213E-9	1.952E-9	-2.67	0.0078

B3: KSS Auxiliary Equations for FIRB

Dependent Variable d_DET FIRB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-1.997E-7	9.1512E-8	-2.18	0.0295
d_DET FIRB_1	1	-0.0413	0.0429	-0.96	0.3358
d_DET FIRB_2	1	-0.0821	0.0428	-1.92	0.0558
d_DET FIRB_3	1	-0.1050	0.0428	-2.45	0.0145
d_DET FIRB_4	1	0.0381	0.0431	0.89	0.3762
d_DET FIRB_5	1	0.0000758	0.0431	0.00	0.9986
d_DET FIRB_6	1	-0.0749	0.0431	-1.74	0.0828
d_DET FIRB_7	1	-0.0236	0.0431	-0.55	0.5842
d_DET FIRB_8	1	0.000838	0.0431	0.02	0.9845

Dependent Variable d_DET FIRB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-1.886E-7	9.083E-8	-2.08	0.0383
d_DET FIRB_1	1	-0.0414	0.0429	-0.97	0.3347
d_DET FIRB_2	1	-0.0860	0.0426	-2.02	0.0439
d_DET FIRB_3	1	-0.1048	0.0428	-2.45	0.0147
d_DET FIRB_4	1	0.0351	0.0430	0.82	0.4142
d_DET FIRB_5	1	-0.001841	0.0428	-0.04	0.9657
d_DET FIRB_6	1	-0.0743	0.0429	-1.73	0.0834
d_DET FIRB_7	1	-0.0240	0.0430	-0.56	0.5770

Dependent Variable d_DET FIRB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-1.891E-7	9.0142E-8	-2.10	0.0364
d_DET FIRB_1	1	-0.0406	0.0426	-0.95	0.3405
d_DET FIRB_2	1	-0.0856	0.0425	-2.01	0.0445
d_DET FIRB_3	1	-0.1064	0.0427	-2.49	0.0130
d_DET FIRB_4	1	0.0375	0.0426	0.88	0.3789
d_DET FIRB_5	1	0.000535	0.0426	0.01	0.9900
d_DET FIRB_6	1	-0.0733	0.0428	-1.71	0.0872

Dependent Variable d_DET FIRB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.095E-7	8.9597E-8	-2.34	0.0197
d_DET FIRB_1	1	-0.0400	0.0426	-0.94	0.3486
d_DET FIRB_2	1	-0.0857	0.0425	-2.01	0.0445
d_DET FIRB_3	1	-0.0968	0.0425	-2.28	0.0231
d_DET FIRB_4	1	0.0442	0.0425	1.04	0.2984
d_DET FIRB_5	1	0.004218	0.0426	0.10	0.9212

B3 continued

Dependent Variable d_DET FIRB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.035E-7	8.8778E-8	-2.29	0.0222
d_DET FIRB_1	1	-0.0412	0.0425	-0.97	0.3329
d_DET FIRB_2	1	-0.0868	0.0422	-2.06	0.0401
d_DET FIRB_3	1	-0.0971	0.0422	-2.30	0.0218
d_DET FIRB_4	1	0.0438	0.0424	1.03	0.3011

Dependent Variable d_DET FIRB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.059E-7	8.7758E-8	-2.35	0.0193
d_DET FIRB_1	1	-0.0452	0.0422	-1.07	0.2840
d_DET FIRB_2	1	-0.0915	0.0419	-2.18	0.0296
d_DET FIRB_3	1	-0.0995	0.0421	-2.36	0.0185

Dependent Variable d_DET FIRB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.214E-7	8.6845E-8	-2.55	0.0110
d_DET FIRB_1	1	-0.0353	0.0421	-0.84	0.4024
d_DET FIRB_2	1	-0.0866	0.0420	-2.06	0.0398

Dependent Variable d_DET FIRB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.243E-7	8.6122E-8	-2.60	0.0095
d_DET FIRB_1	1	-0.0314	0.0422	-0.75	0.4564

Dependent Variable d_DET FIRB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DET FIRB3_1	1	-2.248E-7	8.5013E-8	-2.64	0.0084

B4: KSS Auxiliary Equations for NEDB

Dependent Variable d_DETNEDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-2.718E-8	6.0545E-9	-4.49	<.0001
d_DETNEDB_1	1	-0.1349	0.0424	-3.18	0.0016
d_DETNEDB_2	1	-0.0697	0.0428	-1.63	0.1043
d_DETNEDB_3	1	-0.0631	0.0428	-1.48	0.1404
d_DETNEDB_4	1	-0.009468	0.0429	-0.22	0.8252
d_DETNEDB_5	1	-0.0400	0.0428	-0.93	0.3507
d_DETNEDB_6	1	-0.0633	0.0427	-1.48	0.1392
d_DETNEDB_7	1	-0.0400	0.0428	-0.93	0.3503
d_DETNEDB_8	1	0.0392	0.0422	0.93	0.3536

Dependent Variable d_DETNEDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-2.198E-8	5.668E-9	-3.88	0.0001
d_DETNEDB_1	1	-0.1401	0.0425	-3.30	0.0010
d_DETNEDB_2	1	-0.0786	0.0428	-1.84	0.0666
d_DETNEDB_3	1	-0.0676	0.0428	-1.58	0.1153
d_DETNEDB_4	1	-0.0160	0.0429	-0.37	0.7090
d_DETNEDB_5	1	-0.0460	0.0428	-1.07	0.2836
d_DETNEDB_6	1	-0.0683	0.0427	-1.60	0.1102
d_DETNEDB_7	1	-0.0507	0.0423	-1.20	0.2315

Dependent Variable d_DETNEDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.959E-8	5.4313E-9	-3.61	0.0003
d_DETNEDB_1	1	-0.1401	0.0424	-3.31	0.0010
d_DETNEDB_2	1	-0.0774	0.0428	-1.81	0.0709
d_DETNEDB_3	1	-0.0700	0.0428	-1.63	0.1029
d_DETNEDB_4	1	-0.0128	0.0428	-0.30	0.7654
d_DETNEDB_5	1	-0.0416	0.0427	-0.97	0.3308
d_DETNEDB_6	1	-0.0631	0.0422	-1.50	0.1351

Dependent Variable d_DETNEDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.889E-8	5.1608E-9	-3.66	0.0003
d_DETNEDB_1	1	-0.1378	0.0423	-3.26	0.0012
d_DETNEDB_2	1	-0.0777	0.0427	-1.82	0.0695
d_DETNEDB_3	1	-0.0655	0.0427	-1.53	0.1256
d_DETNEDB_4	1	-0.006976	0.0427	-0.16	0.8703
d_DETNEDB_5	1	-0.0327	0.0422	-0.78	0.4380

B4 continued

Dependent Variable d_DETNEDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.733E-8	4.9619E-9	-3.49	0.0005
d_DETNEDB_1	1	-0.1405	0.0423	-3.32	0.0009
d_DETNEDB_2	1	-0.0763	0.0426	-1.79	0.0739
d_DETNEDB_3	1	-0.0628	0.0426	-1.47	0.1410
d_DETNEDB_4	1	-0.003785	0.0421	-0.09	0.9285

Dependent Variable d_DETNEDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.671E-8	4.7044E-9	-3.55	0.0004
d_DETNEDB_1	1	-0.1407	0.0421	-3.34	0.0009
d_DETNEDB_2	1	-0.0761	0.0424	-1.80	0.0730
d_DETNEDB_3	1	-0.0628	0.0419	-1.50	0.1346

Dependent Variable d_DETNEDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.543E-8	4.5101E-9	-3.42	0.0007
d_DETNEDB_1	1	-0.1361	0.0420	-3.24	0.0013
d_DETNEDB_2	1	-0.0686	0.0419	-1.64	0.1024

Dependent Variable d_DETNEDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.453E-8	4.3729E-9	-3.32	0.0010
d_DETNEDB_1	1	-0.1285	0.0416	-3.09	0.0021

Dependent Variable d_DETNEDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETNEDB3_1	1	-1.512E-8	4.2189E-9	-3.58	0.0004

B5: KSS Auxiliary Equations for STDB

Dependent Variable d_DETSTDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.73E-8	1.3833E-8	-4.14	<.0001
d_DETSTDB_1	1	-0.0705	0.0432	-1.63	0.1037
d_DETSTDB_2	1	-0.0595	0.0431	-1.38	0.1680
d_DETSTDB_3	1	0.0372	0.0430	0.87	0.3870
d_DETSTDB_4	1	0.0212	0.0428	0.49	0.6210
d_DETSTDB_5	1	-0.002114	0.0427	-0.05	0.9605
d_DETSTDB_6	1	-0.0433	0.0428	-1.01	0.3121
d_DETSTDB_7	1	-0.003456	0.0426	-0.08	0.9354
d_DETSTDB_8	1	0.0262	0.0423	0.62	0.5356

Dependent Variable d_DETSTDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.412E-8	1.3849E-8	-3.91	0.0001
d_DETSTDB_1	1	-0.0763	0.0434	-1.76	0.0795
d_DETSTDB_2	1	-0.0665	0.0432	-1.54	0.1242
d_DETSTDB_3	1	0.0350	0.0432	0.81	0.4180
d_DETSTDB_4	1	0.0165	0.0430	0.38	0.7007
d_DETSTDB_5	1	-0.005351	0.0430	-0.12	0.9009
d_DETSTDB_6	1	-0.0448	0.0428	-1.05	0.2960
d_DETSTDB_7	1	-0.006656	0.0426	-0.16	0.8758

Dependent Variable d_DETSTDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.458E-8	1.3736E-8	-3.97	<.0001
d_DETSTDB_1	1	-0.0753	0.0432	-1.74	0.0819
d_DETSTDB_2	1	-0.0662	0.0431	-1.53	0.1255
d_DETSTDB_3	1	0.0356	0.0431	0.83	0.4092
d_DETSTDB_4	1	0.0169	0.0429	0.39	0.6940
d_DETSTDB_5	1	-0.004747	0.0426	-0.11	0.9114
d_DETSTDB_6	1	-0.0440	0.0424	-1.04	0.3004

Dependent Variable d_DETSTDB
NOTE: No intercept term is used. R-squares are redefined.

Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.645E-8	1.359E-8	-4.15	<.0001
d_DETSTDB_1	1	-0.0732	0.0431	-1.70	0.0902
d_DETSTDB_2	1	-0.0648	0.0430	-1.51	0.1325
d_DETSTDB_3	1	0.0365	0.0430	0.85	0.3970
d_DETSTDB_4	1	0.0218	0.0426	0.51	0.6095
d_DETSTDB_5	1	0.000705	0.0423	0.02	0.9867

B5 continued

Dependent Variable d_DETSTDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.591E-8	1.3444E-8	-4.16	<.0001
d_DETSTDB_1	1	-0.0740	0.0430	-1.72	0.0856
d_DETSTDB_2	1	-0.0655	0.0429	-1.53	0.1276
d_DETSTDB_3	1	0.0366	0.0427	0.86	0.3919
d_DETSTDB_4	1	0.0217	0.0422	0.51	0.6079

Dependent Variable d_DETSTDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.531E-8	1.3272E-8	-4.17	<.0001
d_DETSTDB_1	1	-0.0741	0.0429	-1.73	0.0844
d_DETSTDB_2	1	-0.0682	0.0426	-1.60	0.1096
d_DETSTDB_3	1	0.0338	0.0423	0.80	0.4238

Dependent Variable d_DETSTDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.379E-8	1.3063E-8	-4.12	<.0001
d_DETSTDB_1	1	-0.0785	0.0425	-1.85	0.0651
d_DETSTDB_2	1	-0.0728	0.0421	-1.73	0.0844

Dependent Variable d_DETSTDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.646E-8	1.2861E-8	-4.39	<.0001
d_DETSTDB_1	1	-0.0689	0.0422	-1.63	0.1028

Dependent Variable d_DETSTDB					
NOTE: No intercept term is used. R-squares are redefined.					
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
DETSTDB3_1	1	-5.999E-8	1.2588E-8	-4.77	<.0001

