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**AN ASYMMETRIC ECONOMETRIC MODEL OF THE SOUTH AFRICAN  
STOCK MARKET**

by

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**AN ASYMMETRIC MODEL OF THE SOUTH AFRICAN STOCK MARKET**

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**Abstract**

In this study a structural model of the South African stock market, the Johannesburg Stock Exchange (JSE), was developed and estimated econometrically. The study has made three important contributions to the literature. Firstly, a structural model of the South African stock market has been developed, which quantifies the relationships between the stock market and macroeconomic variables while analyzing the impact of foreign markets and phenomena such as contagion, policy changes and structural economic changes on the JSE. This will improve the economic agents' understanding of the functioning of the stock market and potentially assist in forecasting the stock market.

Secondly, investors are generally assumed to be risk and/or loss averse. This study explains how this risk and/or loss aversion of investors can cause asymmetry in stock prices and the study evaluates different types of stock market asymmetry with advanced econometric techniques such as the threshold cointegration test of Siklos and Enders (2001) and a Markov switching regime model. The Markov switching regime model is used to model the South African business cycle and to construct an indicator for the state of the business cycle, which is in turn used to introduce cyclical asymmetry in the stock market model. The Markov switching regime model is in itself a substantial contribution to the literature since no Markov switching regime

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model has been estimated for the South African business cycle yet. Apart from being used to capture cyclical asymmetry in the stock market, the Markov switching regime business cycle model can also be used to identify turning points in the South African economy and to model economic growth.

Finally, the forecasting performance of the stock market model developed in this study is compared to other stock market models. According to the results, this model is preferred to the other stock market models in terms of modelling and forecasting the level and direction of the JSE. This means that investors and policy markets can use this model to simulate the impact of changes in macroeconomic indicators on the future course of the stock market and use it to develop profitable trading rules.

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## CHAPTER 1

### INTRODUCTION AND BACKGROUND

#### 1.1 INTRODUCTION

The stock market plays two crucial roles in the economy. The first role is to channel savings into investment. Put differently, it is the market where new capital is raised for production purposes when new securities are issued. At the same time it also forms the market where capital resources are allocated between different investment opportunities. The second role of the stock market is to provide a market for securities where it can be freely traded in a regulated system – a crucial function in any capitalist economy. In other words, it provides investment liquidity as well as an evaluation of the firms of which securities are traded (Fourie, Falkena and Kok 1999:189). Since the stock market plays such an important role in the economy, it is crucial to understand the functioning of the stock market as well as the interrelationships between the stock market and macroeconomic indicators. In this study, a structural econometric model of the South African stock market will be developed in order to empirically estimate the relationships between the stock market and macroeconomic variables.

This model will have four main purposes, namely to quantify the relationships between the South African stock market and macroeconomic variables, to analyze the relationships between the South African stock market and foreign stock market, to forecast the South African stock market and, since the stock market is a leading indicator, to use this stock market forecast to forecast the direction of the economy. First, since stock prices reflect the expectations of investors on future dividends and hence the performance of the aggregate economy, the stock market is influenced by the economy and is fundamentally driven by economic factors. In order to identify the economic variables that influence the stock market and to quantify these impacts, an econometric model has to be developed that can empirically estimate and evaluate these relationships. This will improve the general understanding of all economic agents of the stock market as well as the relationships between the stock market and

macroeconomic variables. In addition, it will be useful to investors for designing trading rules based on structural relationships which should improve profits in the long-run.

Second, it is widely accepted that there is a strong relationship between the stock market and the aggregate economy, which means that a forecast of the stock market can also be used to give an indication of the direction of the aggregate economy. This mainly stems from the fact that any particular stock price reflects investor expectations on the future performance of the firm, which is in turn substantially affected by the overall performance of the economy. However, this relationship is not contemporaneous, but rather stock markets lead the real economy. Since stock prices reflect expectations of future earnings and dividends, investors attempt to forecast current stock prices based on future and not current earnings and economy activity. When they invest in the stock market based on these expectations, the relationship between the stock market and the macroeconomy becomes self-fulfilling. Although the primary objective of the stock market model developed in this study is structural analysis rather than forecasting, any success in forecasting the stock market can therefore also give an indication of the direction of the aggregate economy.

A third use of a stock market model is to evaluate the relationships between the South African stock market and foreign markets. The so-called “contagion” effect between international stock markets has received considerable attention in recent literature, especially since the emerging market crises. However, if the stock market is found to be driven in the long run by fundamental domestic factors, then contagion influences only short-run fluctuations and not the long-run level or intrinsic value of the stock market. This issue is very important since it has crucial implications for the role of stock markets in the broader economic development process. Stock markets can support the process of economic development by increasing the growth in savings, and improving the efficient allocation and utilization of investment resources (Leigh 1997)<sup>1</sup>. However, stock markets can only fulfill these roles if they are being driven by economic fundamentals, so that their pricing and allocation of capital within the

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<sup>1</sup> According to the IMF (2003:70), local securities markets can also be a “more stable source of local currency funding... thereby mitigating the funding difficulties created by sudden stops in cross-border capital flows” as well as a “vehicle for improving the efficiency and stability of financial intermediation”.

economy properly reflect risk and expected returns. If stock markets are not economically efficient in the broad sense of allocating financial capital efficiently to competing uses, they are unlikely to make a positive contribution to economic development, but would more closely resemble gambles (Jefferis and Okeahalam 2000). The only way in which these relationships can be evaluated is by estimating an empirical model that can distinguish between the long-run and determinants short-run dynamics of the stock market.

Finally, the model can be used to forecast the stock market. Forecasts of the level of the stock market also imply forecasts of the direction of the stock market, which can be used by investors as trading rules. So although the model is not developed as a trading tool, it can be used as one.

Stock market movements are difficult to understand and forecasting it is even more difficult. This creates a need for empirical structural analysis, which can assist in understanding the functioning of the stock market and potentially assist in forecasting the stock market. Most studies on stock markets are done for developed countries. This study attempts to address the gap in the literature on analyzing emerging stock markets and in particular the lack of studies on the South African stock market.

## **1.2 OBJECTIVES AND RESEARCH METHODOLOGY**

The primary objective of this study is to develop and estimate a structural econometric model of the South African stock market, the Johannesburg Stock Exchange (JSE). The model will primarily be used for structural analysis, but its forecasting ability will also be evaluated. The model will expose the macroeconomic variables that influence the stock market as well as the magnitudes of these impacts. In addition, the role of phenomena such as globalization, policy shifts and contagion will be evaluated.

There are two alternative approaches that can be followed in modeling stock markets, namely technical analysis and fundamental analysis. Technical analysis builds on the belief that stock prices move in trends that persist. It believes that the patterns in

financial markets repeat themselves and therefore their stock market models and analyses are aimed at capturing historical patterns which they then use to forecast the stock market. Technical analysts believe that when new information comes to the market, it is not immediately available to everybody but rather disseminated from professional investors to the aggressively investing public and then to the great bulk of investors. Therefore it is possible to outperform a buy-and-hold strategy with a trading rule based on historical price data.

This is in direct contrast to even the weak form of the efficient market hypothesis, according to which security prices adjust rapidly to reflect all new information (Reilly 1989:244). This means that if capital markets are efficient, prices fully reflect all the relevant information, so that trading based only upon past data cannot be profitable since by the time information is publicly available it is already reflected by the share prices. It has been shown in the literature that the South African stock market is operationally efficient (Thompson and Ward 1995), which means that share prices cannot be predicted on the basis of historical share prices alone and hence technical analysis is not the relevant approach to model the South African stock market.

In contrast with technical analysis, fundamental analysis focuses on determining the fundamental factors that drive the stock market and base any modeling on the structural and theoretically justifiable relationships between the stock market and economic variables. However, while economic theory should be able to explain the long-run trend of the stock market, the short-run movements are potentially driven not only by the variables dictated by theory but also by variables reflecting market sentiment as well as other factors such as political instability, emerging market crises, exchange rates etcetera (Jefferis and Okeahalam 2000). The influence of these short-run determinants can only be determined empirically (Harasty and Roulet 2000). The long-run behavior of stock prices are usually modeled based on the expected present value model and then the short-run fluctuations of the market around this long-run trend are determined empirically.

The technique of cointegration makes it possible to distinguish between the long-run equilibrium level or intrinsic value of the stock market and the short-run fluctuations around the equilibrium level by estimating both a cointegration equation and an error

correction model (ECM). In the long-run or cointegration equation, the intrinsic value or long-run level of the stock market is modeled based on the relationship between the stock market and economic variables dictated by theory. According to theory, stock prices are a function of future dividends discounted by a discount rate. In the error-correction model, fluctuations around the long-run and the speed of adjustment to a new equilibrium is modeled. In the short-run, not only the economic variables dictated by theory but also variables reflecting market sentiment and important socio-political changes and other non-fundamental factors play a role. However, none of these relationships necessarily have to be symmetric. This study will describe the potential causes of asymmetry and then empirically test whether stock market behavior is asymmetric.

### **1.3 CONTRIBUTIONS OF THIS STUDY**

This study makes two important contributions to the literature. First, it develops and estimates a structural model of the South African stock market. There is a wealth of literature modeling stock markets and examining the relationship between share prices and various economic factors, both theoretically and empirically. However, most studies use data for developed countries in their analyses and very little literature exists for the South African stock market. The most important studies analyzing the structural determinants of the JSE are those of Van Rensburg (1995, 1998, 1999), Jefferis and Okeahalam (2000) and Bar and Kantor (2002). Van Rensburg studied bivariate relationships between the JSE and economic variables and Bar and Kantor developed an econometric model of South African economy focusing on the linkages between the real and financial markets and between domestic and foreign financial markets. Jefferis and Okeahalam estimated an atheoretical stock market model. However, no theoretical, structural econometric model of South African stock market has been estimated yet. The main contribution of this study to the literature is the development of a structural model of South African stock market will be estimated econometrically using cointegration techniques and error correction modeling.

The second contribution of this study is to incorporate the potential asymmetric effects introduced by the risk and loss aversion of investors. Risk aversion refers to

the tendency of rational investors to prefer certainty to risk *ceteris paribus* (Reilly 1989:10,255; Renwick 1971:400). Loss aversion, on the other hand, refers to the inclination of economic agents to be more sensitive to reductions in their levels of well-being than to increases (Bernartzi and Thaler 1995). Two explanations have been given in the literature on why investors' risk and/or loss aversion induces stock market asymmetry. First, Chalkley and Lee (1998) argues that risk aversion encourages economic agents to react promptly on receiving bad news, while it prevents them from acting quickly when receiving good news. A downturn in the relevant economic data (which influences the particular stock price) may be indicative of other economic agents receiving bad news (or expectations) or it might be a random change, but in either case the cautious (i.e. risk averse) response is to act immediately as if the bad data is truly reflecting adverse conditions. In this case (adverse economic data) or "bad" news, risk aversion and uncertainty about the information value of aggregate data work together, leading informed agents to quickly respond to the downturn in economic data and other agents to quickly respond to that response. Of course, there is also uncertainty about the interpretation of an upturn in economic data, but in this case risk (and loss) aversion works against reacting to such a signal since investors will wait until the "good" news is confirmed before they act on it.

It can therefore be expected that investors will react more reluctantly to an upturn in economic data and vice versa. When the behavior of these individual investors are aggregated it implies that the stock market will react quicker during good conditions or on good news or expectations, or put differently, that its adjustment to equilibrium will be slower during adverse economic conditions and faster during positive economic conditions. The "upturn" and "downturn" of data in the Chalkley and Lee (1998) framework originally referred to good or bad conditions as reflected in the state of the business cycle. Since stock prices are discounted future dividends and since real economic activity is one of the main determinants of dividends, an economic upswing (downswing) will cause higher (lower) dividends and an indicator of the state of the business cycle can therefore be used to measure the upturn or downturn in economic data.



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The second explanation for asymmetric investor (and hence stock market) behavior is driven by the potential loss (profit) in and overvalued (undervalued) stock market. Following the same line of reasoning as Chalkley and Lee (1998), Phelps and Zoega (2001) and Siklos (2002) also hypothesized different speeds of adjustment but they introduced a different driving force for the asymmetry by redefining the good and bad news or conditions that prompts the asymmetric behavior of investors. Their theory on stock market asymmetry is based on the paradigm of the structural slump developed by Phelps (1967). A structural slump is characterized by a steep decline in share prices followed by a gradual rise in unemployment. A structural boom, on the other hand, entails a steep rise in share prices followed by a decline in unemployment. In the case of a structural boom, investors calculate that this signals a jump in future asset returns and, consequently, the valuation of these assets as reflected in the stock market. The resulting rise in the profitability of investment signals a falling unemployment rate. The boom ends when the productivity rise increases investment costs.

Theoretically, this scenario works symmetrically, but Phelps and Zoega (2001) argued that it might in practice work asymmetrically since other factors may influence the progress of the business cycle. The potential asymmetry was first evaluated empirically by Siklos (2002). His results showed that the relationships between the economy and the stock markets of the UK and the US were indeed asymmetric.

Although Siklos (2002) tested the stock market asymmetry based on the relationship between the stock market and unemployment, the asymmetry also holds for any other stock market model. If the stock market is undervalued it means that the market prices of shares are below their intrinsic value, so that a profit opportunity created since investors can buy shares at the low current market price and eventually resell it at a higher price once the market has corrected the discrepancy between the market and intrinsic value. In contrast, when the stock market is overvalued market prices of shares are above the intrinsic values. Eventually the market will correct this discrepancy so that share prices fall, in which case investors will lose money. Since investors are loss averse it is more important to avoid the potential loss if the market is overvalued than to make the profit if the market is undervalued. Therefore, if

investors are uncertain, they will react faster to an overvaluation that poses a potential loss than to an undervaluation that poses a potential profit.

The techniques of cointegration and error correction modeling are ideally suited for modeling different speeds of reaction of investors. In the error correction model, the adjustment to equilibrium is modeled and the speed of adjustment is estimated. Usually the coefficient measuring the speed of adjustment is assumed to be constant, but the model can easily be adapted to capture different speeds of adjustment in different circumstances. Econometrically, the two potential causes of asymmetric investor (and stock market) behavior have to be modeled differently. Siklos and Enders (2001) developed a threshold cointegration technique with which different speeds of adjustment can be modeled for overvalued and undervalued series. This test can be applied directly to under- or overvaluation of the stock market. However, this test is not applicable when the asymmetry is caused by different states of the business cycle and this type of asymmetry therefore has to be evaluated differently. In the case of asymmetry with respect to the state of the business cycle, a variable is needed that reflects the different states of the business cycle. In this study, the state variable will be constructed using a Markov switching regime model of the South African business cycle. The Markov switching regime model can be used to simultaneously estimate the probability of the economy being in an expansion or recession and the expected economic growth rate.

The estimation of the Markov switching regime model is in itself a significant contribution to the literature since no Markov switching regime model has been estimated for the South African business cycle yet. Apart from its use in the stock market model to capture the potential asymmetry, the Markov model can be used for two additional purposes. First, it estimates the data generating process (DGP) of the variable under consideration, which is real economic growth in this study. Second, it estimates a probability of the economy or business cycle being in either of two possible states, for example being in a recession or an expansion, for each period. Since this time series of probabilities reflects the likelihood of a recession or expansion, it can therefore be used to classify each observation into one of two regimes. For example, the economy is regarded as being in a low-growth (high-growth) or recession (expansion) regime or state if the probability of being in

recession (expansion) is higher than the probability of being in an expansion (recession). In addition, the probabilities may be used to reflect the degree of certainty of economic agents regarding the state of the business cycle, if it is assumed that a recession probability of one (zero) indicates that the economic agent is absolutely certain that the economy will (not) be in a recession, while a probability of 0.5 indicates that a recession or expansion is equally likely and therefore there are no certainty regarding the state of the business cycle. In other words, the closer the recession probability is to zero or one, the higher the certainty regarding the state of the business cycle. On the other hand, the closer the recession probability is to 0.5, the higher the uncertainty regarding the state of the business cycle.

The estimated Markov-switching regime business cycle model can therefore be used not only to forecast economic growth, one of the most important macroeconomic indicators, but also to forecast the occurrence of recessions and expansions. The only indicator currently available to reflect recessions and expansions is that of the South African Reserve Bank, but their indicator is only available with a considerable time lag. It is therefore not useful for forecasting purposes at all. The Markov-switching regime indicator can fill this gap and will consequently be extremely useful for policy-makers, investors and producers that want to plan their economic decisions or actions.

To summarize, in this study a structural model of South African stock market incorporating both the fundamental factors driving stock prices as well as the influence of the risk aversion of investors are estimated. Cointegration techniques will be used to distinguish between the long-run behavior and short-run fluctuations of the stock market, allowing for the possibility that fundamental factors might drive the long-run behavior but that additional factors come into play in the short-run. Two potential causes of asymmetric investor (and hence stock market) behavior will be evaluated. First, the Siklos and Enders (2001) threshold cointegration test will be used to evaluate asymmetric adjustment in under- and overvalued stock markets. Second, asymmetry with respect to the state of the economy will be evaluated, which necessitates the construction of a state variable. A Markov switching regime model will be developed to estimate the probability of the state of the economy, reflecting

both the expected direction of the business cycle as well as the certainty regarding this expectation.

#### **1.4 OUTLINE OF THE STUDY**

In the next chapter the characteristics of the Johannesburg Stock Exchange (JSE) as well as the unique socio-economic and political environment in which it functions are described. These factors have an important influence on the course and behavior of the stock market and are therefore crucial for the empirical analysis. A brief description of the JSE will be presented as well as an overview of three aspects of the South African economy that have an important impact on the JSE, namely the socio-political environment, the policy setting and the influence of globalization and the revolution in international financial markets.

Chapter three gives a detailed exposition of two theoretical models, the efficient market hypothesis and the expected present value model, which dominate the literature on stock market modeling. According to the efficient market hypothesis, capital markets are efficient in the sense that stock prices adjust rapidly and unbiasedly to reflect new and relevant price sensitive information. This has important implications for the empirical analysis, since trading based solely on historical prices, technical analysis cannot yield abnormal profits if the stock market is efficient and hence necessitates a structural model of the stock market.

According to the expected present value model, the price of a security equals the present value of the expected future income stream. This has been simplified by Gordon and Shapiro (1956) to the constant growth model according to which stock prices are a positive function of expected dividends and a negative function of the discount rate. However, recent studies have argued that these relationships and stock market behavior in general are not necessarily symmetric. Chalkley and Lee (1998) hypothesize that the stock market may be asymmetric conditional on the state of the business cycle, while Siklos (2002) hypothesize that the stock market asymmetry may be conditional on the over- or under-valuation of the stock market. Both types of asymmetry will be evaluated in the empirical analysis. The evaluation of business

cycle asymmetry requires an indicator of the state of the business cycle, which is constructed with a Markov switching regime model in chapter five.

In chapter four an exposition of the empirical studies that modeled international and South African stock markets is given. This will expose the empirical validity and the practical implications of the theories reviewed in chapter three.

In chapter five a state of the business cycle indicator is constructed to evaluate the potential asymmetry of the stock market conditional on the business cycle. This indicator should ideally reflect not only whether the economy is in a recession or an expansion, but also the degree of certainty with which investors can regard the economy as being in a recession or expansion. Such an indicator is developed by estimating a Markov switching regime model for the South African business cycle.

In chapter six a structural model for the South African stock market will be developed and estimated based on the theory presented in chapter three. Using cointegration techniques and error-correction modelling, the long run and short-run behaviour of the stock market will be modelled separately. Nonlinear cointegration tests and the state of the business cycle indicator developed in chapter five will be used to allow and test for the potential asymmetry described in chapter three.

The cointegration model of the South African stock market that will be developed and estimated in chapter six will make a contribution to the literature by establishing the factors that determine the level of the stock market in both the long-run and the short run. However, this model can also be used to forecast the stock market. This will enable investors to simulate the impact of change in macroeconomic indicators on the future course of the stock market and accurate forecasts of the stock market could be used by economists to forecast other macroeconomic indicators that lag the stock market such as consumption and investment<sup>2</sup>. In addition, forecasts of the stock

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<sup>2</sup> Gallinger (1994) gives three reasons why share prices are leading consumption and investment. First, changes in share prices are synonymous with changes in wealth, which influence the future demand for investment goods and consumption (Barro 1990). Second, the stock market is a leading indicator of the economy and reflects information about real activity before it occurs. Finally, an increase in real economic activity increases the demand on existing production capacity, which increases the return on assets and therefore induces increases in future capital investment.

market will predict the future direction of share prices and can hence be used by investors to construct trading rules that can increase profits.

In chapter seven the accuracy of the cointegration model will be compared to other stock market models. This comparison will be done separately for the in-sample and forecast periods. First the models' accuracy in modeling the level of the stock market will be compared. Then the models will be used to develop trading rules in order to compare its profitability and accuracy in modeling the direction of the stock market. Chapter eight provides a summary of the study and indicates some potential extensions for future research.

## CHAPTER 2

### THE SOUTH AFRICAN STOCK MARKET AND THE ECONOMIC ENVIRONMENT

#### 2.1 INTRODUCTION

The unique characteristics of the Johannesburg Stock Exchange as well as the socio-economic and political environment in which it functions have an important influence on the course and behavior of the stock market. The performance and trends of the Johannesburg Stock Exchange (JSE) must hence be seen in perspective, taking account of the changes and characteristics of this unique environment. Therefore, a brief description of the JSE will be presented as well as an overview of three aspects of the South African economy, namely the socio-political environment, the policy setting and the influence of globalization and the revolution in international financial markets.

The exceptional socio-political situation in South Africa has had a profound impact on the economy and especially the financial markets. For most part of recent history, political instability caused huge scale capital withdrawal by investors who were either averse to the additional risk that it introduced, or who protested against the political regime. The capital outflow, later combined with economic sanctions and a debt standstill, significantly influenced asset prices.<sup>1</sup> This situation was reversed after the democratic elections in 1994<sup>2</sup>.

Monetary policy directly influences the stock market through its influence on interest rates, which is one of the main determinants of the discount rate that investors use to

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<sup>1</sup> For example, during 1985, the year of president P.W. Botha's Rubicon speech and the introduction of international sanctions against South Africa, the country had a net capital outflow of R4 394 million (www.reservebank.co.za). This contributed to the low growth rate in the JSE all share index of 7,4 percent compared with 20,4 percent from 1980-1984 (www.reservebank.co.za).

<sup>2</sup> South Africa had net capital inflow in 1994 of R4 359 million compared with a net capital outflow of R5 669 in 1993 (www.reservebank.co.za). With the exception of 2001 South Africa had positive net capital inflows from 1994 (www.reservebank.co.za).

discount future dividends in their calculation of the intrinsic value of stocks<sup>3</sup>. In addition, monetary policy has an indirect influence on the stock market through its influence on future economic growth which has a crucial influence on expected dividends and hence on stock prices. Furthermore, interest rates influence the exchange rate, which affects the dollar returns of South African assets and therefore the attractiveness and the demand for (and hence the price of) South African financial assets including shares.

Since South Africa is a small open economy its markets, especially its financial markets, are not only influenced by the domestic economic environment but also by international markets. Globalization has increased this influence of international markets on South Africa's financial markets. In addition to the changes brought about by globalization, the role of South African financial markets in the international economy was influenced dramatically by South Africa's classification as an "emerging market". Since investors regard emerging markets as a single asset class, any change in an emerging market is rapidly transferred to the other emerging markets.