APPENDIX C

Choice of KSS Auxiliary Model Type - Zero-Mean, De-Meaned or De-Trended

Dependent Variable		ABSA			
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	1	13238	61.2518	216.12	<.0001
t	1	2.9661	0.1882	15.76	<.0001
=====					
Dependent Variable		CAPB			
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	1	15432	101.7165	151.71	<.0001
t	1	11.2758	0.3125	36.08	<.0001
=====					
Dependent Variable		FIRB			
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	1	1730	15.4501	111.97	<.0001
t	1	1.9368	0.0475	40.80	<.0001
=====					
Dependent Variable		NEDB			
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	1	12273	65.2958	187.96	<.0001
t	1	10.8132	0.2006	53.90	<.0001
=====					
Dependent Variable		STDB			
Parameter Estimates					
Variable	DF	Estimate	Standard Error	t Value	Approx Pr > t
Intercept	1	9924	49.4601	200.64	<.0001
t	1	1.9492	0.1520	12.83	<.0001

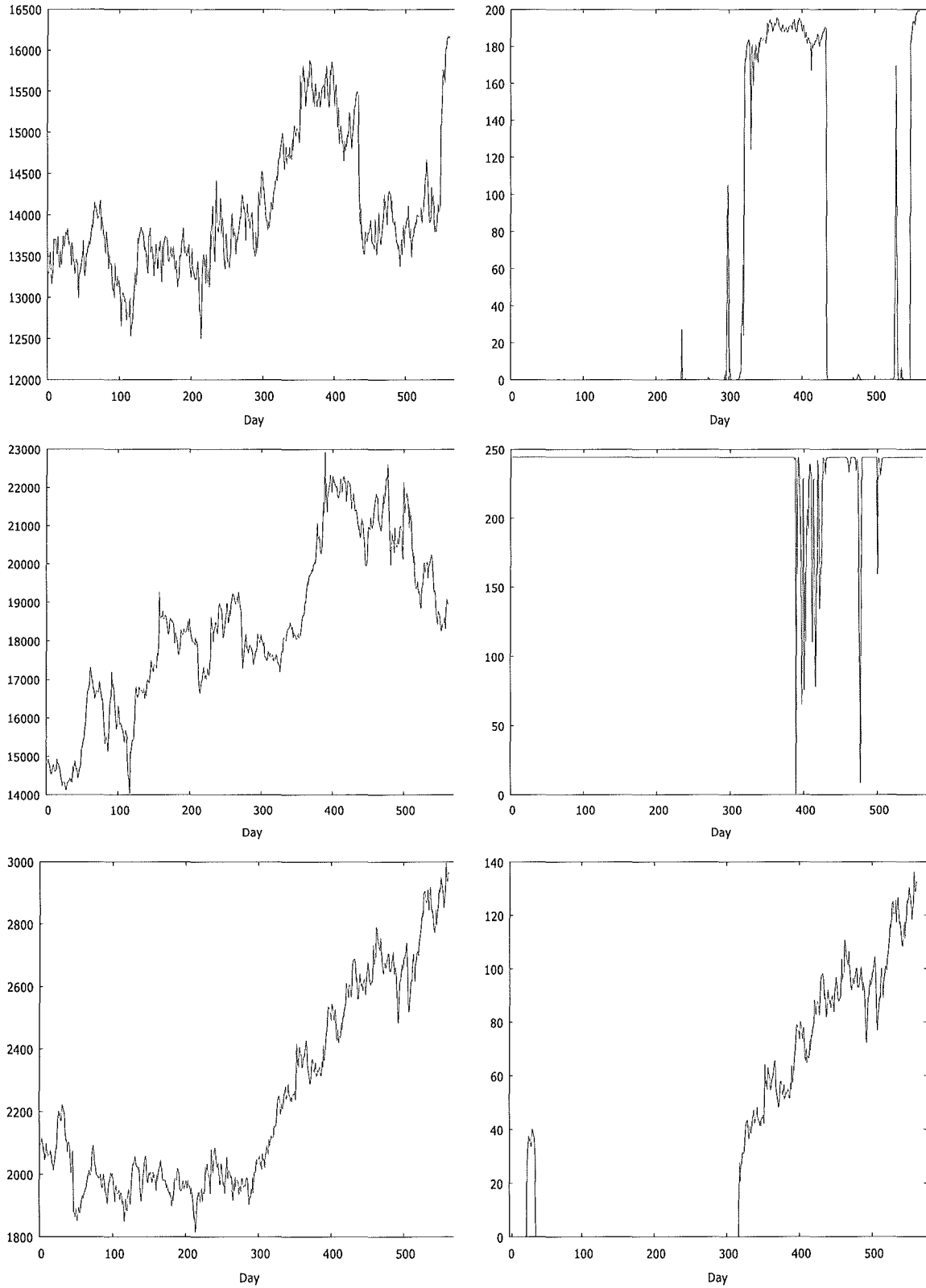
APPENDIX D

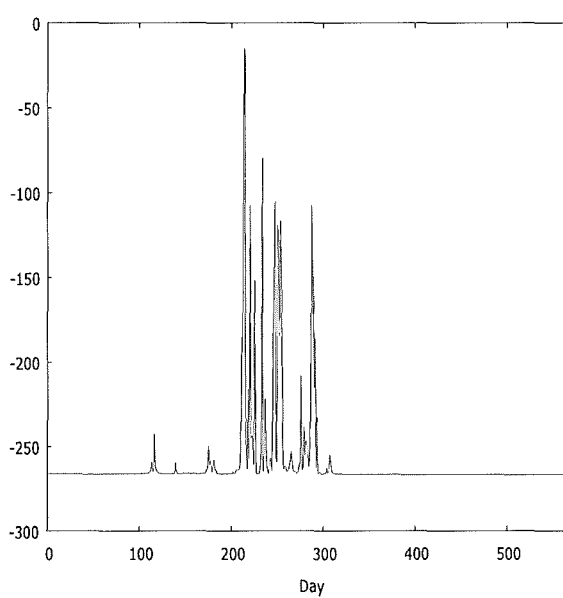
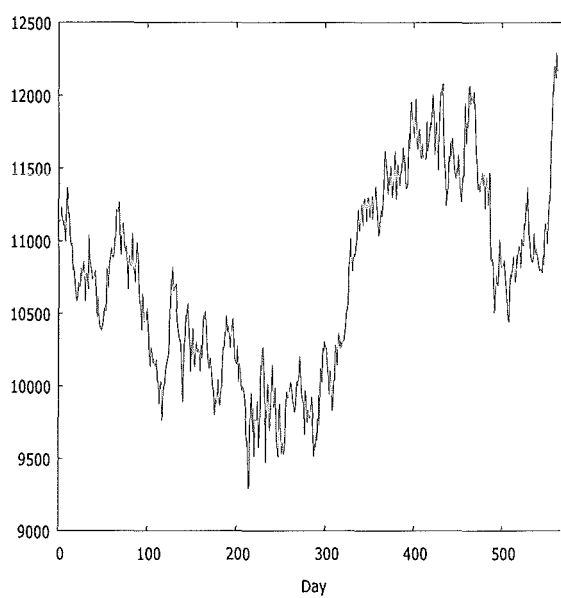
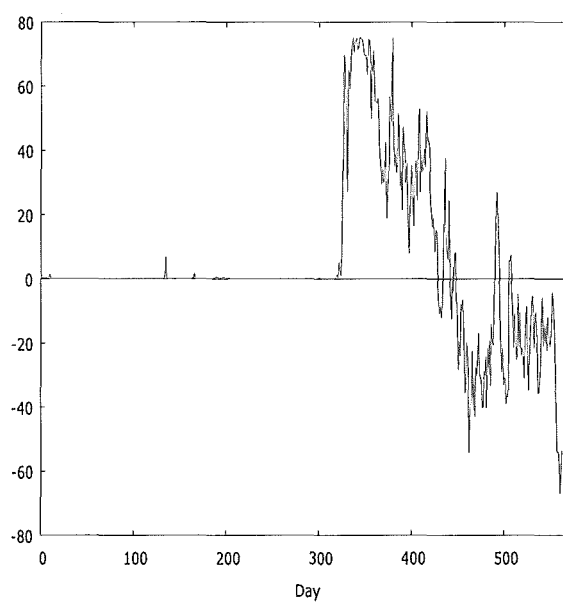
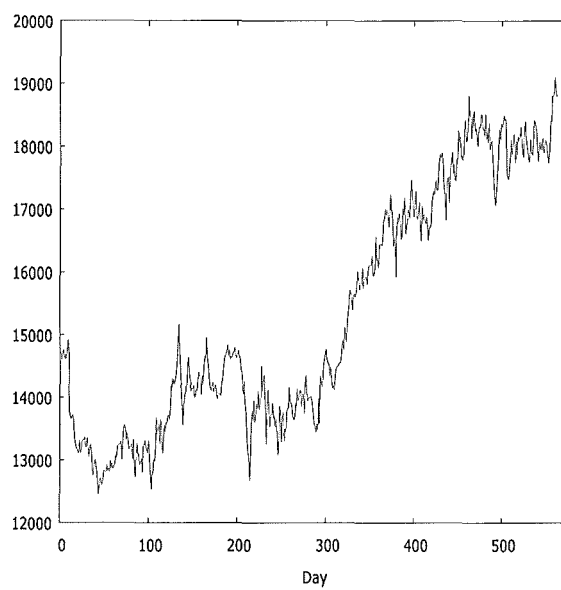
Optimal Lag Structure of Endogenous Variables

Variable	Lag	SBC
ABSA	1	10.667
	2	10.681
	3	10.706
	4	10.725
	5	10.738
CAPB	1	11.235
	2	11.268
	3	11.268
	4	11.287
	5	11.308
FIRB	1	7.206
	2	7.227
	3	7.224
	4	7.258
	5	7.280
NEDB	1	10.840
	2	10.845
	3	10.852
	4	10.868
	5	10.892
STDB	1	9.843
	2	9.864
	3	9.867
	4	9.896
	5	9.924

APPENDIX E

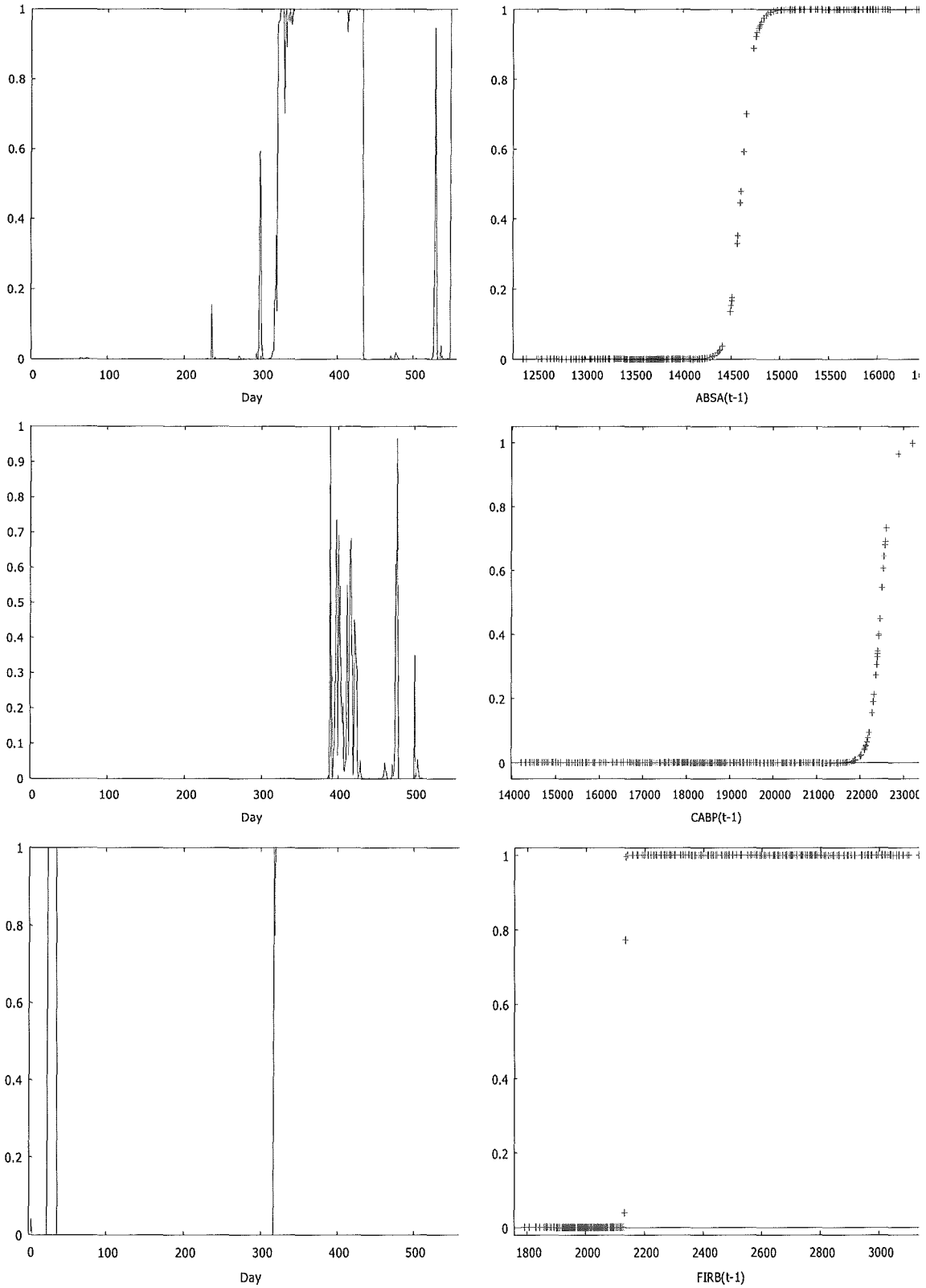
Plots of Linear and Nonlinear Parts of Estimated LSTR Models