In this chapter a brief overview of the socio-economic background and institutional setting of the South African stock market will be given. In addition, important changes in financial markets in general, as well as South Africa in particular, will be described as well. Figure 2.1 presents the most important events diagrammatically.

## **2.2 THE STRUCTURE OF THE JOHANNESBURG STOCK EXCHANGE**

The Johannesburg stock exchange (JSE) was founded in November 1887, 14 months after proclamation of the Witwatersrand goldfields, to enable the new mines and their financiers to raise capital for the development of the mining industry. Both the number and type of companies listed on the JSE have changed dramatically over the years. As the economy expanded and developed, the mining companies that were

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<sup>3</sup> The present value model, according to which share prices are determined by the discounted value of all future income, is discussed in chapter three. According to this theory, the discount rate that investors use in this calculation is determined by interest rates and a risk premium.



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initially listed on the JSE were joined by an increasing number of industrial companies that listed on the JSE. Today most of the companies listed on the JSE are not mining companies. The rapid growth of the JSE is reflected in the growth in the number of listed companies which grew from only 151 mining, financial and industrial companies listed in 1932, compared to 659 companies in 1998 (see table 2.1) (Van Zyl *et al* 2003:289). The rapid growth is also evidenced from the necessity to relocate to bigger buildings six times within 90 years.

**Table 2.1      Characteristics of the JSE**

	<b>1985</b>	<b>1990</b>	<b>1995</b>	<b>1998</b>	<b>2002</b>
Number of stocks listed	462	732	640	668	852
Market capitalization (R million)	141 785	350 726	1 022 656	1 001 556	1 584 100
Market capitalization (US\$ million)	55 439	137 540	280 526	170 252	181 998
Annual trading value (R million)	6 241	21 130	63 237	323 682	808 662
Annual trading value (US\$ million)	2 836	8 158	17 048	58 444	92 949
Market index	1 323	2 720	6 228	5 431	10 288

Source: Jefferis and Okeahalam (2000) and [www.jse.co.za](http://www.jse.co.za)

The mushrooming of listed companies worldwide during 1980s also took place on the JSE and necessitated the creation of two new categories of shares, namely the Development Capital Market (DCM) which caters for smaller companies and have fewer requirements in terms of profits and company size and the Venture Capital Market (VCM) on which accepted companies undertaking greenfield ventures can be listed provided they meet certain requirements (Van Zyl *et al* 2003:288). In addition, the JSE announced the first exchange in Africa that will list small and medium

growing companies, the AltX, which will open for trading in October 2003 ([www.jse.co.za](http://www.jse.co.za) and [www.altx.co.za](http://www.altx.co.za))<sup>4</sup>. The purpose of AltX is to create an alternative exchange where small companies can raise capital in order to stimulate the small and medium enterprises (SMEs)<sup>5</sup>. Following the international trend, floor trading ended in June 1996 when the JSE switched to electronic trading on the JET (JSE Equities Trading) System.

The reintegration of South African into the world economy after the abolishment of sanctions and the 1994 democratic elections had a substantial impact on the JSE. Like the rest of the economy the JSE was also caught up in this process of reintegration and it has become deeply entangled in the globalized trading environment characterized by 24-hour share trading. This made the JSE more susceptible for the influence of events and trends in the rest of the world, especially those in other emerging market economies (Van Zyl *et al* 2003). The JSE has benefited from huge capital inflows since 1994, but these were mostly portfolio flows, which increased the vulnerability for international events and sentiment as was evident during the recent emerging market crises.

Since the reintegration of South African into the world economy, foreign investors play a more substantial role on the JSE. Total foreign investment now accounts for more than 20 percent of the market capitalization of the JSE and foreign investors sometimes account for more than half of its daily trading (Van Zyl *et al* 2003:305). For example, during 2002 the total value of trading on the JSE was R808 662 million of which the value of trading by foreigners was R419 066 million ([www.jse.co.za](http://www.jse.co.za)). Several factors contributed to this phenomenon (Van Zyl *et al* 2003:305): (i) foreign confidence was boosted by the abolition of exchange controls in March 1995 (see section 2.4) when foreign investors gained unrestricted access to shares on the JSE. Not all emerging markets give foreign investors unrestricted access to their stock market, for example some countries have a ceiling on the amount or the type of shares that foreigners are allowed to hold. Since South Africa's abolition of exchange

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<sup>4</sup> The AltX is similar to the AIM exchange in the UK, which also lists small, growing companies. More than 850 companies have been listed on the AIM exchange, raising more than US\$ 10 billion since it opened in 1995.

<sup>5</sup> According to the Department of Trade and Industry (DTI), who endorses and supports the AltX, it should also promote black economic empowerment and assist in creating sustainable employment ([www.jse.co.za](http://www.jse.co.za)).

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controls on foreigners in 1995, foreign investors have been net buyers in excess of R9.3 billion, compared to only R0.185 billion in 1994. (ii) Foreign investors have also welcomed the scrapping of the 15 percent non-resident shareholders' tax in October 1995. (iii) Many investors that previously left South Africa due to their disagreement with the political regime returned with the introduction of the new political dispensation in 1994. (iv) Foreign investors welcomes the development of financial instruments such as futures and options markets in the rand and share indices in South Africa which enable them to hedge currency and equity risks especially since the JSE is relatively volatile.

**Table 2.2 African Stock Markets (Ranked by Turnover) 1998**

Country	Capitalization (US\$ million)	Annual Turnover (US\$ million)	Ratio of Turnover to GDP (%)	Number of stocks
Zambia	293	N/a	N/a	8
Swaziland	85	0.2	0.2	5
Namibia	429	13	2.6	15
Cote d'Ivoire	1818	39	2.6	35
Ghana	1384	60	4.8	21
Botswana	724	70	10.6	14
Kenya	2024	79	4.0	58
Mauritius	1849	102	5.9	40
Nigeria	2887	161	5.2	186
Zimbabwe	1310	166	9.2	67
Tunisia	2268	189	8.3	38
Morocco	15676	1385	10.2	53
Egypt	24381	5028	22.3	861
South Africa	170252	58444	30.4	668
Total	225087	65735	29.2	2061

Source: Jefferis and Okeahalam (2000)

The JSE is the oldest and biggest stock market in Africa. In 1998, the JSE was the 17<sup>th</sup> largest stock market in the world and third largest emerging stock market after China and Taiwan measured by market capitalization. It also accounts for three quarters of total capitalization of African stock markets (see table 2.2). The JSE is relatively illiquid compared to world markets and therefore, measured by turnover, by 1998 JSE was the 20<sup>th</sup> largest stock market and sixth largest emerging market. The relative illiquidity is also reflected in other characteristics of the JSE such as the domination of share ownership by a small number of large conglomerate companies (Jefferis and Okeahalam 2000).

## **2.3 THE ROLE AND FUNCTIONING OF THE SOUTH AFRICAN FINANCIAL MARKET AND THE JOHANNESBURG STOCK EXCHANGE**

### **2.3.1 The Role and Functioning of the South African Financial Market**

The financial market can be broadly divided into two parts, namely the primary and the secondary markets. Securities are issued in the primary market by institutions that want to borrow money. In South Africa securities are issued by the Treasury, public corporations (e.g. Eskom), public utilities (e.g. Telkom and Transnet), local authorities and private sector companies when they need to finance their activities. The demand for the securities issued in the primary financial market is generally from banks, building societies, insurance companies, pension funds, mining houses, stockbrokers and the Public Investment Commissioners (Fourie *et al.* 1992:121).

The way in which securities are issued depends on the type of security. Government bonds are sold on a tap or tender basis. In the case of a tap issue, the Reserve Bank buys stock from the Treasury at a rate at which the Bank can sell a fairly large volume to the market and then resell it to the public. In the case of a tender issue, the date of the issue and amount of stock available are announced to the public and sold to the highest bidders. Other fixed-interest securities as well as all variable-interest securities are either sold by the issuer or by an underwriter, usually a merchant bank,

acting on behalf of the issuer. The issue may either be by way of a public issue where the terms and conditions are announced to the public at large, or by way of a private issue where it is offered only to selected investors (Fourie *et al.* 1999:185; Fabozzi 1992:523).

The securities issued in the primary market are traded in the secondary market. The financial intermediary sector is the principal supplier of funds to the secondary financial market, in particular insurers, pension funds and building societies, which simply channel the surplus funds of the household sector to appropriate investments. Other banking institutions, the Public Investment Commissioners and other financial intermediaries such as participation mortgage bond schemes and the National Housing Commission are also lenders in the financial markets (Fourie *et al.* 1992:41). The main traders of securities in the secondary financial market are divided into five categories, namely financial intermediaries, the government, corporate business enterprises, households and the foreign sector.

Foreign participants, in other words foreign households, businesses, institutional investors and governments, act in the South African financial markets in the same way as domestic households, businesses, investors and the government. However, technological development and the process of globalization have dramatically increased the importance and role of foreign participants in the domestic capital and other financial markets. Globalization has resulted in the acceleration of international financial transactions and international financial interdependence<sup>6</sup> has increased substantially. Advances in computer technology, coupled with advanced telecommunication systems, link market participants throughout the world and allow the transmission of real-time information on security prices and other key information to many participants in many places. This enables many investors to monitor global markets and simultaneously assess how this information will impact on the risk/reward profile of their portfolios (Fabozzi 1995:15).

The number of new securities issued in the primary market has a substantial influence on the demand for and price of securities in the secondary market. The secondary

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<sup>6</sup> See e.g. Arshanapalli *et al* (1995) and Sheng and Tu (2000).

market serves as a barometer of changes in the markets and reflects these changes in the prices and volumes of traded securities. This gives the issuers in the primary market a good idea of the correct price and interest rate at which they should issue new securities – key decisions for a successful issue. The secondary market also provides investors with the assurance that they will be able to resell their securities and adjust their portfolios, provides an indication of the general availability of funds and enables the Reserve Bank to buy and sell securities in order to influence the liquidity of the financial markets (Fourie 1999:13; Faure *et al.* 1991:10).

### **2.3.2 The Role and Functioning of the Johannesburg Stock Exchange**

The two main roles of a stock exchange can be identified from the distinction between primary and secondary markets. The main function of the JSE is to raise primary capital ([www.jse.co.za](http://www.jse.co.za)) by re-channeling capital into productive economic activity and thereby building the economy while stimulating the creation of wealth and job opportunities. Issuing shares is a way for companies to raise large sums of capital for expansion, to finance new businesses and to create new employment opportunities without borrowing money. This function is essential in any market economy. The second role of the stock market is to provide a market for securities where it can be freely traded in a regulated system. In other words, it provides new investment opportunities, investment liquidity as well as an evaluation of the firms of which securities are traded. (Fourie, Falkena and Kok 1999:189). Liquidity is the most important objective of any stock market since the success of the primary market in fulfilling the function of raising new investment capital depends critically on it.

## **2.4 THE SOCIO-ECONOMIC ENVIRONMENT**

The socio-economic circumstances in South Africa since 1960 can broadly be divided into four decades with distinct characteristics. The 1960s were literally and metaphorically golden years for South Africa, characterized by high and relatively stable economic growth. South Africa, one of the world's largest gold producers, was heavily influenced by the gold mining industry especially since there was a continuous global demand for gold due to the gold standard regime that prevailed at

the time. Gold exports was not only one of the major earners of foreign currency for South Africa, but also one of the biggest employers, an important source of tax revenue and an important stimulant of industries that provide products or services to gold mines.

The wealth of gold and other commodities meant that South Africa was receiving sufficient foreign capital to maintain a positive balance on the capital account, which could be used to finance a deficit on the current account. Even after the political instability following the Sharpeville riots of 1960-1961, the persistent surplus on the capital account was sufficient to finance the current account deficit despite the huge capital withdrawals of foreign investors. The persistent capital account surplus meant that stimulatory monetary and fiscal policies could be adopted, in contrast with the situation during the 1970s. In order to reduce the capital outflows, exchange controls were introduced by converting foreign investors' funds into "blocked rand" accounts (Van Zyl *et al* 2003:336). This meant that funds from foreign investors could only be repatriated by purchasing JSE securities and selling them to other foreigners or by buying certain approved South African bonds and repatriating their proceeds after five years.

The oil price shock of 1973 set the tone for the 1970s as it led to higher inflation and lower economic growth worldwide. South Africa did not escape these problems and inflation became the main priority of policy makers. The problems were aggravated by political problems domestically, where the apartheid policies caused widespread violent protests and riots. Partially due to the increased uncertainty created by these protests and partially to express their disapproval with the apartheid regime, investors started to withdraw their money on a huge scale. After the 1976 Soweto riots capital inflows declined to such an extent that the current account deficit could no longer be financed by the capital account. During 1977, South Africa had a net capital outflow of R126 million ([www.reservebank.co.za](http://www.reservebank.co.za)). Policies had to be redirected to aim at balancing the current account. In the 1976 Budget speech, Owen Horwood introduced an era of "fiscal discipline" and reprioritized policy objectives so that maintaining balance of payments equilibrium was the most important objective, followed by curbing the double-digit inflation. Restrictive monetary and fiscal policies had to be adopted.

South Africa was caught in the “debt trap”; the economy could not grow by more than about 2.5 percent without incurring a current account deficit. After the abolishment in 1971 of the Bretton Woods system of fixed but adjustable exchange rates (Salvatore 1995:696), a variety of exchange rate policies were implemented. The exchange control system also evolved continuously and the blocked rand accounts were replaced by the “securities rand” system which allowed the direct transfer of securities rands into foreigners’ accounts. In 1979 a dual exchange rate was introduced when the securities rand was replaced by the financial rand, which could be used to buy a wider variety of South African assets (Van Zyl *et al* 2003:337). The system was abolished and reinstated several times until it was finally scrapped in 1995 (Van Zyl *et al* 2003:337).

The situation has worsened during the 1980s. The introduction of the tricameral parliamentary system for Whites, Indians and Coloured people (with the exclusion of Black people) led to prolonged unrest from 1984. Consumer boycotts, stayaways and violent protests peaked in 1986 and after the introduction of economic sanctions against South Africa and the 1985 debt standstill agreement, a state of emergency was declared. The extensive capital outflows combined with the debt standstill caused a liquidity shortage and it became necessary to have a surplus on the current account. Consequently, the Reserve Bank’s ability to allow economic expansion was inhibited and this was one of the main reasons for the low economic growth rates over this period.

The 1986 budget speech introduced a major policy shift and employment and the economic conditions for social and policy reform were given the highest priority. In addition to the balance of payments and political problems, the gold price started to decline after peaking in January 1980. This, along with double-digit inflation introduced the steady depreciation of the rand, which made South Africa even less attractive to foreign investors.

The situation was reversed during the 1990s when economic sanctions against South Africa were lifted and South Africa re-entered the international economy. The political tension and the radical social change once again manifested in the economy



and equity prices. The period 1990-94 was characterized by pre-election destabilization, but after the first democratic elections in 1994 foreign capital became available again. The availability of capital made it once again possible to run a deficit on the current account.

To summarize, the socio-economic environment in South Africa since 1960 can be divided into four sub-periods. The period 1960 to 1975 was characterized by high economic growth, low inflation and a balance of payments surplus. From 1976 to 1985, high inflation and the balance of payments constraint necessitated restrictive policies which contributed to low economic growth rates. During the period 1985 to 1994, the need to generate balance of payments surpluses led to even lower economic growth rates. The situation was reversed after 1994 when capital became available again and a current account deficit could be financed. Economic growth almost doubled from an average of 1,24 percent during the period 1985 to 1994, to 2.6 percent from 1994 to 2000 ([www.reservebank.co.za](http://www.reservebank.co.za)).

## 2.5 THE INSTITUTIONAL AND POLICY SETTING

Changes in the socio-economic environment have always had a crucial influence on the priorities and hence course of monetary policy in South Africa. During the 1960s and 1970s the focus of monetary and fiscal policy was employment, which was achieved by stimulatory economic policies at the cost of higher inflation (Fourie *et al* 1999:310). During the 1960s, the Reserve Bank attempted to slow down an excessive expansion of liquidity in the banking sector by introducing a required cash reserve ratio<sup>7</sup> in the Bank Act of 1965 and a supplementary reserve requirement in 1968 (Botha 1997). After the promulgation of the Banks Act, there were years of brisk economic activity, increasing inflationary pressures and a rapidly expanding liquidity base of the banking system. Cash reserve requirements proved inadequate, which led to the introduction of variable liquid asset controls, a measure that recognized the potential of near money as a means of credit creation (Botha 1997).

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<sup>7</sup> The initial cash reserve ratio in 1965 was eight percent of short-term liabilities. In March 1968 this was increased so that banks had to invest 12 percent of their increases in short term liabilities with the Reserve Bank and 20 percent with the National Finance Corporation.

Capital outflows after the 1960 Sharpeville protests were two-fold in nature: capital flight that reflected the nervousness of foreign investors caused by the political instability and speculative capital outflow caused by expectations of a devaluation due to the steady decline in foreign reserves and the weakening of the rand (Franzen 1983). In reaction to the capital flight, monetary authorities introduced a package of restrictive measures including higher liquid asset requirements, tighter import controls and more intense exchange control on residents.

The oil price shock of 1973 led to higher inflation worldwide and inflation became a policy priority in South Africa. During his tenure, Dr De Jongh (Reserve Bank Governor from 1967 to 1980) implemented a series of additional direct controls such as a ceiling on advances, deposit rate controls, exchange control, import deposits and some direct consumer credit controls in an effort to contain the persistent increases in money supply and the inflationary tendency (Botha 1997). Despite the stringent controls, money supply grew at an average rate of 15 percent per annum – much higher than the inflation rate that only exceeded 10 percent in 1974 and the real economic growth rate of nine percent per annum (Botha 1997).

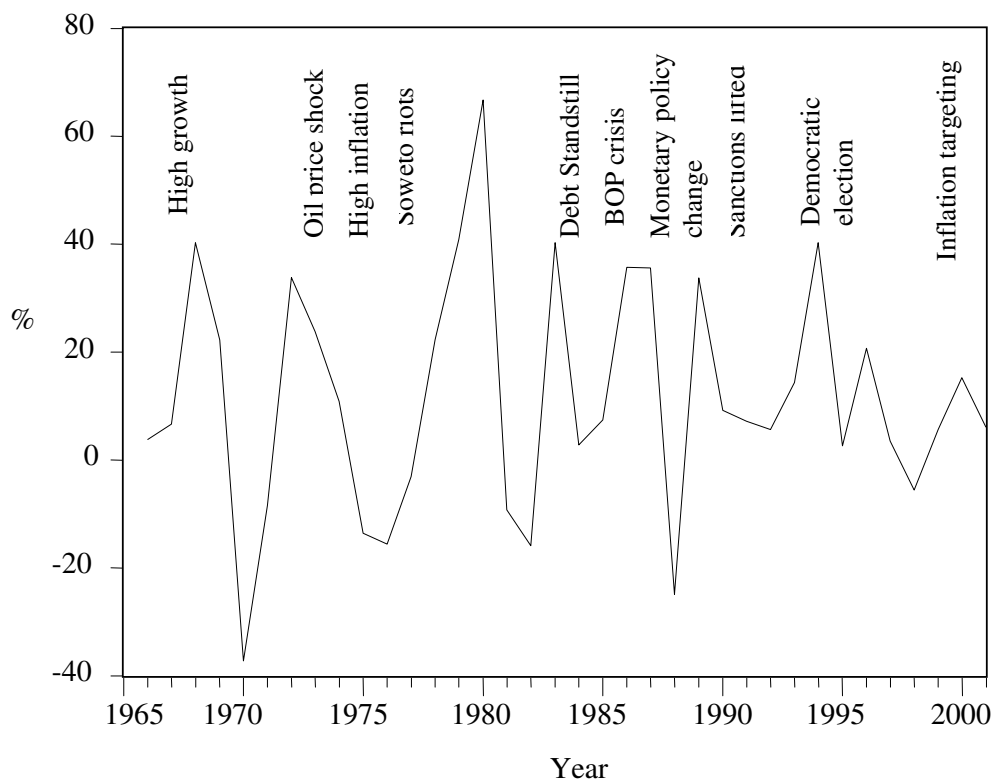
The controls of the 1960s and 1970s gave way in the 1980s to a general recognition of the need to abolish as many restrictions as possible in a shift towards market-oriented policies (Fourie *et al* 1999:314, Van Zyl *et al* 2003:84, Botha 1997). The growing influence of the policy approach of the Thatcher government in the United Kingdom and the Reagan administration in the United States in the 1980s, caused a definite shift across the globe in favor of market-oriented policy measures. This shift in policy approach was further encouraged by the liberalization of international financial markets. South Africa followed and also adopted a more market-oriented approach after the report of the De Kock commission in 1984/1985. The trend gained momentum. In line with the international trend at the time the Reserve Bank, under Dr De Kock<sup>8</sup>, started to align its policies with developments in markets, rather than to force markets in a predetermined direction (Botha 1997). More emphasis was placed on using interest rate adjustments rather than direct credit extension restrictions.

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<sup>8</sup> Reserve Bank Governor from 1981 to 1989.

The 1980s was undoubtedly a very difficult decade in the history of the Reserve Bank, operating with the limited indirect intervention in the face of widespread international hostility and growing resistance as a result of the economic and racial policies of the government at the time. After President PW Botha’s Rubicon speech in August 1985, international sanctions and the debt standstill agreement<sup>9</sup> were introduced against South Africa. This led to an immediate outflow of huge amounts of capital, with a total net capital outflow of R4 359 million during 1985. In an attempt to reduce capital outflows and to attract foreign capital, interest rates were kept high during the period of international isolation (Botha 1997; Fourie *et al.* 1999:314).

**Figure 2.1 Returns on the JSE and the South African Social, Economical and Political Environment From 1960**



Source: [www.jse.co.za](http://www.jse.co.za)

<sup>9</sup> With the debt standstill agreement in 1985 all foreign banks ceased lending to South Africa. In reaction the South African government prohibited South African banks from repaying foreign obligations to foreign creditors.

Although monetary policy did not change much in the 1990s under Dr. Stals as governor of the South African Reserve Bank, this period was characterized by dramatic socio-political changes. In the early 1990s sanctions were abolished after the first democratic election in 1994 political barriers were removed. South Africa became more exposed to world financial markets. Since 1994, South Africa has adopted a clearly defined policy of actively participating in the process of financial globalization and has implemented a number of economic policies to facilitate the process of its participation in globalization (Stals 1999). Following countries such as Canada and Sweden, South Africa adopted an inflation-targeting regime in February 2000<sup>10</sup>. This framework does not require significant changes in monetary policy, but the new aim of monetary authorities is to play an active role in reducing the inflation expectations of economic agents.

## **2.6 THE IMPACT OF GLOBALIZATION AND SOUTH AFRICA'S EMERGING MARKET STATUS ON THE JSE**

### **2.6.1 Globalization and Global Financial Revolution**

When South Africa re-entered the international economy in the early 1990s, globalization and the revolution in financial markets have transformed the structure and functioning of markets as well as the interaction between international markets. Globalization changed the world into a global village in which national borders and distance no longer matter and the political, social and economic interaction between different countries have increased dramatically. In addition, globalization and deregulation led to the liberalization of trade, finance and investment of which the liberalization and revolution of financial markets have been the most pronounced. Investors can now truly diversify internationally and a portfolio comprising international assets became universal.