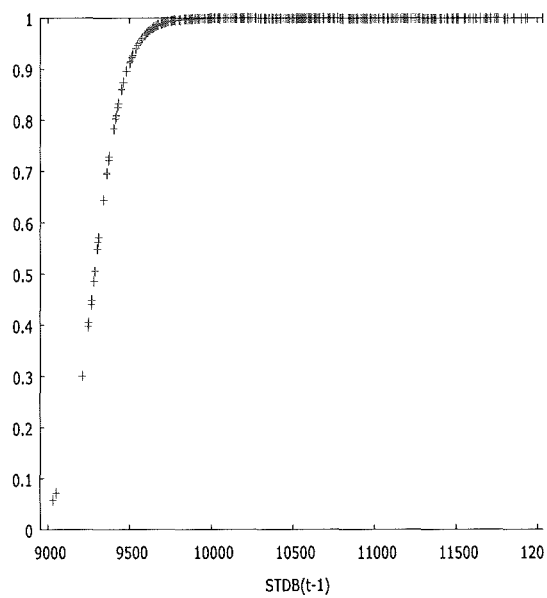
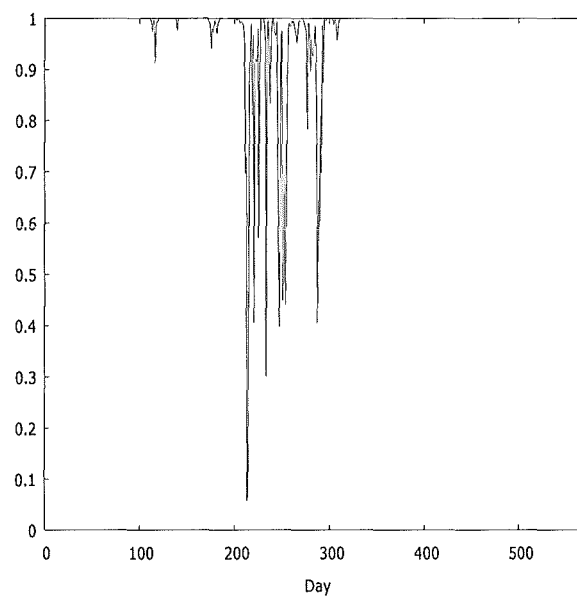
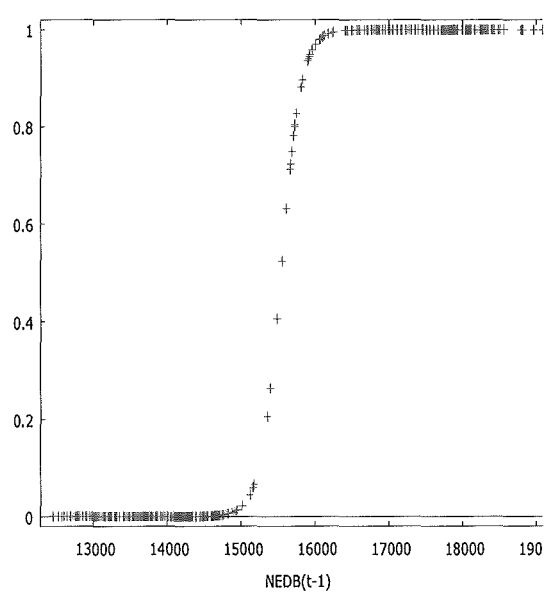
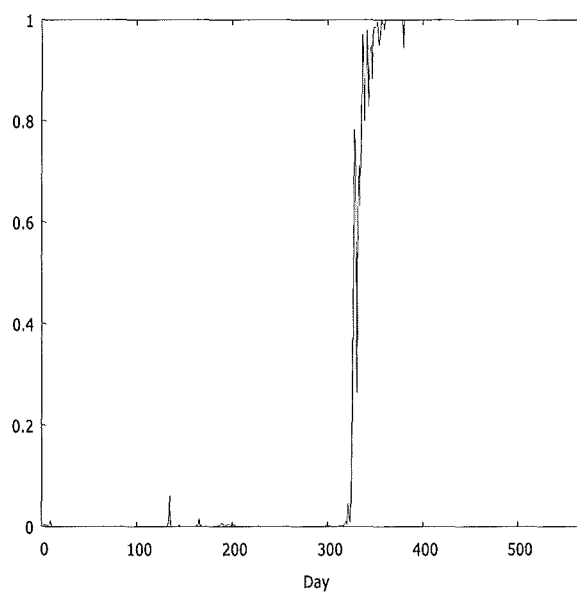




Appendix F

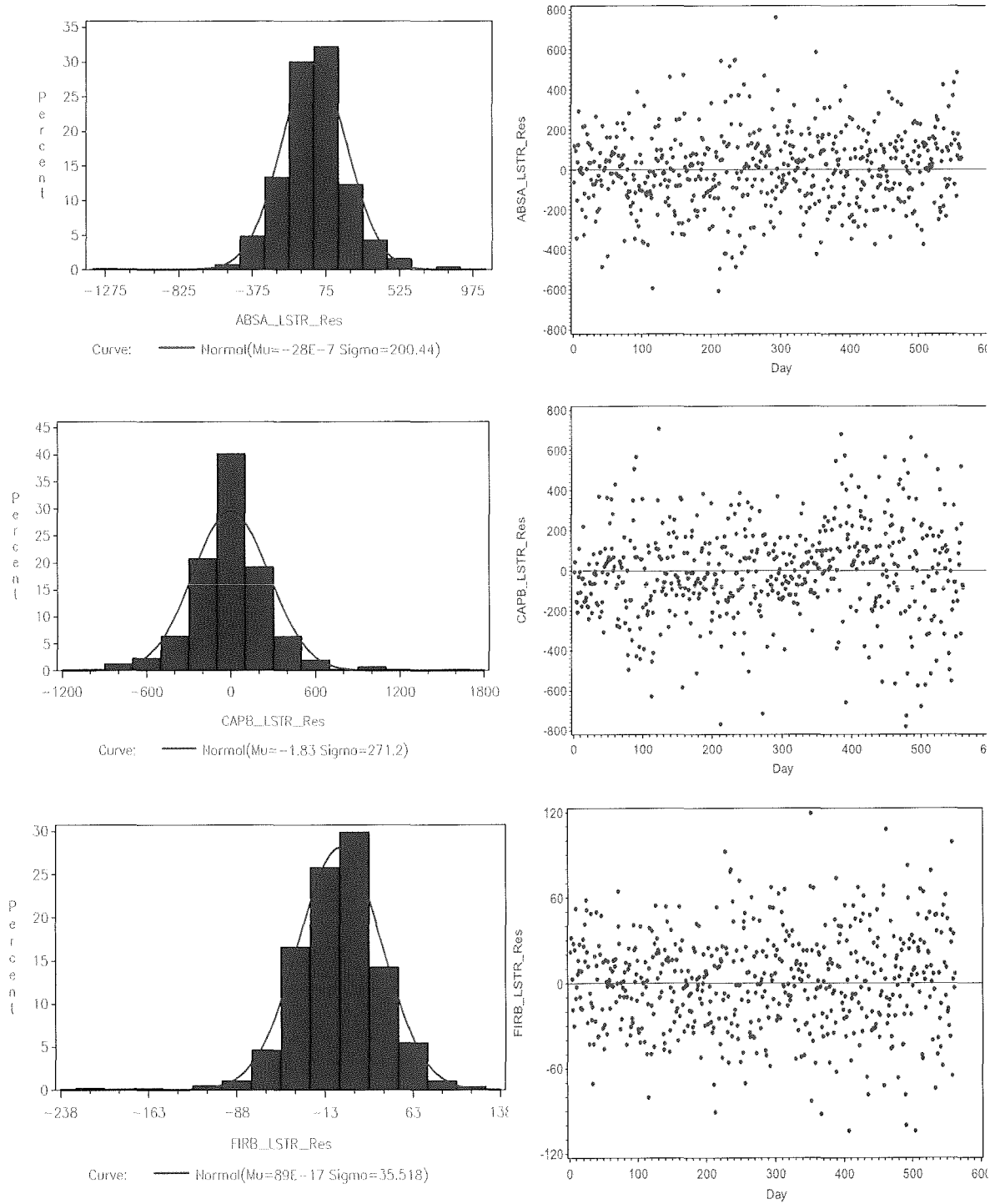
Plots of LSTR Transition Functions of Variables

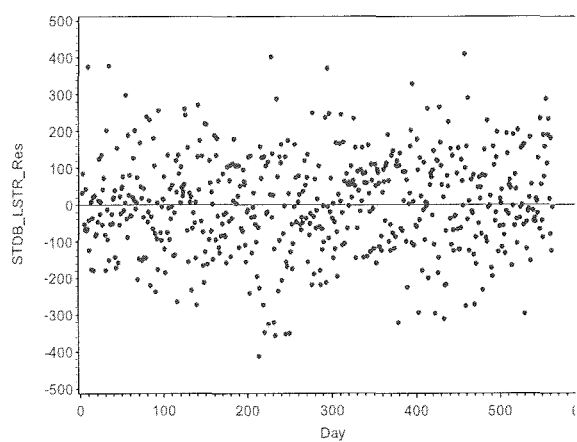
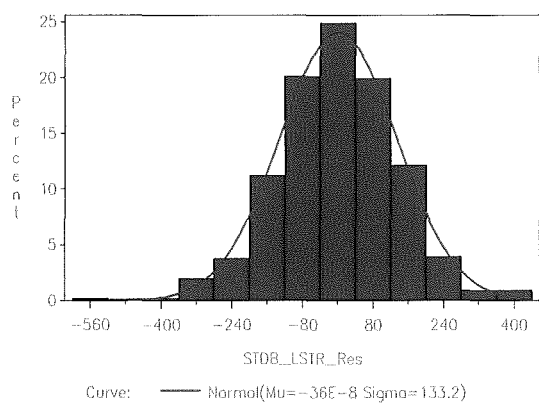
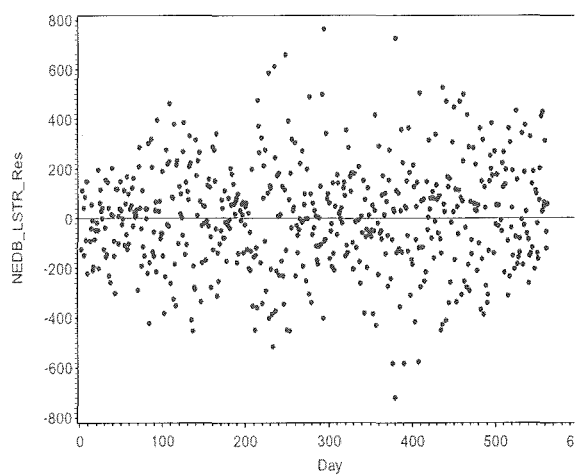
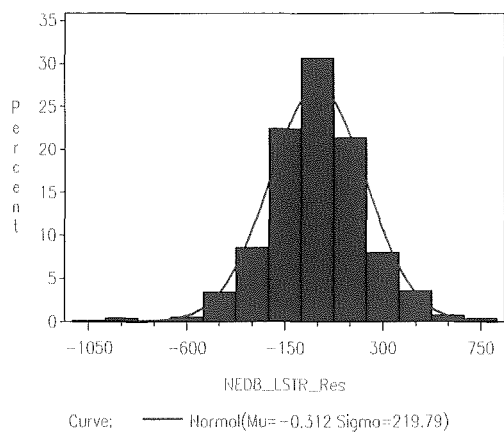