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<sup>10</sup> In 2000 the Reserve Bank adopted an inflation-targeting regime, with a target range for average CPIX inflation, in other words headline consumer inflation excluding mortgage cost. The initial target was between three and six per cent for 2002 and 2003 and between three and five per cent for 2004 and 2005. The target for 2004 was subsequently amended to between three and six percent.

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The financial revolution caused irreversible and revolutionary changes in financial markets. Innovations in technology and communication transformed the functioning of financial markets and enabled the development of infinitely more instruments and markets (Handley and Mills 1996:74). International interdependence, especially amongst financial markets, has increased substantially (Arshanapalli et al. (1995) and Sheng and Tu (2000)). Deregulation has changed financial market structures and investors now have instant access to most asset markets worldwide.

The financial revolution that took place in South Africa was partially an adoption of the changes that occurred in the rest of the world, but a couple of domestic factors also contributed to the need for change (Jones and Muller 1992:323). Changes in the structure of the economy led to the expansion of the size and importance of the industrial sector relative to traditionally important sectors such as the agricultural sector. This changed the profile and needs of corporate clients. The higher income per capita increased the wealth of private individuals and banks had to change in order to accommodate the need of their wealthy private clients for a more sophisticated banking system. Technological improvements facilitated the automation of transaction processing and the availability of information. The financial revolution in South Africa was characterized by changed ownership of the leading banks, changes in the function of banks in the economy, increasingly specialized financial institutions, the development of a domestic money market, the transformation of building societies to banks, the increased influence of insurers and the introduction of credit cards and automatic teller machines (ATMs) (Jones and Muller 1992:325).

As a consequence of the transformations brought about by globalization and financial liberalization, financial markets have become more efficient but also more volatile and increasingly subject to speculation practices. Some countries benefit greatly from the opportunity to attract unprecedented inflows of capital. However, international markets tend to ignore countries that are not performing well and capital flight is increasingly prevalent in countries that are perceived not to provide competitive opportunities for investment (Handley and Mills 1996:74).

The structural changes caused by globalization have been particularly profound for the small open economies such as South Africa. The structure and functioning of

South African markets were changed dramatically by globalization and the revolutionary changes in international financial markets. Previously, South African financial and real markets mainly operated in isolation. This all changed when sanctions were abolished in the early 1990s and South Africa became part of the global economy. Domestic markets no longer operate in isolation, but rather form part of the global financial system and are therefore extremely susceptible to changes in foreign markets. In fact, foreign markets play a significant role in driving domestic markets.

### **2.6.2 The Emerging Market Syndrome**

In addition to the changes brought about by globalization, the role of South African financial markets in the international economy was influenced dramatically by South Africa's classification as an "emerging market". No universally accepted definition of emerging market exists, but most are based on a combination of factors such as market turnover, per capita income, the degree of freedom from regulations, capital market size and the restrictions on inflows and outflows of funds<sup>11</sup> (Fifield, Lonie and Power 1998). The group of emerging countries is an evolving, rather than a static group of countries.

Despite the lack of universally accepted definition, emerging market securities received growing recognition as eligible portfolio assets during the past thirty years. In 1971 the International Financial Corporation (IFC) established a unit responsible for capital market development and they succeeded in focusing attention of country members of the World Bank Group on importance of securities markets as an essential mechanism to mobilize domestic savings and to attract foreign capital to developing economies (Fifield, Lonie and Power 1998). With the formation of the Templeton Emerging Markets Fund in the US in 1987, investment in emerging markets became a recognized investment category.

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<sup>11</sup> The most widely accepted definition is the one proposed by the IFC, which classifies the stock markets of all the developing countries as emerging stock markets. They adopt the criteria of the World Bank, whose classification is based on per capita income, in defining "developing" (Fifield, Lonie and Power 1998).

During the 1980s and 1990s, the group of emerging countries experienced higher economic growth than rest of the world. On average, emerging economies had real economic growth rates of four percent and 4,1 percent during the 1980s and 1990s respectively, compared with the 3,4 percent and 3,3 percent of the world economy (World Bank 2000). This attracted huge capital flows to this group of countries, but these capital flows are mostly portfolio flows and extremely volatile. For example, portfolio flows to developing countries increased from \$2,7 billion in 1990 to \$51 billion in 1993, before it fell to \$16 billion in 1998 following the Asian crises (World Bank 2000).

South Africa receives a high percentage of portfolio flows relative to other emerging markets due to an extremely liquid equity market relative to other emerging economies (Loots 2002, Smith 2001). However, since emerging markets are viewed by investors as a single asset class, any perceived risk in an emerging market is rapidly transferred to the other emerging markets, as was demonstrated by the so-called “contagion” during the 1994 Mexican Tequila crises, the Asian crisis in 1998 and recently the crises in Russia, Turkey and Argentina. This had an important influence on the vulnerability of South Africa’s financial markets to changes in other financial markets, especially those of other emerging markets. South Africa’s classification as an emerging market meant that not only is it influenced by the dominant world markets, but it became extremely susceptible to changes in the financial markets of other emerging countries since investors view them as a single asset class. As a consequence a shock in any of the emerging markets will immediately spill-over to the other emerging markets, as was evident during the various emerging market crises during the last decade.

## **2.7 CONCLUSION**

In this chapter a brief overview was presented of the characteristics of the JSE as well as the socio-economic background and institutional setting in which it operates. In addition, important changes in financial markets in general, as well as South Africa in particular, were also described.

The exceptional socio-political situation in South Africa has had a profound impact on the economy and especially financial markets. For most part of recent history, political instability caused huge scale capital withdrawal by investors who were either averse to the additional risk that it introduced, or who protested against the political regime. The capital outflow, later combined with economic sanctions and a debt standstill, significantly influenced asset prices. This situation was reversed after the first democratic election in 1994.

Monetary policy directly influences the stock market through its influence on interest rates, which in turn is one of the main determinants of the discount rate that investors use to discount future dividends to calculate the intrinsic value of stocks. Monetary policy in South Africa has traditionally to a large extent been determined by the socio-political environment. During the 1960s South Africa earned sufficient foreign currency by commodity and gold exports, so that a current account deficit could be financed by the capital account and therefore stimulatory monetary and fiscal policies could be adopted. This changed during the 1970s, when the oil price shocks led to a worldwide increase in inflation and monetary policy had to be more restrictive. During the 1980s, political instability led to the debt standstill and the introduction of economic sanctions against South Africa by the international community. This forced monetary authorities to adopt more restrictive policies since the current account deficit could no longer be financed by the capital account. In line with the international trend of the time, monetary policy became more market-oriented during this time. In the late 1990s an inflation-targeting regime has been introduced.

However, no market operates in isolation, changes in international financial markets and the changing role of South Africa in the international economy has had a profound impact on the stock market. Globalization transformed the world into a global village in which national borders and distance no longer matters and in which the political, social and economic interaction between different countries has increased dramatically. In addition, deregulation and revolutionary changes in communication and technology gave international investors instant access to any financial assets. This means that the domestic stock market has become even more vulnerable to changes in international markets and that a change or crises in a financial anywhere in the world is rapidly transmitted to all other markets.



In addition to the changes brought about by globalization, the role of South African financial markets in the international economy was influenced dramatically by South Africa's classification as an "emerging market". Since emerging markets are viewed by investors as a single asset class, any perceived risk in an emerging market is rapidly transferred to the other emerging markets, as was demonstrated by the so-called "contagion" during the 1994 Mexican Tequila crises, the Asian crisis in 1998 and recently the crises in Russia, Turkey and Argentina. South Africa's classification as emerging market meant that not only is it influenced by the dominant world markets, but it became extremely susceptible to changes in the financial markets of other emerging countries. As a consequence a shock in any of the emerging markets will immediately spill-over to the other emerging markets, as was evident during the various emerging market crises during the last decade. Therefore, any attempt to model the stock market has to take into account the influential role of foreign markets, especially other emerging markets, in driving the domestic markets.

## CHAPTER 3

### STOCK MARKET THEORY

#### 3.1 INTRODUCTION

This chapter gives a detailed exposition of two theoretical models, the efficient market hypothesis and the present value model, which dominate the literature on stock market modeling. Intuitively the efficient market hypothesis asserts that stock prices adjust rapidly and unbiasedly to reflect new and relevant price sensitive information. Although these price adjustments are not always correct, it is unbiased so that the under- and over-adjustments are unpredictable. Since new information are random and independent and the large number of investors adjust stock prices rapidly to reflect this new information, price changes are independent and random (Reilly 1989:212). This means that trading based solely on historical prices, in other words technical analysis, cannot yield abnormal profits.

Initially, most of the empirical research on the efficient market hypothesis was done in terms of the random walk theory, which was based on empirical analysis without a theoretical foundation. Fama (1970) presented the first synthesis of the efficient market theory in terms of the fair game model and Samuelson (1965) and Mandelbrot (1963) showed that the fair game model is analytically equivalent to the expected present value theory of security valuation (also called the present value model). According to this theory, stock prices are a function of all the expected future dividends discounted at the discount rate.

Although the present value model provides a theoretical foundation for modeling stock prices, the macroeconomic variables that can be used to estimate it empirically has to be identified since the explanatory variables in the model is in practice usually replaced by

proxies and supplemented by additional variables. Therefore, this chapter extends the theoretical foundation with some empirical implications.

Recently, the potential asymmetry in stock market behavior has received considerable attention in the literature. It is generally assumed in investment theory that investors are risk averse, since any rational investor will prefer certainty to risk *ceteris paribus* (Reilly 1989:10,255; Renwick 1971:400). This risk aversion leads to asymmetric behavior on the part of investors, which in turn causes asymmetry in the behavior of their investments, especially in the stock market. In section 3.3 an overview of the theory underlying stock market asymmetry is presented.

### **3.2 THE EFFICIENT MARKET HYPOTHESIS AND THE PRESENT VALUE MODEL**

#### **3.2.1 The Efficient Market Hypothesis and Implications for Stock Market Modeling**

The efficient market hypothesis holds that prices adjust rapidly and unbiasedly to new and relevant price sensitive information. The three assumptions underlying the efficient market hypothesis are: (i) A large number of profit-maximizing investors that operate independently of each other. (ii) New information regarding securities comes to the market in a random fashion and the announcements over time are generally independent of one another. (iii) Investors adjust security prices rapidly to reflect the effect of the new information. While these price adjustments are not always correct, it is unbiased so that the under- and over-adjustments are unpredictable. Since new information are random and independent and the large number of investors adjust stock prices rapidly to reflect this new information, price changes are independent and random (Reilly 1989:212).

Three forms of the efficient market hypothesis exist namely the weak form, semi-strong form and the strong form (Marx *et al* 2003:35). According to the strong form of the

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efficient market hypothesis, security prices fully reflect all the relevant public and private information and that financial markets are “perfect markets” in the sense that all information is free and available to everybody simultaneously. The semi-strong form relaxes these assumptions somewhat and assumes that security prices adjust rapidly to reflect all public information, which are defined as market information as well information such as economic and political news and company news such as earnings, dividend announcements, mergers and acquisitions. The weak form assumes that security prices adjust rapidly to reflect all security market information, including security prices, trading volume and rates of return.

The efficient market hypothesis has crucial implications for stock market investors and their approach to stock market trading. If capital markets are efficient and security prices fully reflect all relevant information as postulated by the efficient market hypothesis, any trading rule solely based on past data cannot yield above-average returns, since by the time the information is public, the price adjustment has taken place. Therefore, trading based on technical analysis where the basic philosophy is that security prices tend to move in trends so that their trading rules are past price movements will not be able to yield above-average returns (Reilly 1989:658, 245).

In contrast, the philosophy underlying fundamental analysis is that the intrinsic value of a security is determined by the underlying economic variables. Fundamental analysts analyze and estimate macroeconomic prospects such as economic growth, inflation and interest rates and then identify industries that will gain most from these conditions. The fundamental analyst subsequently determine the intrinsic value of the companies within these industries, in order to identify and invest in those that are undervalued, that is, for which the market price is lower than the intrinsic value. It is possible for the market price and the intrinsic value of a security to differ, but the market will eventually correct this discrepancy. Therefore, an analyst capable of making a better than average estimate of the intrinsic value will be able to make above-average profits.

Initially, most of the empirical research on the efficient market hypothesis was done in terms of the random walk theory, which was based on empirical analysis without a theoretical foundation. Fama (1970) presented the first synthesis of the efficient market theory in terms of the fair game model. In contrast to the random walk hypothesis, which dealt with the behaviour of prices over time, the fair game model focuses on the price in a specified period. The model is built on the assumption that the security's price fully reflects all the relevant information available up to that period. A fair game model is defined as follows: Let the expected theory of price formation be described by the following equation:

$$E(P_{j,t+1} | \phi_t) = [1 + E(r_{j,t} | \phi_t)]P_{j,t} \quad (3.1)$$

where  $E$  is the expected value operator,  $P_{j,t}$  is the price of security  $j$  in period  $t$ ,  $r_{j,t}$  is the rate of return on security  $j$  during period  $t$  and  $\phi_t$  is the shared information set. Further, let  $x_{j,t+1}$  be the difference between the actual and expected prices in period  $t$ :

$$x_{j,t+1} = P_{j,t+1} - E(P_{j,t+1} | \phi_t). \quad (3.2)$$

The sequence  $\{x_{j,t}\}$  is called a “fair game” if  $E(x_{j,t} | \phi_t) = 0$ . According to the efficient market hypothesis this should be the case for  $x_{j,t}$  since it is impossible to consistently earn abnormal returns based on the shared information due to the competition between investors.

### 3.2.2 The Present Value Model

Samuelson (1965) and Mandelbrot (1963) showed that the fair game model (see section 3.2.1) is analytically equivalent to the expected present value theory of security valuation (also called the present value model). Assume that return on any security  $i$  in period  $t$ ,  $r_{i,t}$ , minus a security specific constant  $k_i$  is a fair game, which means that

$$E(r_{j,t} | \phi_t) - k_i = 0. \quad (3.3)$$

By substituting the definition of returns as the dividend yield ( $D_{i,t-1}/P_{i,t}$ ) plus capital gains ( $(P_{i,t-1}-P_{i,t})/P_{i,t}$ ), the equation becomes

$$\frac{E[(P_{i,t-1} + D_{i,t-1}) | \phi_t] - P_{i,t}}{P_{i,t}} - k_i = 0. \quad (3.4)$$

Which is equivalent to

$$P_{i,t} = \frac{E[(P_{i,t-1} + D_{i,t-1}) | \phi_t]}{(1 + k_i)}. \quad (3.5)$$

By substituting for  $P_{t+1}$  and replacing  $t$  with  $t+1$ , equation 3.5 becomes

$$P_{i,t} = \frac{E[(D_{i,t}) | \phi_t]}{(1 + k_i)} + \frac{E[P_{i,t+2} + D_{i,t+2}]}{(1 + k_i)^2}. \quad (3.6)$$

If it is assumed that  $k_i > 0$  and this process is repeated  $n$  times, then

$$\lim_{n \rightarrow \infty} \frac{E[D_{i,t+n}]}{(1 + k_i)^n} = 0. \quad (3.7)$$

This yields the familiar expected present value model first presented by Smith (1925) and Burr-Williams (1938):

$$P_{i,t} = \sum_{n=1}^{\infty} \frac{E[D_{i,t+n}]}{(1 + k_i)^n}. \quad (3.8)$$

The current share price can be solved from equation 3.8 by setting  $t=0$

$$P_{i,0} = \sum_{n=1}^{\infty} \frac{E[D_{i,n}]}{(1 + k_i)^n}. \quad (3.9)$$

Equation 3.9 shows that the price of a security is equal to the present value of the expected future dividend receipts of the asset. In this formula the expected capital gain realized upon the sale of the security is subsumed, since its magnitude also depends on the present value of the expected future dividend stream. Under the assumption that expected dividends grow at a constant rate, Gordon and Shapiro (1956) replaced the problem of forecasting an infinite number of future dividends with that of estimating a single expected growth rate  $g$ . This means that equation 3.9 can be written as

$$P_{i,0} = \sum_{n=1}^{\infty} \frac{D_{i,0}(1 + g_i)^n}{(1 + k_i)^n} \quad (3.10)$$

where  $P_{i,0}$  is the price of security  $i$  in period 0,  $D_{i,0}$  is the dividend in period 0,  $g_i$  is the expected growth rate of security  $i$  and  $k_i$  is the rate at which the dividends are discounted. By using the properties of the sum to infinity of a geometric series, equation 3.10 can be reduced to the *constant growth model*

$$P_{i,0} = \frac{E(D_{i,1})}{k_i - g_i} = \frac{D_{i,0}(1 + g_i)}{k_i - g_i}. \quad (3.11)$$

Therefore, the equilibrium prices of security  $i$  is determined by its dividend ( $D_i$ ), the growth rate ( $g_i$ ) and the discount rate ( $k_i$ ).

### 3.3 EMPIRICAL IMPLICATIONS OF THE PRESENT VALUE MODEL

In practice the explanatory variables in the present value model (dividends, growth and the discount rate) is in practice usually replaced by proxies and supplemented by

additional variables. Therefore, although the present value model provides a theoretical foundation for modeling stock prices, the macroeconomic variables that can be used to estimate it empirically still has to be identified.

### 3.3.1 The Discount Rate

In order for the present value model to be useful for empirical analysis, the discount rate ( $k_i$ ) has to be defined more specifically. The discount rate is determined by three factors: (i) the economy's real risk-free rate, (ii) the expected rate of inflation and (iii) a risk premium (Reilly 1989:326). Investors want to be compensated for expected inflation, so that their money does not lose purchasing power over time. In addition, they want to receive the real risk-free rate to compensate them for the opportunity cost of parting with their money. Finally, a risk premium is added to the discount rate to compensate for the uncertainty regarding the expected returns of the security.

#### (i) *The risk premium*

Unlike the expected inflation and real risk-free rate, the risk premium for different assets may differ, reflecting the different risk or uncertainty of their returns. A risk-free investment can be defined as an investment of which both the amount and timing of the expected income stream are certain. However, the timing and amount of expected income from most investments are not certain and hence investors require a risk premium on top of the risk-free rate to compensate for the risk involved in their investment. The risk associated with investment includes several major sources of uncertainty, namely business risk, liquidity risk, exchange rate risk, interest rate risk, purchasing power risk, management risk, default risk and industry risk (Marx *et al* 2003:174). These risks can be categorized as either firm-specific risks, which differs between the securities of different firms, and general risks, which are common across all the securities of firms operating in a particular country.



The firm-specific risks associated with a security can broadly be divided into industry risk, business risk and management risk. Industry risk includes the uncertainty of operating within a particular industry, such as the financial services or natural resources industries. This risk influences all the firms operating in this particular industry. The uncertainty of income flows caused by the nature of the firm's business is known as business risk (Reilly 1989:16). Usually investors consider the distribution of a firm's income and assign a risk premium accordingly. The uncertainty of income caused by the basic business of the firm is typically measured by the distribution of the firm's operating income (defined as earnings before interest and taxes) over time. The more volatile the firm's operating income is over time relative to its mean income, the greater the business risk. Finally, management risk is the uncertainty or risk introduced by the management team of the specific firm in terms of their management style and strategy.

Related to the firm-specific risks mentioned above, securities are also subjected to liquidity and default risk which are both to a large extent firm-specific. Default risk refers to the variability of returns caused by changes in the creditworthiness of the firm in which the investment is made (Marx *et al* 2003:10). Liquidity risk is the risk of not being able to quickly convert an asset into cash without a substantial price concession (Reilly 1989:16). The greater the uncertainty of being able to sell an asset quickly without a loss, the greater the liquidity risk.

In addition to these firm-specific risks, securities are also subject to the risks of investing in the particular country in which the firm operates, which are homogenous across investments within that country. Interest rate risk is the potential influence of changes in the market interest rate on returns (Marx *et al* 2003:9). The value of a security is determined by discounting all future income expected from the security to determine its present value and therefore the value will move inversely with changes in market interest rates. The uncertainty regarding the future behavior of interest rates therefore poses a risk in the sense that it introduces uncertainty regarding the correct valuation of share prices and hence a possible loss (or gain) to the extent that this valuation differs from the true intrinsic value of the share(s).

Purchasing power or inflation risk is the uncertainty or risk associated with changes in the inflation rate. The returns generated by the investment should be sufficient to at least keep pace with inflation and hence preserve the purchasing power of the initial investment. Fluctuations in the rate of inflation therefore introduces an uncertainty regarding the required rate of return as well as the risk that the purchasing power of the investment will deteriorate due to future increases in inflation.

Exchange rate risk is the uncertainty involved when investing in a foreign currency (Reilly 1989:16). Globalization and deregulation have made a portfolio comprising international assets universal. When investing globally, the return on an investment in the foreign currency has to be converted to the domestic currency to calculate the return for the investor. This means that investors have to take into account the risk that the exchange rate between their domestic currency and the foreign currency in which the investment is made might change.

Although the risks discussed in the previous paragraphs are relevant for the pricing of a particular security, the firm-specific risks became redundant in the pricing of the general stock market. Since the aggregate stock market reflects the average of the prices of individual shares, only the risks influencing all shares such as interest rate risk and purchasing power risk are relevant in pricing the aggregate stock market. The firm-specific risks are then added to this when a specific share is priced. Therefore the risk premium used in modeling the stock market should reflect only the risks that are not firm-specific.

(ii) *Interest rates*

According to the expectations hypothesis, the shape of the term structure is explained by the interest rate expectations of market participants. The long-term interest rate is the rate that the long-term investor would expect to earn through successive investments in short-term securities over an investment horizon equal to the term to maturity of the long-term

issue. In other words, the long-term interest rate on a security is the average of all the expected future short-term interest rates expected to prevail over the duration of the security. Expressed algebraically:

$$(1+R_n)=[(1+r_1)(1+r_2)\dots(1+r_{n-1})]^{1/N}$$

where  $R_n$  is the actual long-term interest rate,  $N$  is the term to maturity (in years) of the long-term issue,  $R$  is the current one-year rate and  $r_{t+1}$  is the expected one-year yield during some future period  $t+1$  (Reilly 1989:416).

According to the expectations hypothesis if market participants expect short-term interest rates to rise in the future then the long-term interest rate will be higher than current short-term interest rates and the yield curve will be upward-sloping. On the other hand, if short-term interest rates are expected to fall then the long-term interest rate will be below short-term interest rates, so that the yield curve will be downward-sloping.

Since the expected future short-term interest rates are used to discount future returns in a present value model of stock prices, the long-term rate can be used as discount factor since it captures the expected short-term interest rates. Harasty and Roulet (2000) showed that the stock market is cointegrated with the long-term interest rate and a proxy for dividends in 17 developed countries. Zhou (1996) interest rates significant in explaining stock returns. Ansotegui and Esteban (2002) showed that the stock market is cointegrated with industrial production, inflation and the long-term interest rate.

### 3.3.2 Dividends and Growth

Theoretically, the present value model asserts that security prices are determined by dividends and the discount rate. It follows trivially that any factor that influences the stream of cash flows or the discount rate will systematically influence stock prices. Since the seminal article by Chen *et al* (1986), the influence of variables such as interest rates and inflation on the discount rate and of the industrial production growth on the expected

cash flows or dividends has been well established. In empirical studies, these and other variables are usually used to proxy the influence of dividends on stock prices. Jondeau and Nicolai (1993) have shown that only in the US do dividends directly explain stock prices and in other countries dividends have to be replaced by proxies.