APPENDIX G

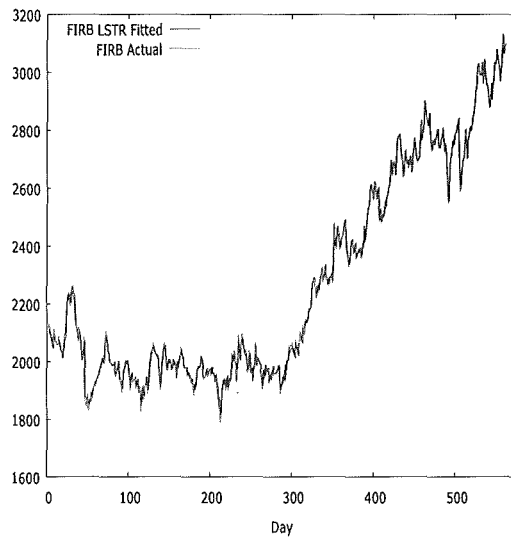
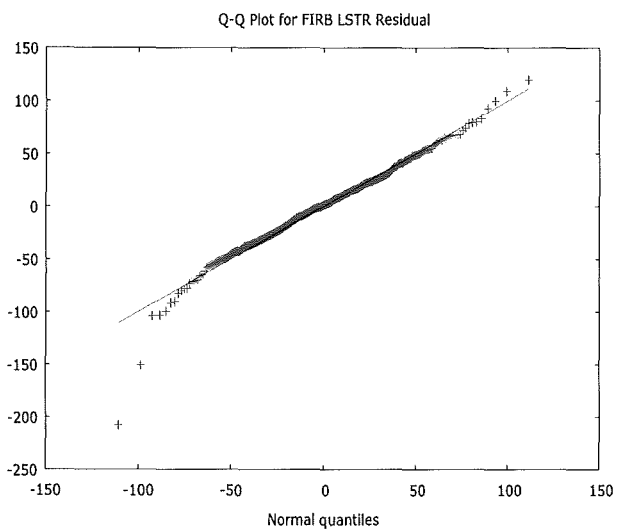
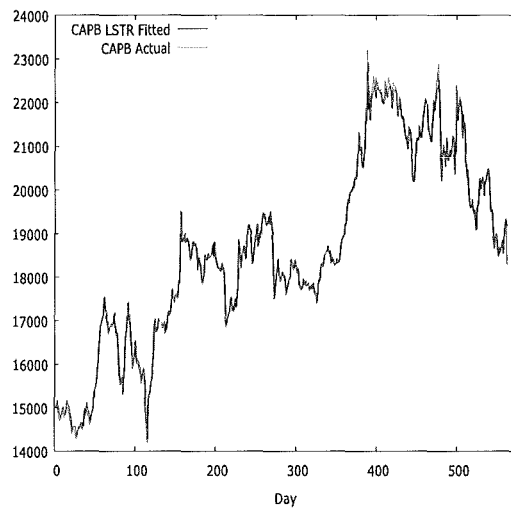
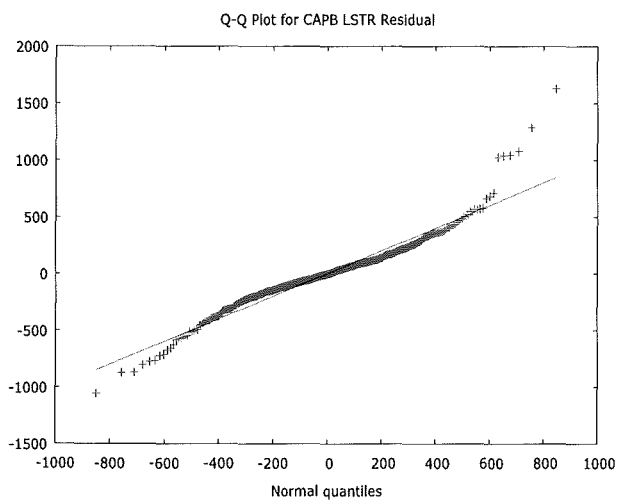
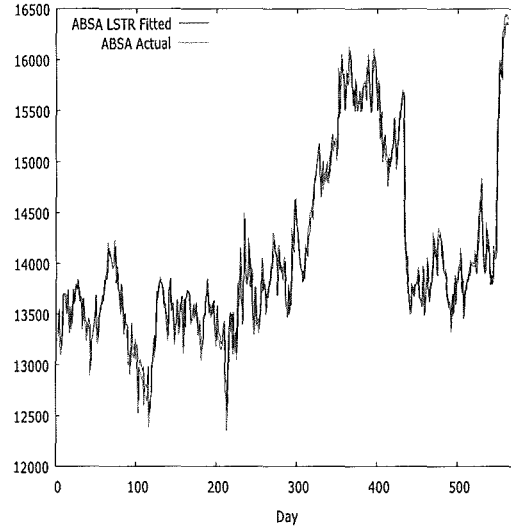
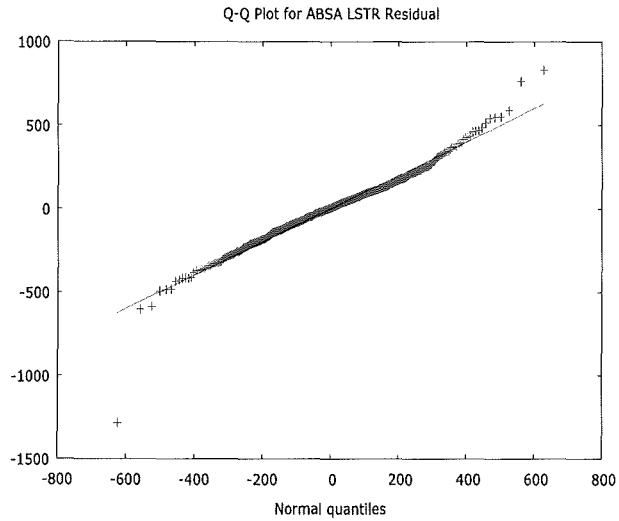
Residual Diagnostics from LSTR Models

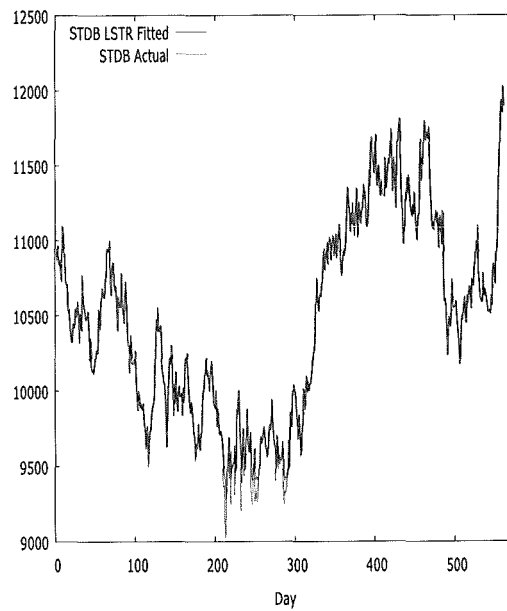
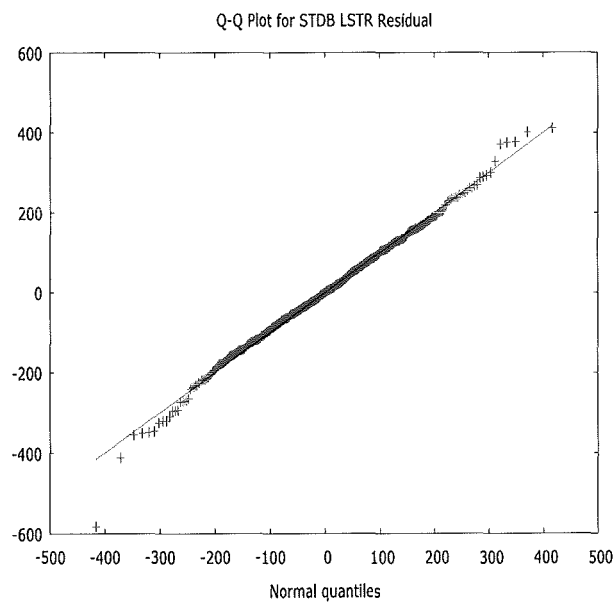
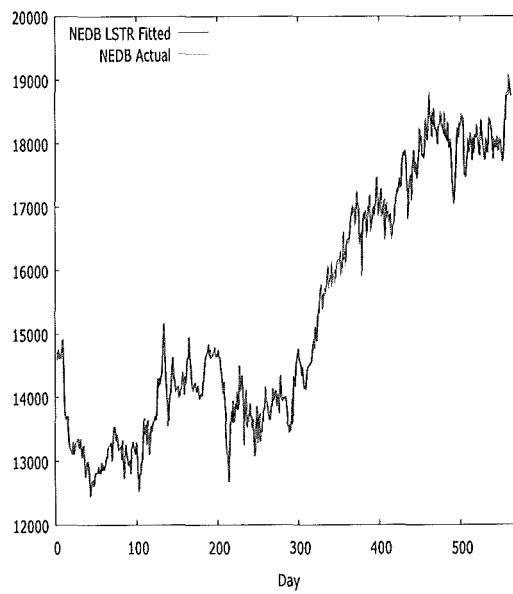
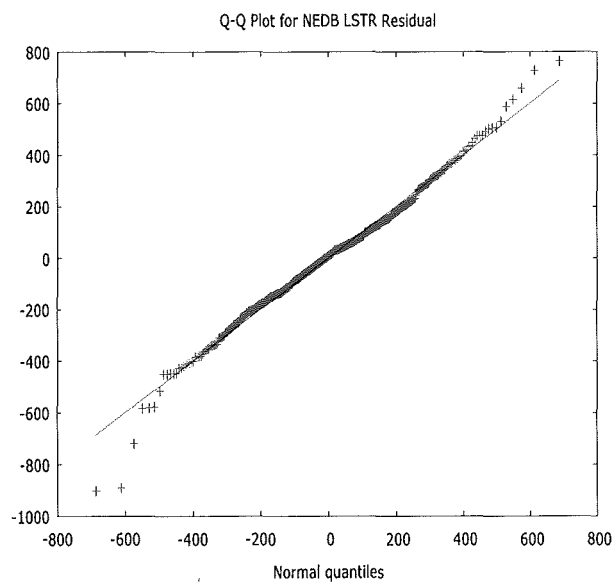