In the literature, dividends are usually replaced by proxies such as industrial production, unemployment or the state of the business cycle in empirical analyses. Since most firms are more profitable during periods of high economic growth than low economic growth, the state of the business cycle should positively impact on the stock market through its influence on dividends. Brocato and Steed (1998) have shown that total returns of equity assets rise (fall) during expansions (recessions). Ansotegui and Esteban (2002) used industrial production as proxy for dividends and showed that the stock market is cointegrated with industrial production, inflation and the interest rate. In contrast, Domian and Louton (1995 and 1997) showed that the unemployment rate, which is often used as an indicator of the state of the economy, influences the stock market returns in the US. Since the stock market tends to be forward-looking, several studies have modeled stock market returns as a function of the future (instead of current) state of the business cycle. For example, Chen (1991) has shown that variables reflecting the future state of the economy are positively related to the expected excess market return.

Fama and Schwert (1977), Solnik (1983) and Spyrou (2001) found a negative relationship between inflation and stock market returns and ascribed this to the negative correlation between inflation and real output growth. In other words, since stock returns are positively related to real activity and real activity is negatively related to changes in the level of prices, stock returns are negatively related to inflation. Kaul (1990) empirically proves that this is also the case for the US stock market. Ansotegui and Esteban (2002) proxied dividends with industrial production and showed that the stock market is cointegrated with inflation, industrial production and the interest rate.

### 3.4 STOCK MARKET ASYMMETRY

It is generally assumed in investment theory that investors are risk averse (Reilly 1989:10, 255). When an investor is faced with a choice between two investments with the same expected rate of return, he/she will choose the one with the smallest risk. Theoretically, investors are risk averse since their utility functions are assumed to exhibit decreasing marginal utility of wealth. In other words, they have concave utility functions, or mathematically

$$U''(w) < 0 \tag{3.12}$$

where  $w$  is wealth,  $U$  is utility and  $U''$  is the second derivative of the utility function with respect to wealth.

Rabin and Thaler (2001) argued that an explanation for risk aversion should also incorporate loss aversion. Loss aversion refers to the inclination of economic agents to be more sensitive to reductions in their levels of well-being than to increases (Benartzi and Thaler 1995). Kahneman and Tversky (1979) presented the following loss aversion utility function:

$$-\lambda E\left[(-\chi)^{(1-\gamma_1)} \mathbf{1}_{\{\chi \leq 0\}}\right] + E\left[(-\chi)^{(1-\gamma_2)} \mathbf{1}_{\{\chi > 0\}}\right] \tag{3.13}$$

where  $\mathbf{1}$  is an indicator variable,  $\chi = W - B_0$  is the gain or loss of final wealth ( $W$ ) relative to a benchmark  $B_0$ . This utility function has the problem that it gives different preferences if  $\chi$  is expressed in different units unless  $\gamma_1 = \gamma_2$  or the difference between  $\gamma_1$  and  $\gamma_2$  is small. However, this can be overcome by expressing  $\chi$  in returns.

Risk and loss aversion mean that investors are more sensitive to losses than gains, which means that they will behave differently when expecting gains than when expecting losses. In other words, their behavior is asymmetric with respect to positive or negative returns.

Therefore, since the stock market is driven by the behavior of investors, this potentially causes asymmetry in stock prices as well.

Two explanations have been given in the literature on why investors' risk and/or loss aversion induces stock market asymmetry. First, Chalkley and Lee (1998) argues that risk aversion encourages economic agents to react promptly on receiving bad news, while it prevents them from acting quickly when receiving good news. The cautious response of investors at the individual level aggregates to result in economy-wide asymmetric behavior. They developed a complex Markov-switching model showing that the risk aversion of economic agents does result in asymmetric behavior conditional on the state of the business cycle. However, the derivation of their model is beyond the scope of this study and only their intuitive explanation will be presented here.

Assume that investors are faced with a choice between high activity and low activity and that the desirability of each choice depends on the state of nature, so that low activity is preferred when state is bad and vice versa. Suppose also that low activity is safer, so that the expected utility of low activity is higher when both states are equally likely. Then investors will require a strong belief in favor of the good state to choose the high level of activity, but only a weak belief in the bad state to choose the low level of activity.

A downturn in the economic data that is used to evaluate share prices may be indicative of other economic agents receiving bad news or it might be a random change, but in either case the cautious response is to choose low activity. In this case (a downturn in economic data), risk aversion and uncertainty about the information value of aggregate data work together, leading informed agents to quickly respond to bad news or conditions and other agents to quickly respond to that response. Of course, there is also uncertainty about the interpretation of an upturn in the relevant economic data, but in this case risk aversion works against reacting to such a signal. When agents are reluctant to react to an upturn in economic data signals, it is reasonable to infer that an upturn is more likely a consequence of noise than any genuine good news and hence reticence is rational.

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Therefore, it can be expected that investors will react more reluctantly to good news, expectations and vice versa. When the behavior of these individual investors are aggregated it implies that the stock market will react quicker during good conditions or on good news or expectations, or put differently, that its adjustment to equilibrium will be slower during adverse economic conditions and faster during positive economic conditions. The “upturn” and “downturn” of data in the Chalkley and Lee (1998) framework originally referred to good or bad conditions as reflected in the business cycle. According to the present value model stock prices are a function of the discount rate and dividends and since real economic activity is one of the main determinants of dividends an economic upswing (downswing) will cause higher (lower) dividends and can therefore be considered as good (bad) news or conditions.

The second explanation for asymmetric investor (and hence stock market) behavior is driven by the potential loss (profit) in an overvalued (undervalued) stock market. Following the same line of reasoning as Chalkley and Lee (1998), Phelps and Zoega (2001) and Siklos (2002) also hypothesized different speeds of adjustment but they introduced a different driving force for the asymmetry by redefining the good and bad news or conditions that prompts the asymmetric behavior of investors.

Their theory on stock market asymmetry is based on the paradigm of the structural slump developed by Phelps (1967). A structural slump is characterized by a steep decline in share prices followed by a gradual rise in unemployment. A structural boom, on the other hand, entails a steep rise in share prices followed by a decline in unemployment. In the case of a structural boom, investors calculate that this signals a jump in future asset returns and, consequently, the valuation of these assets as reflected in the stock market. The resulting rise in the profitability of investment signals a falling unemployment rate. The boom ends when the productivity rise increases investment costs.

Theoretically, this scenario works symmetrically, but Phelps and Zoega (2001) argued that it might in practice work asymmetrically since other factors may influence the progress of the business cycle. The potential asymmetry was first tested empirically by

Siklos (2002). His results showed that the relationships between the economy and the stock markets of the UK and the US were indeed asymmetric.

Although Siklos (2002) tested the stock market asymmetry based on the relationship between the stock market and unemployment, the asymmetry also holds for any other stock market model. If the stock market is undervalued it means that the market prices of shares are below their intrinsic value, so that a profit opportunity is created since investors can buy shares at the low current market price and eventually resell it at a higher price once the market has corrected the discrepancy between the market and intrinsic value. In contrast, when the stock market is overvalued market prices of shares are above the intrinsic values. Eventually the market will correct this discrepancy so that share prices fall, in which case investors will lose money. Since investors are loss averse it is more important to avoid the potential loss if the market is overvalued than to make the profit if the market is undervalued. They will therefore react faster to an overvaluation that poses a potential loss than to an undervaluation that poses a potential profit.

### **3.5 CONCLUSION**

This chapter reviewed the basic theoretical foundations, the efficient market hypothesis and the present value model for modeling stock markets. According to the efficient market hypothesis, capital markets are efficient in the sense that stock prices adjust rapidly and unbiasedly to reflect new and relevant price sensitive information. The price adjustment, although not always correct, is unbiased so that the under- and over-adjustments are unpredictable. Since new information is random and independent and the large number of investors adjust stock prices rapidly to reflect this new information, price changes are independent and random (Reilly 1989:212). This means that trading based solely on historical prices, in other words technical analysis, cannot yield abnormal profits.



Fama (1970) presented the first synthesis of the efficient market theory in terms of the fair game model and Samuelson (1965) and Mandelbrot (1963) showed that the fair game model is analytically equivalent to the expected present value theory of security valuation. According to this theory, stock prices are a function of all the expected future dividends discounted at the discount rate. Dividends are usually replaced in empirical studies with proxies measuring the state of the business cycle or the performance of the aggregate economy. The discount rate can be constructed as the sum of the risk-free rate and a risk premium.

Rational investors are assumed to be risk and loss averse and this potentially leads to asymmetric behavior that in turn results in stock market asymmetry. Two explanations have been given in the literature on why this might cause asymmetric investment behavior. First, it encourages investors to react promptly on receiving bad news while it prevents them from acting quickly when receiving good news (Chalkley and Lee 1998). Second, it is more important to avoid the potential loss if the market is overvalued than to profit if the market is undervalued and hence investors will react faster in an overvalued market. The cautious response of investors at the individual level aggregates to result in economy-wide asymmetric behavior.

Therefore, any empirical stock market model has to be built on the theoretical foundation of the present value model, taking into account the implications of the efficient market hypothesis as well as the potential asymmetry caused by investors' risk and loss aversion. In the next chapter studies modeling stock markets will be reviewed in order to analyze the empirical implications of the present value model, the efficient market hypothesis and investor asymmetry.

## CHAPTER 4

### A REVIEW ON EXISTING STOCK MARKET MODELS

#### 4.1 INTRODUCTION

Studies modeling stock markets can be divided into two broad categories, namely those that test stock market efficiency and those that model stock prices or stock returns. Studies modeling stock market efficiency are basically evaluating the efficient market hypothesis and the random walk model. On the other hand, studies that model stock market prices or returns are based on the theory of the present value model. Within the latter category, studies can be classified as either structural models that try to develop and estimate a model of the stock market, or studies that evaluates the relationship between stock market and macroeconomic variables.

In this study a structural model of the South African stock market will be estimated and therefore the focus of the literature review will be on literature estimating structural stock market models rather than the literature evaluating stock market efficiency. However, stock market efficiency has important implications for the profitability of a trading rule based on technical analysis versus trading based on a structural model. Therefore, although the focus of this study and hence the focus of the literature review will be on the structural models of the stock market, it is important to also include a brief overview on the literature evaluating stock market efficiency.

In this chapter, a brief overview of studies modeling stock markets will be given. First, the literature on international stock market models will be reviewed, differentiating between studies evaluating stock market efficiency and those that estimate structural models of the stock market or analyze the relationship between the stock market and specific macroeconomic variables. The latter category will distinguish between studies that modeled stock prices or those that modeled stock returns. This is followed by an overview of the literature on empirical studies of the

South African stock market, again distinguishing between studies evaluating the efficiency of the JSE and studies modeling stock prices or stock returns.

## **4.2 INTERNATIONAL STUDIES**

### **4.2.1 Studies Evaluating Stock Market Efficiency**

Stock market efficiency has fundamental implications for stock market analysis and trading. If stock markets are not efficient, stock prices are forecastable from past price behavior alone. The random walk theory, which assumes that consecutive price changes are independent and identically distributed over time, is central to the testing of the ability of past returns to predict future returns (Thompson and Ward 1995). If prices follow a random walk, it means that yesterday's price change should not be related to the price change of today, or any other day since it should be independent. The implication for trading is that future price movements cannot be predicted successfully on the basis of historic price movements.

Empirical studies have mainly used three econometric techniques to evaluate stock market efficiency, namely serial correlation tests, the runs test and the variance ratio test. Tests for weak form efficiency can be divided into two broad categories. The first group includes studies that test whether trading rules based on exploiting possible systematic patterns in share prices can yield abnormal profit, in other words can beat a random selection of securities. Spectral analysis, serial correlation tests and the runs test are usually utilized to analyze the dependence of share prices. Although share prices are seldom perfectly independent, stock market investors are mostly concerned with whether the dependence is sufficient to allow the history of the series of price changes to be used to predict the future in such a way that the expected returns would be greater than under a simple buy-and-hold model (Thompson and Ward 1995).