Appendix H

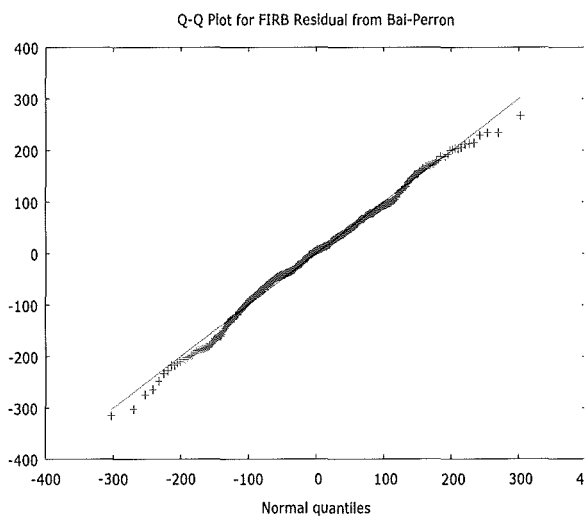
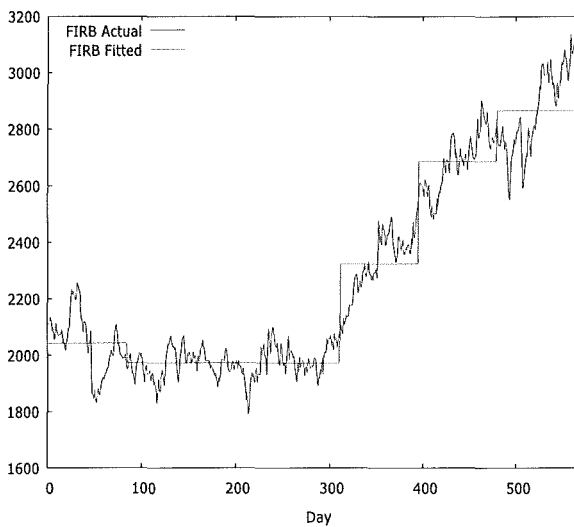
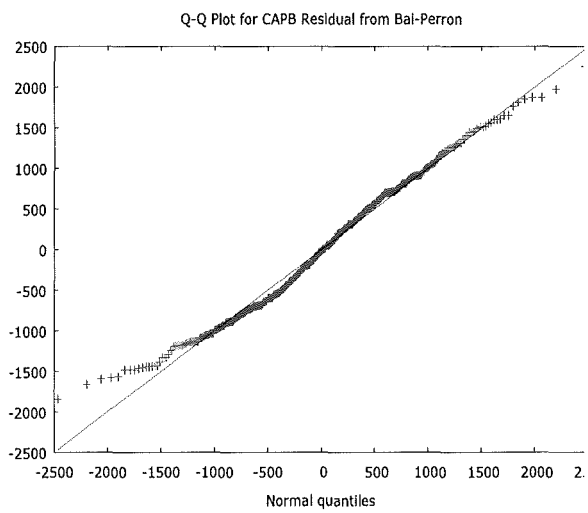
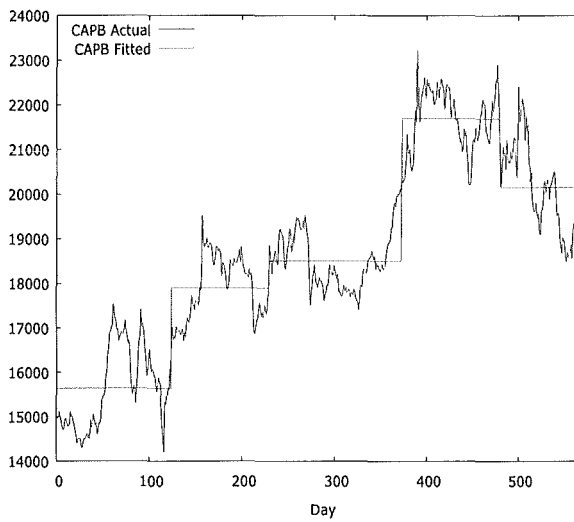
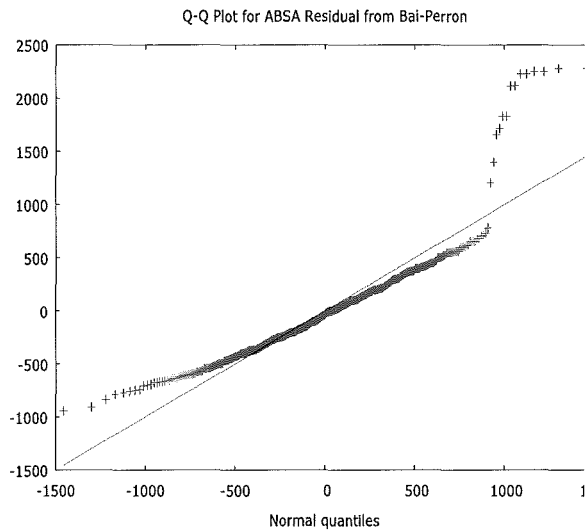
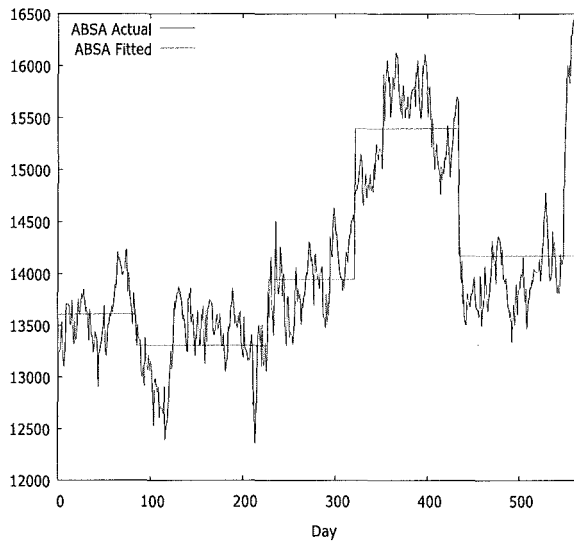
Residual Plots and Overlay Plots of Actual and Estimated LSTR Models

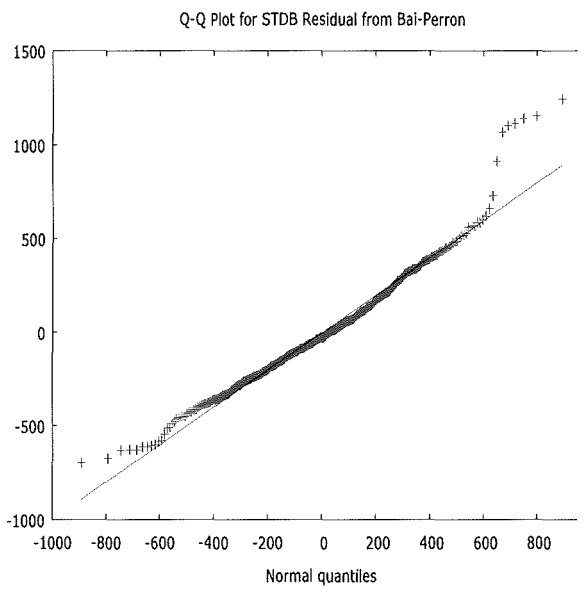
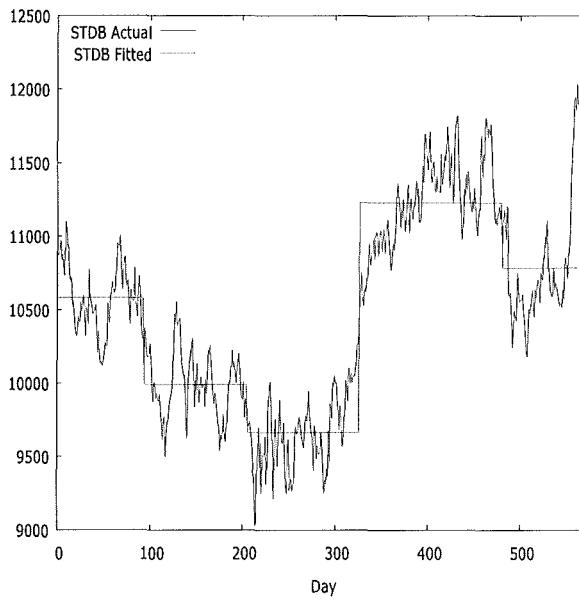
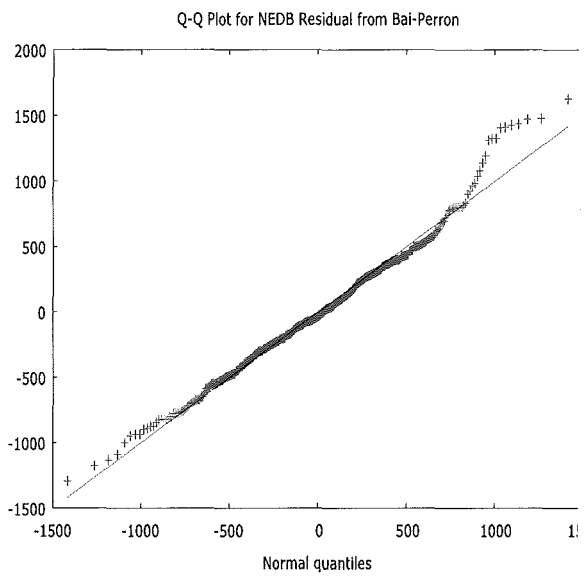
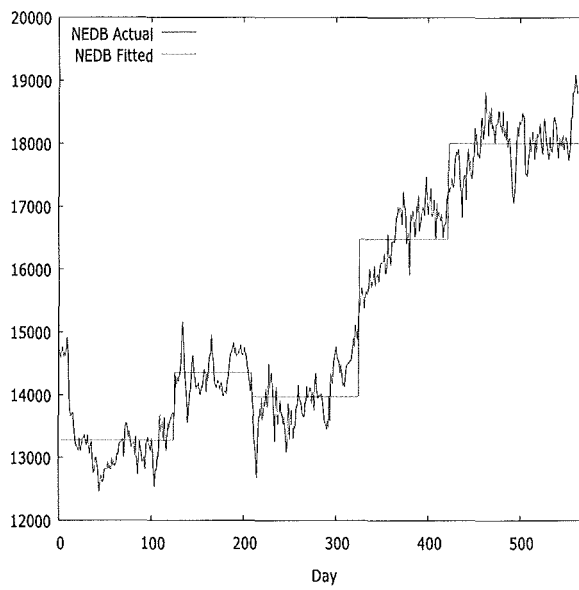




APPENDIX I

TAR Regimes and Residuals from Bai-Perron Breakpoint Tests





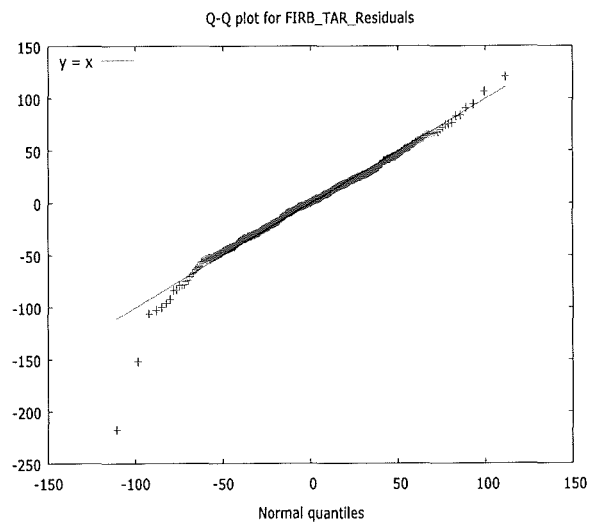
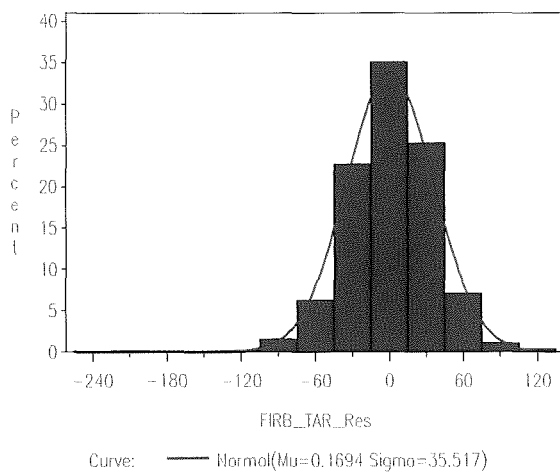
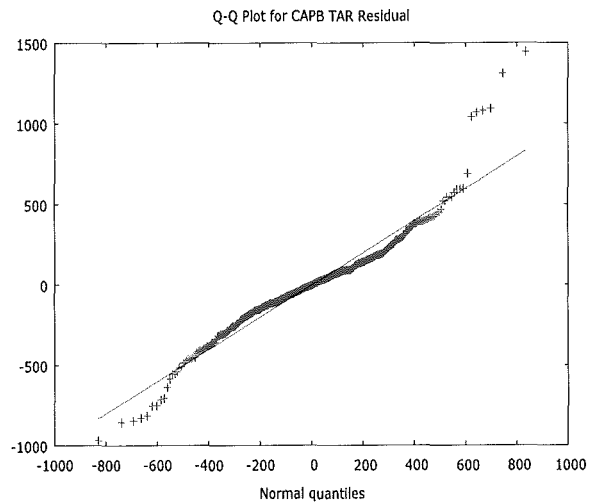
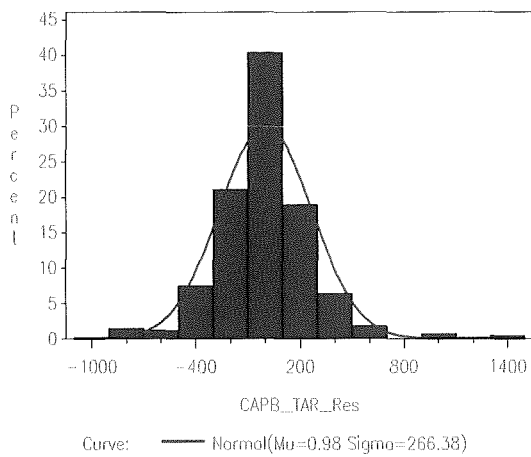
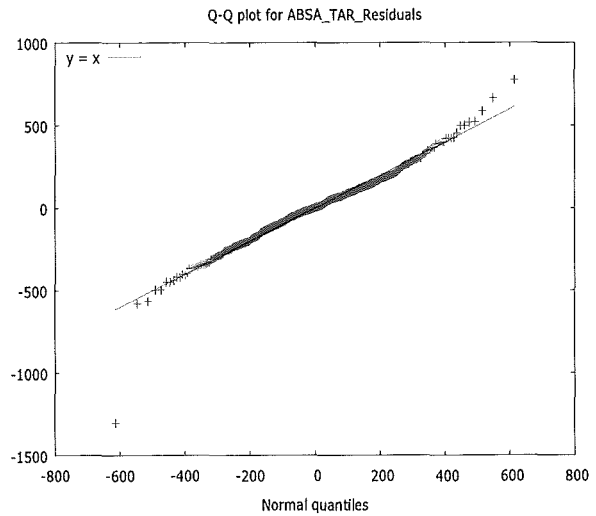
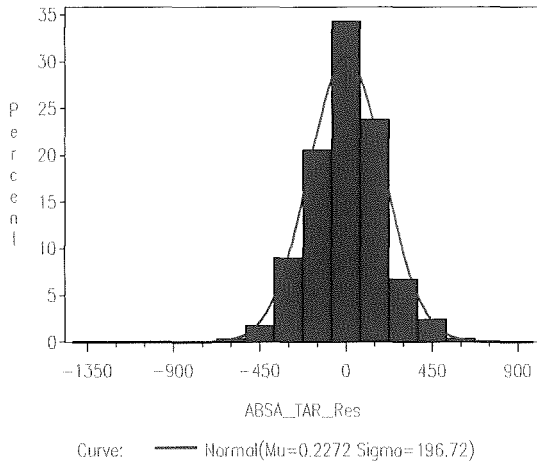
APPENDIX J

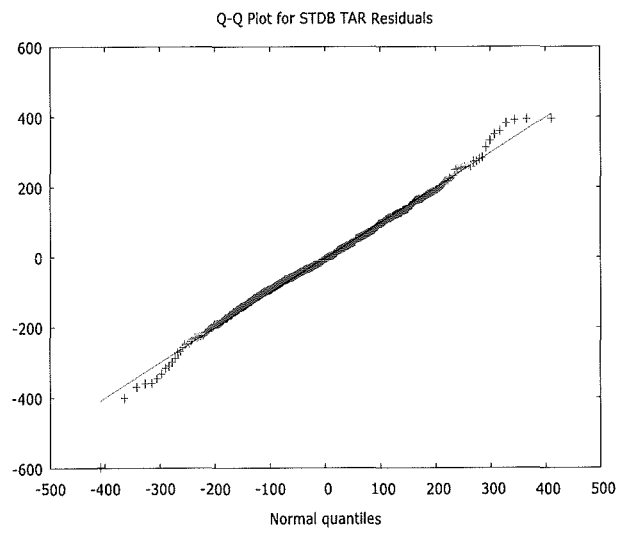
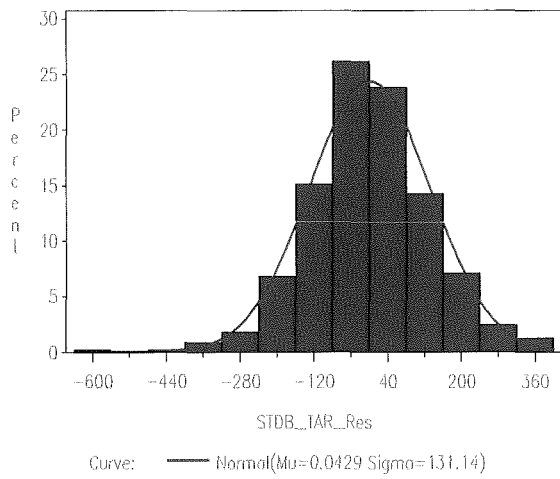
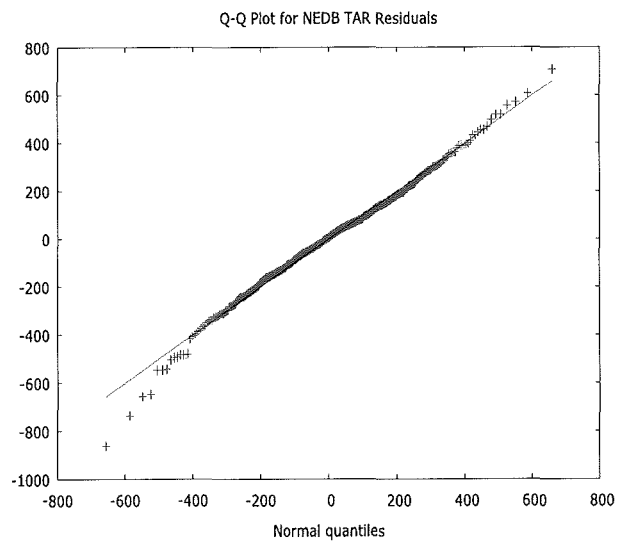
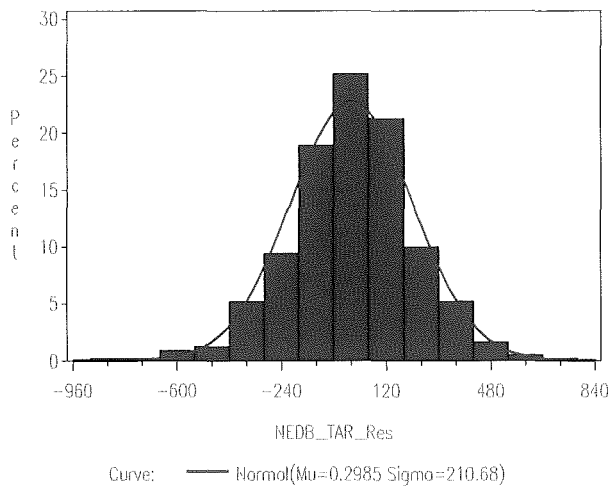
Optimal Lag Length Selection for Various Regimes

	Lag	Schwartz Bayesian Criterion (SBC)				
		Regime 1	Regime 2	Regime 3	Regime 4	Regime 5
ABSA	1	13.02798	13.44375	13.67851	13.28729	13.40464
	2	13.08408	13.45644	13.72006	13.31725	13.43732
	3	13.09055	13.49643	13.74531	13.36303	13.46098
	4	13.14590	13.53877	13.79375	13.40811	13.49012
	5	13.16094	13.56681	13.81504	13.45173	13.49920
CAPB	1	13.7892	13.77776	13.34929	14.52162	14.66544
	2	13.81478	13.83166	13.35285	14.52452	14.70348
	3	13.82003	13.86428	13.38557	14.52032	14.73401
	4	13.86377	13.91701	13.41193	14.57631	14.76509
	5	13.89603	13.95913	13.42523	14.61095	14.79890
FIRB	1	10.07145	9.777602	10.23522	10.13927	10.51161
	2	10.13610	9.803696	10.29034	10.19589	10.52480
	3	10.19801	9.828008	10.33714	10.23679	10.57116
	4	10.26050	9.855042	10.39536	10.29935	10.62679
	5	10.30995	9.876614	9.995732	10.36569	10.68422
NEDB	1	13.26315	13.15753	13.90366	13.79058	13.77497
	2	13.30997	13.13212	13.92469	13.79861	13.80887
	3	13.31232	13.11257	13.90458	13.78256	13.82495
	4	13.35114	13.17579	13.93058	13.81536	13.83328
	5	13.39828	13.23070	13.96538	13.85711	13.86026
STDB	1	12.45451	12.42133	13.01966	12.56655	12.74162
	2	12.50281	12.42162	13.06200	12.60590	12.79515
	3	12.51693	12.46457	13.10938	12.62970	12.85532
	4	12.55550	12.50819	13.15608	12.65343	12.87084
	5	12.61879	12.56233	13.20317	12.68217	12.84962

APPENDIX K

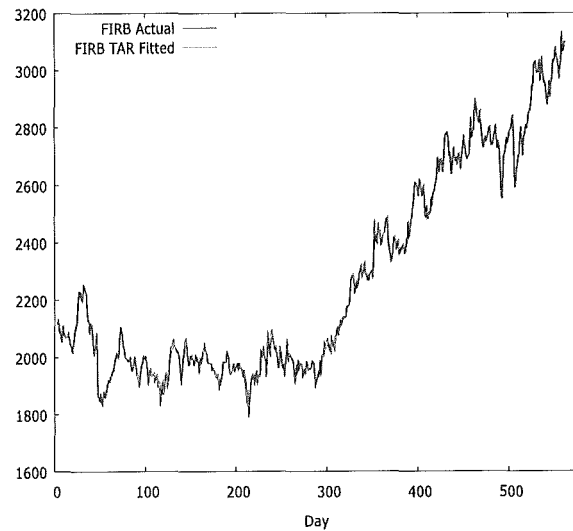
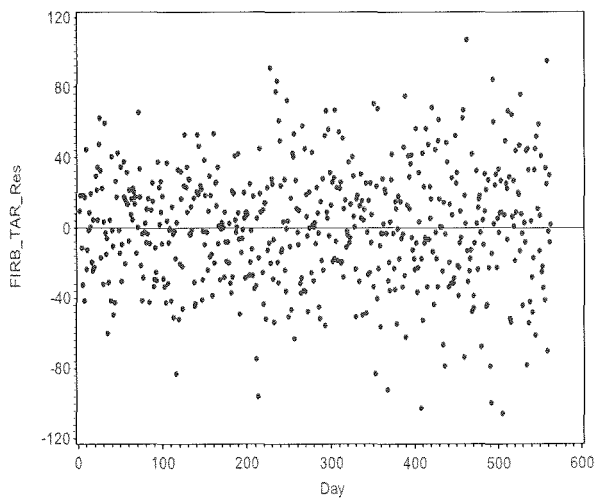
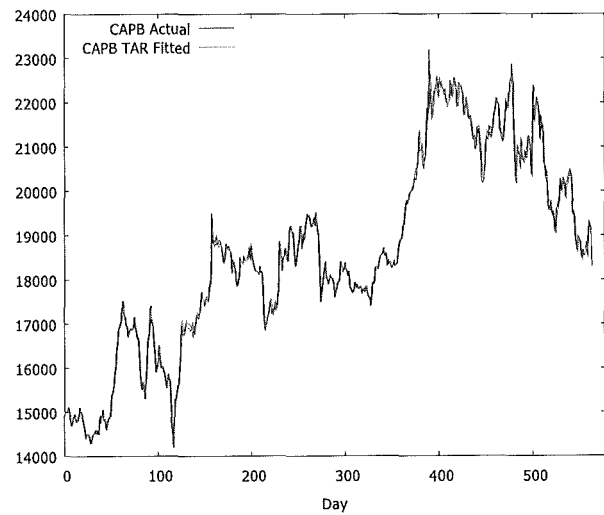
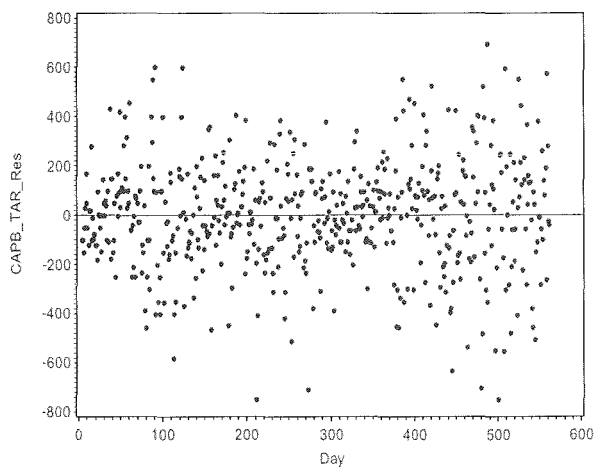
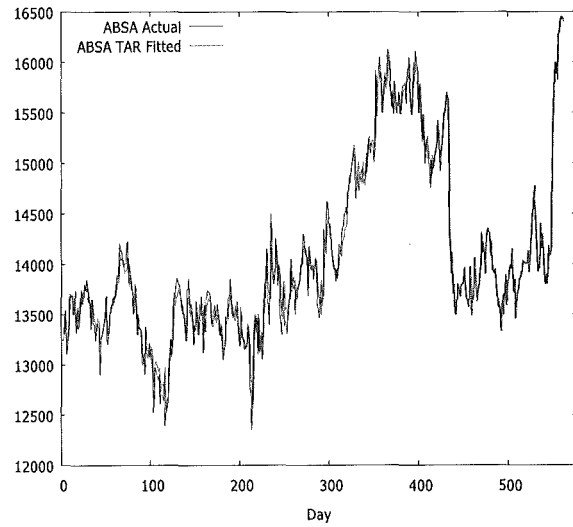
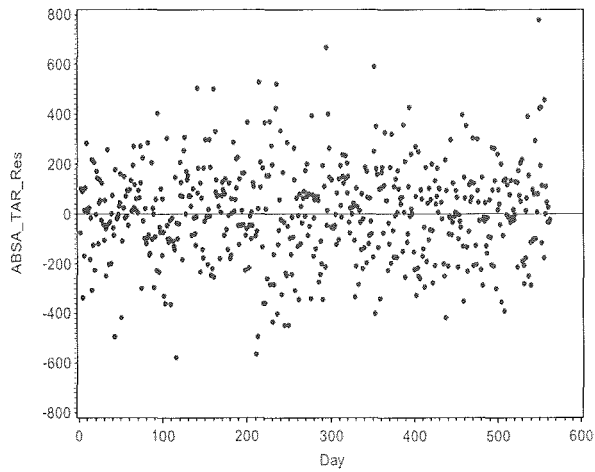
Residual Diagnostics from Estimated TAR Models

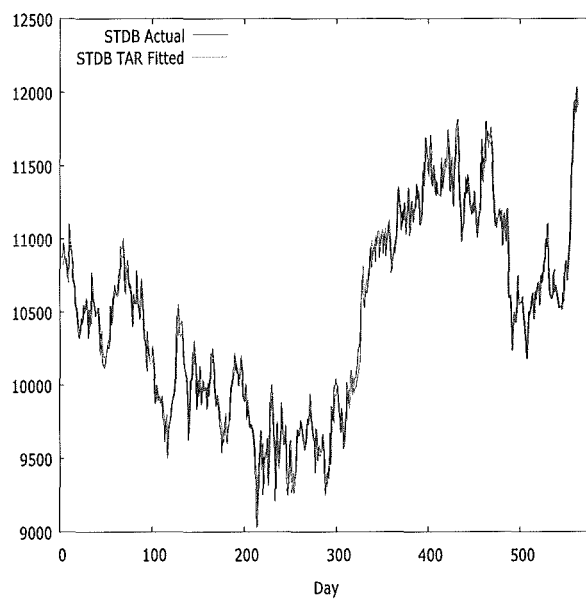
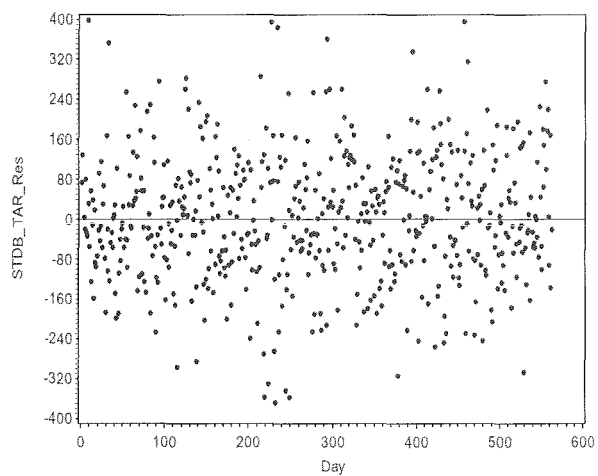
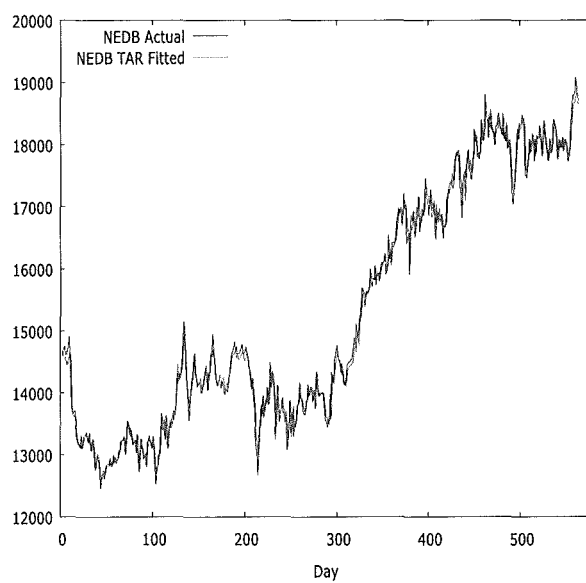
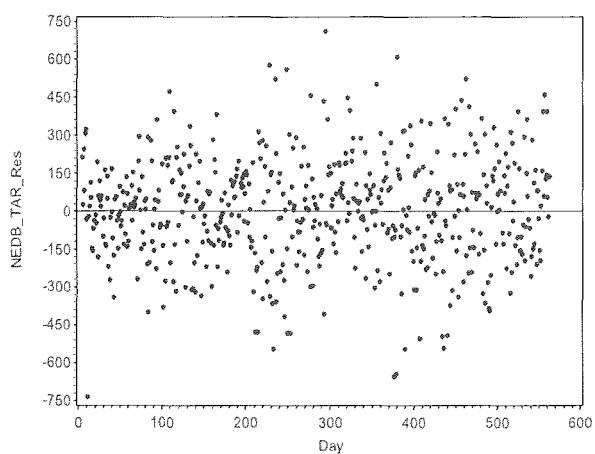




Appendix L

Residual Plots and Overlay Plots of Actual and Estimated TAR Models





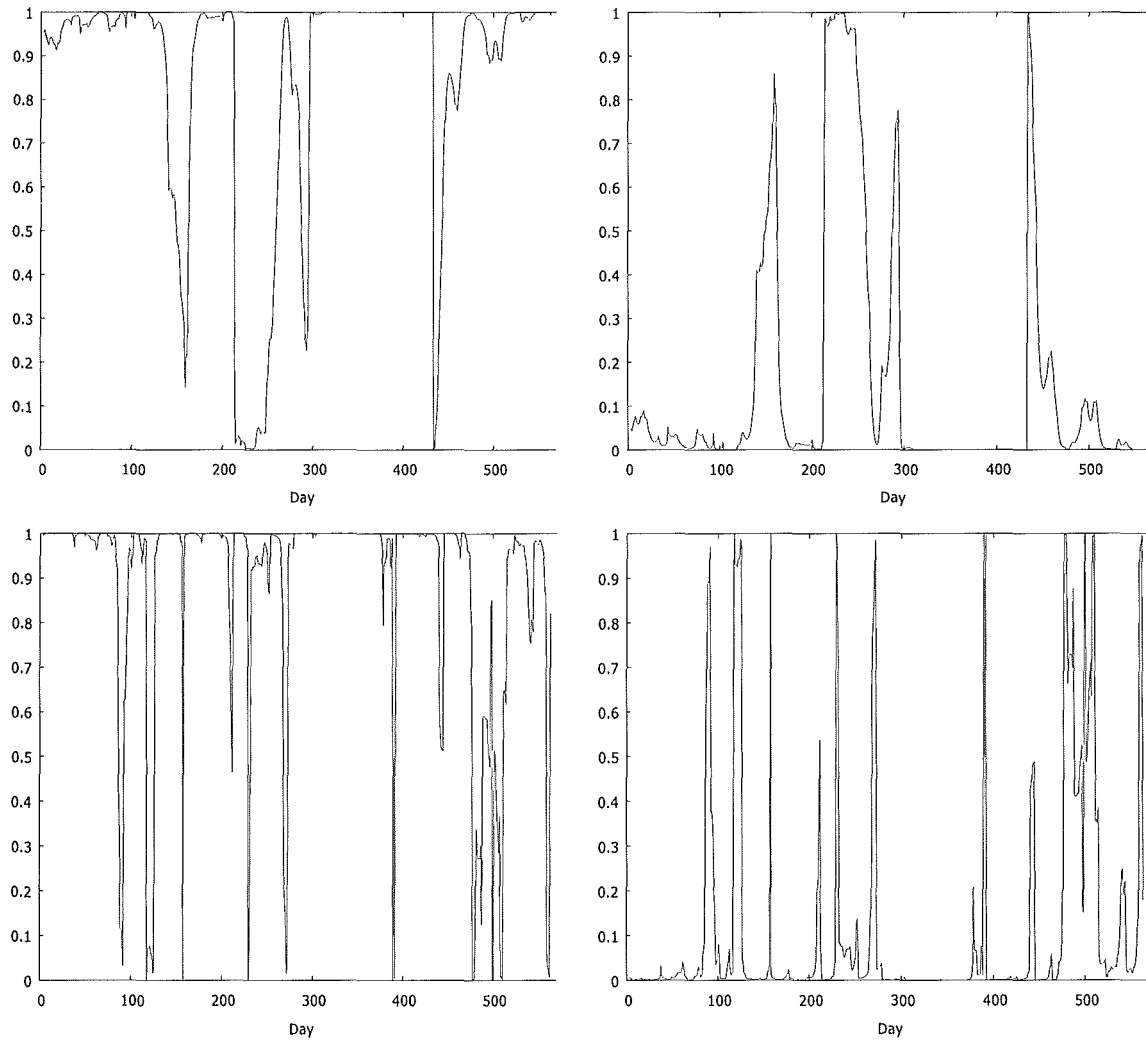
Appendix M

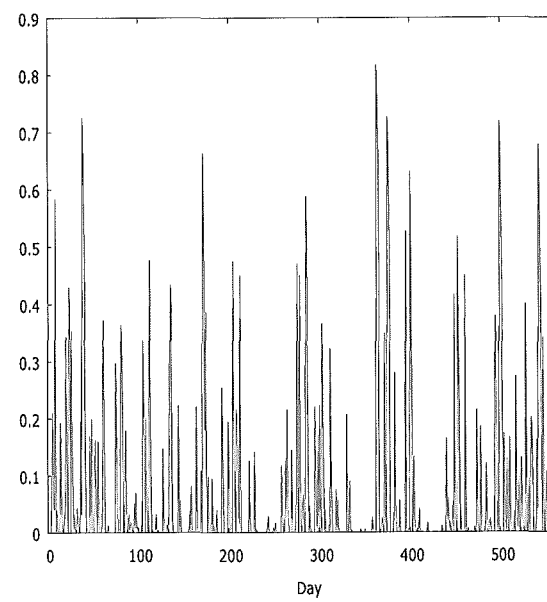
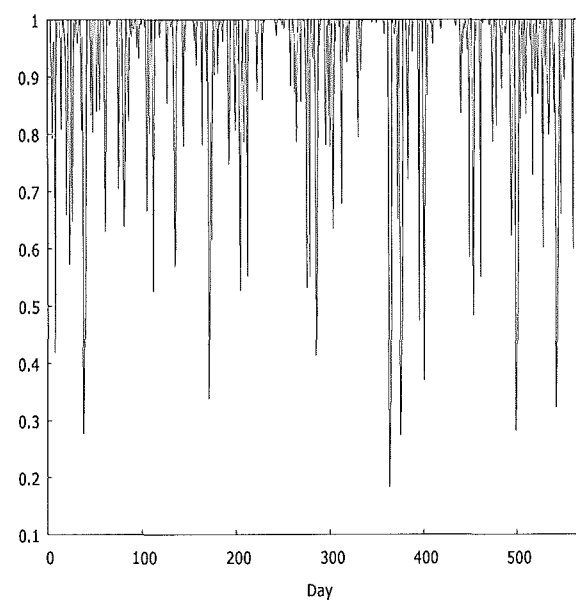
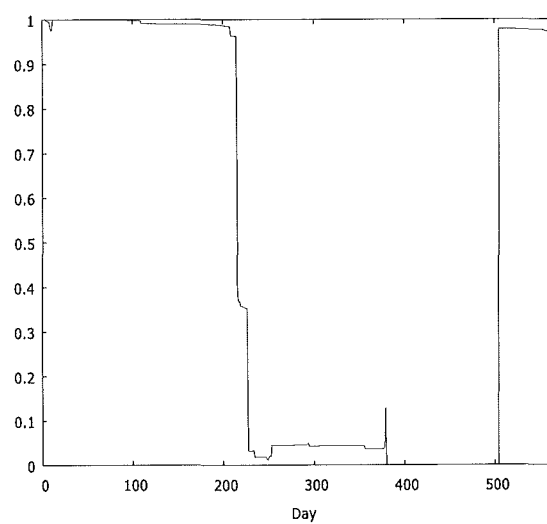
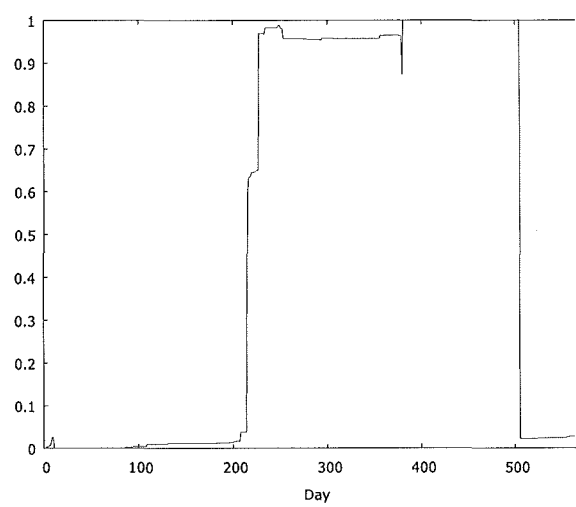
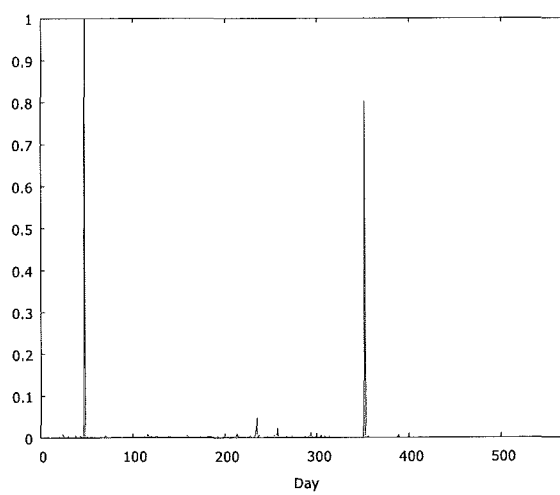
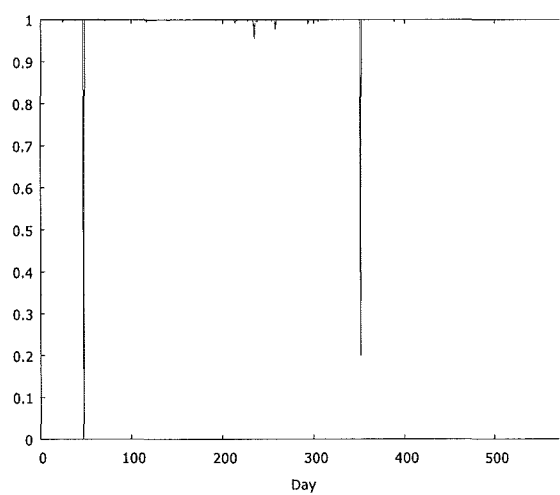
Schwartz Bayesian Criteria (SBC) From Two-Regime MS-AR Model Identification

AR Lag, p	ABSA	CAPB	FIRB	NEDB	STDB
1	13.46487	13.88768	10.03544	13.61097	12.73145
2	13.47251	13.91295	10.07151	13.70889	12.75810
3	13.59242	13.93030	10.07839	13.66788	12.73734
4	13.61415	13.95129	10.15116	13.76884	12.80347
5	13.63616	19.97345	10.17336	13.79278	12.82227

APPENDIX N

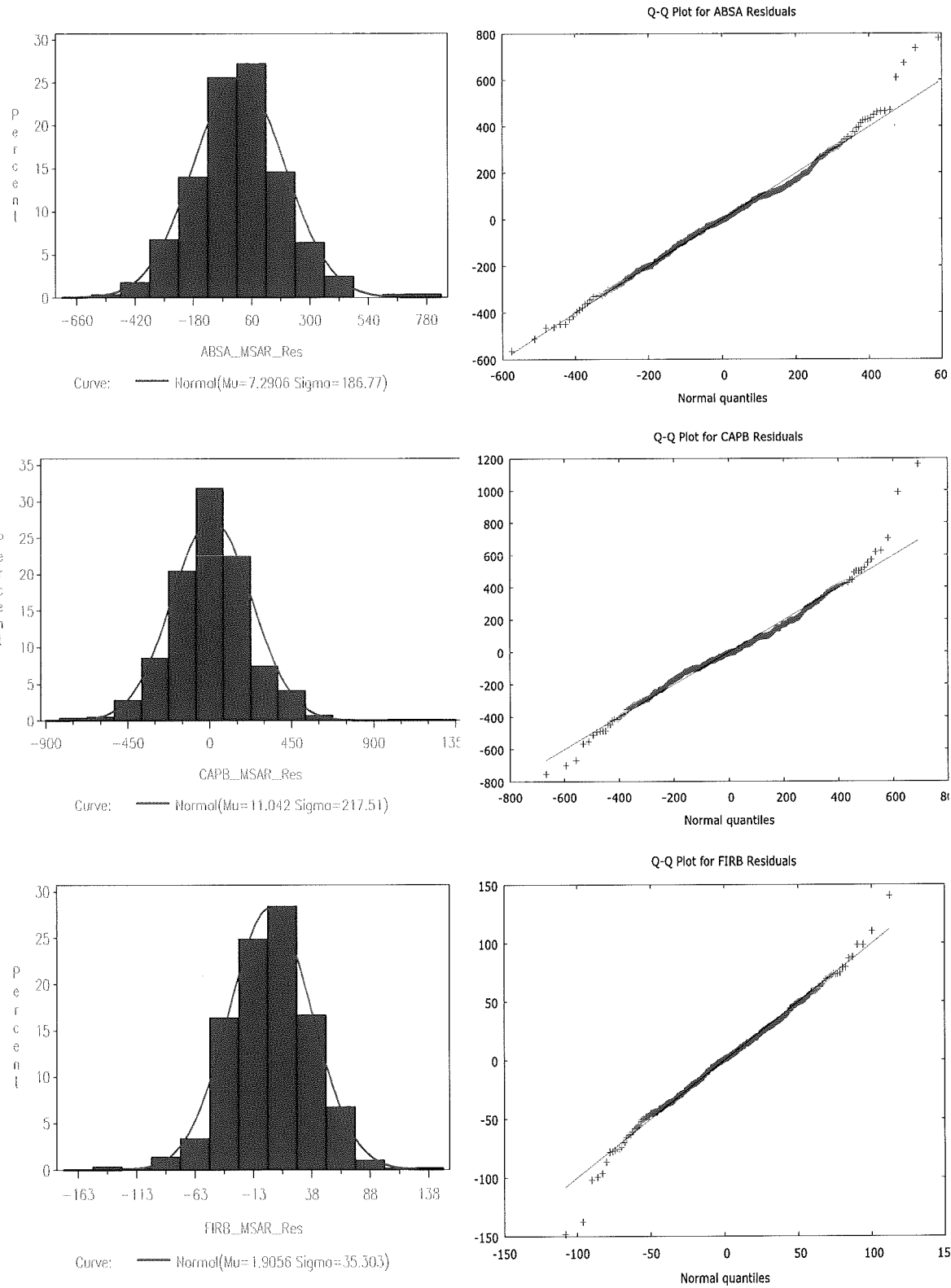
Smoothed Probabilities of Regime 1 and Regime 2

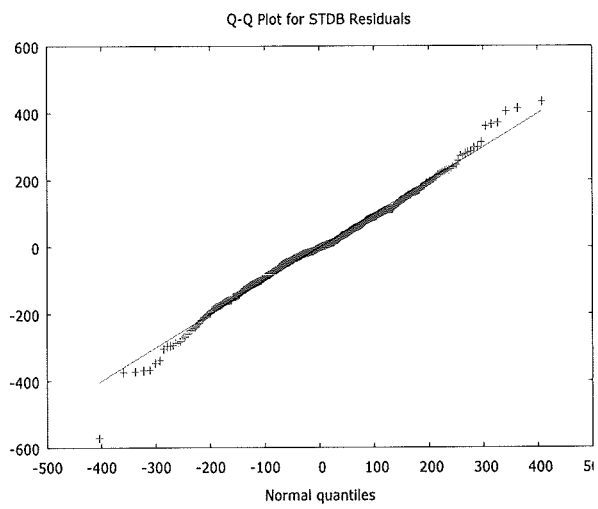
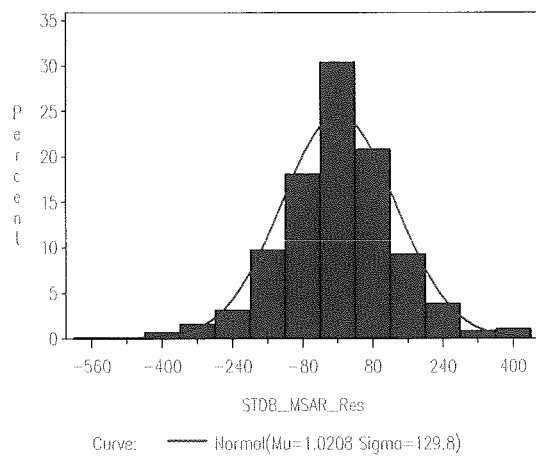
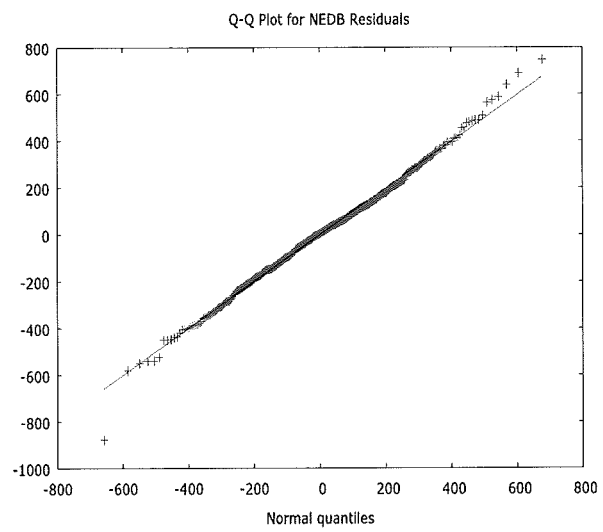
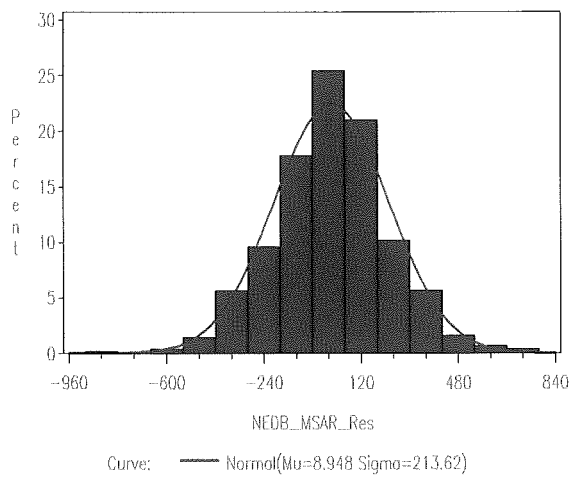




APPENDIX O

Residual Diagnostics from Estimated MS-AR Models





Appendix P

Residual Plots and Overlay Plots of Actual and Estimated MS-AR Models