The second group of weak form efficiency tests comprises studies testing the statistical dependence in changes in share prices, attempting to determine whether share prices have sufficient dependence to make it possible for investors to predict future share prices by studying past trends. Weak form efficiency is invalidated if a

trading rule, in other words a strategy for buying and selling securities based on objective signals, *consistently* outperforms a simple buy-and-hold portfolio with equivalent risk (Thompson and Ward 1995).

Tests of semi-strong form market efficiency generally evaluate the speed and accuracy of market adjustment to specific new information that affects the intrinsic value of the security. These studies test whether the market moved in the right direction and the speed of market adjustment following a specific type of information generating event. Information generating events include earnings announcements, changes to dividend policy, capitalizations, large secondary offerings of common stock, changes in the discount rate and changes to accounting methods. The main methodology followed in these studies is to compare expected share prices to actual share price performance, where the expected share prices are usually determined with some form of asset pricing model. The residuals are then analyzed to determine the impact of the information on share prices and whether share prices adjusted rapidly and accurately to this information (Thompson and Ward 1995).

Tests of strong form market efficiency entail evaluating whether specific investors or groups of investors have monopolistic access to non-public information relating to price formation. The rates of return on portfolios of investors that have access to private information, usually professional portfolio managers of unit trusts and investment funds, are compared to that of a passive buy-and-hold-the-market strategy. If such an investor consistently and significantly outperforms the market, it indicates either exceptional skills or access to special information, which negates the strong form of the efficient market hypothesis (Thompson and Ward 1995).

The empirical evidence on market efficiency in international stock markets has been inconclusive. While many studies found that markets are efficient (see e.g. Kavussanos and Dockery 2001; Chen, Kwok and Rui 2001; Nieto, Fernandex and Munoz 1998), there are also studies that found evidence against market efficiency (see e.g. Omet, Khasawneh and Khasawneh 2002; Siourounis 2002; Hasan, Samarakoon and Hasan 2000; Mecagni and Sourial 1999).

#### 4.2.2 Structural Stock Market Models

(i) *Stock price models*

The literature on modeling stock market prices instead of modeling stock market returns (i.e. changes in the stock market prices) is quite sparse. Studies that did model stock prices all employed cointegration techniques and used the present value model as theoretical basis. Even though most of these studies used the Gordon-Shapiro (i.e. constant growth) version of the present value model, different studies interpreted the empirical implications of this model differently.

According to the present value model, stock prices are a function of future dividends, the discount rate and the growth rate. In empirical studies, dividends are often proxied by variables such as economic growth or industrial production, while the discount rate is specified as the long-run interest rate to which a risk premium is sometimes added (see section 3.3.1).

Harasty and Roulet (2000) used cointegration techniques to model the stock prices of 17 developed countries. They argue that economic theory can explain the long-run trend of the stock market, but that short-run movements are driven by variables other than those dictated by theory and hence it can only be determined empirically. Therefore, they estimate the long-run behavior of stock prices based on the present value model and then empirically try to explain the fluctuations of the market around this long-run trend. Using the Engle-Granger cointegration technique, they showed that stock prices are cointegrated with earnings (a proxy for dividends) and the long-term interest rate in each country (except the Italian market for which the short-term interest rate was used). The main variables that explained the short-term fluctuations were short-term interest rates, exchange rates and the spreads between domestic long-term and short-term interest rates, as well as between domestic and foreign interest rates.

Following a similar approach to model the long-run behavior of Spanish stock prices, Ansotegui and Esteban (2002) also based their model on the present value model. They showed that stock prices cointegrate with industrial production (used as proxy

for dividends), inflation and the interest rate. Han (1996) interpreted the present value model differently and tested for cointegration between stock prices and dividends of the Standard and Poor stock index. He found that neither the levels nor the logarithmic transformations of stock prices and dividends are cointegrated and therefore concluded that the present value model doesn't hold for the Standard and Poor stock index. However, Yuhn (1996) argues that the present value model doesn't imply cointegration between stock prices and dividends. By using extensive mathematical derivations, he shows that the present value model rather implies that the sum of current stock prices and dividends should cointegrate with lagged stock prices. When he tests the present value model with this specification, he found little evidence supporting linear cointegration but overwhelming evidence of non-linear cointegration.

There is evidence that the present value model has been interpreted in various ways in the literature. This resulted in different model specifications in different studies, which has a crucial impact on their results especially in terms of whether they reject validity of the present value model. In addition to the model specification differences, different authors have used different proxies for dividends and discount rates.

(ii) *Stock return models*

The studies that have modeled actual, expected or excess stock market returns can be divided into two categories. The first category includes studies that test whether stock markets are efficient, while studies in the second category analyze the relationship between the stock market and macroeconomic variables. Studies in the latter category either evaluate the bivariate relationship between stock prices and a macroeconomic variable, or try to build a model for stock prices

As set out in chapter three, the present value model asserts that stock prices are determined by dividends and the discount rate and are hence influenced by macroeconomic variables that influences or proxies dividends or the discount rate. It follows trivially that the systematic forces that influence stock prices and hence returns, are those that influence the discount factor or dividends. Since the seminal article by Chen *et al* (1986), the influence of variables such as interest rates and

inflation on the discount rate and of the economic growth on dividends has been well established. However, different studies have defined the discount rate differently and also used different proxies for economic growth and dividends.

The relationship between stock prices and interest rates has received considerable attention in the literature. A distinction has to be made between the influence of the long-term and the short-term interest rates, since the rationale for their relationships with the stock market differs. The proxy hypothesis of Fama (1981) argues that expected inflation is negatively correlated with anticipated real activity, which in turn is positively related to returns on the stock market. Therefore, stock market returns should be negatively correlated with expected inflation, which is often proxied by the short-term interest rate. On the other hand, the influence of the long-term interest rate on stock prices stems directly from the present value model through the influence of the long-term interest rate on the discount rate (see section 3.3).

Lee (1997) used three-year rolling regressions to analyze the relationship between the stock market and the short-term interest rate. He tried to forecast excess returns (i.e. the differential between stock market returns and the risk-free short-run interest rate) on the Standard and Poor 500 (S&P500) index with the short-term interest rate, but found that the relationship is not stable over time. It gradually changes from a significantly negative to no relationship, or even a positive although insignificant relationship.

Zhou (1996) also studied the relationship between interest rates and stock prices using regression analysis. He found that interest rates have an important impact on stock returns, especially on long horizons, but the hypothesis that expected stock returns move one-for-one with ex ante interest rates is rejected. In addition, his results show that long-term interest rates explain a major part of the variation in price-dividend ratios and suggests that the high volatility of the stock market is related to the high volatility of long-term bond yields and may be accounted for by changing forecasts of discount rates.

Rather than using either short-term or long-term interest rates, Campbell (1987) analyzed the relationship between the yield spread and stock market returns. He

argues that the same variables that have been used to predict excess returns in the term structure also predicts excess stock returns, deducing that a simultaneous analysis of the returns on bills, bonds and stock should be beneficial. His results support the effectiveness of the term structure of interest rates in predicting excess returns on the US stock market.

Kaul (1990) studied the relationship between expected inflation and the stock market, which, according to the proxy hypothesis of Fama (1981) should be negatively related since expected inflation is negatively correlated with anticipated real activity, which in turn is positively related to returns on the stock market. Instead of using the short-term interest rate as a proxy for expected inflation (like for example Lee (1997)), Kaul (1990) explicitly models the relationship between expected inflation and stock market returns. His results is supportive of Fama's (1981) proxy hypothesis and showed that the relationship between stock returns and expected inflation in the US is significant and negative.

Spyrou (2001) also studied the relationship between inflation and stock returns but for the emerging economy of Greece. Consistent with Kaul's results, Spyrou (2001) found that inflation and stock returns are negatively related, but only up to 1995 after which the relationship became insignificant. He ascribes the change in the relationship to the increased role of monetary fluctuations, in line with the argument of Marshall (1992) that the negative relationship between stock returns will be less pronounced during periods when inflation is generated by monetary fluctuations.

In addition to inflation and interest rates, Leung, Daouk and Chen (2000) included the lagged stock market index and economic growth as explanatory variables in their stock market models for the US, UK and Japan. They model not only the stock market index, but also turning points in the stock market index in order to compare the profitability of trading rules based on the two approaches. To model stock prices they employ adaptive exponential smoothing techniques, the VAR-Kalman Filter, a transfer function and neural networks. They model turning points in the stock market with linear discriminant analysis, a logit model and neural networks. Their results suggest that classification models outperform level estimation models in terms of predicting the direction of the stock market movement and maximizing returns.



Fang (2002) argued that exchange rates could also influence stock prices. This should especially be relevant in the current globalized economy. His results confirmed that currency depreciation adversely affects stock returns and increases market volatility over the period of the Asian crises (1997-1999). The implication for investors is that they have to evaluate the stability of foreign exchange markets prior to investing in stock markets. However, this study only covered crisis periods and the results might differ for normal periods.

Black and Fraser (1995) argue that the predictable variation in excess stock returns is a rational response to the general level of expected business conditions. Following the present value model, stock prices are in part determined by future dividends, which in turn are influenced by the future state of the economy. Since current financial variables reflect the expected future state of the economy, it should be able to predict the conditional risk component of excess returns. The results of their Garch-M model are supportive of their hypothesis that financial variables, specifically the term spread, default spread and dividend yields, influence UK stock returns.

Chen (1991) follows a similar line of reasoning than Black and Fraser (1995). He argues that stock market returns are a function of expected economic growth through its influence on dividends and economic growth in turn is a function of so-called “state variables” such as interest rates, interest rate spreads and dividend yields. In addition, the uncertainty regarding future economic growth (or dividends) also plays a role in determining the stock prices, so his stock market model also includes the volatility of economic growth as explanatory variable. He empirically showed that lagged economic growth, the default spread, the term spread, short-term interest rates and the dividend-price ratio are important determinants of future stock market returns in the US. In addition, expected excess market return is negatively related to recent economic growth and positively related to future growth.

There are several studies on the relationship between the business cycle and the stock market. Fama and French (1989) and Perez-Quiros and Timmerman (1996) showed that expected stock market returns are lower when economic conditions are strong and higher when economic conditions are weak. Fama and French (1989) argue that when

business conditions are poor, income is low and expected returns on bonds and stocks must be high to induce substitution from consumption to investment. In contrast, when times are good and income is high, the market clears at lower levels of expected returns. They showed that dividend yields can be used to forecast stock returns.

The relationship between the stock market and the business cycle has important implications for stock market investments and investment strategies. Lucas, Van Dijk and Kloek (2002) formulated alternative investment strategies, including both once-and-for-all choices of a particular style and state-dependent choices of investment styles. They use the yield spread and the composite index of leading indicators to indicate the state of the economy. They found that business cycle oriented approaches to style rotating investment strategies outperform purely statistical models for style rotation in the US. Brocato and Steed (1998) studied the optimal asset allocation of nine types of assets over business cycle and compared the returns and correlations of nine asset types during recessions and expansions. Their results indicated that total returns of equity assets rise during expansions while those of fixed income debt instruments do better during downturns.

Recently, the potential asymmetry in the relationship between the stock market and the business cycle has received considerable attention in the empirical literature. Studies analyzing this asymmetric relationship can be classified into two categories, namely those that studied the direct relationship between the stock market and the business cycle and those that studied the relationship between the stock market and macroeconomic variables conditional on the state of the business cycle. In the former category, Domian and Louton (1995) argued that the business cycle asymmetries identified by Neftci<sup>1</sup> (1984) could potentially cause the relationships between the business cycle and other series, such as the stock market, to be asymmetric. They used regression analysis to show that an asymmetric relationship exists between stock index returns and unemployment. Consistent with their earlier results, Domian and Louton (1997) uses threshold autoregressive models to show that negative US stock returns are followed by sharp decreases in increases in industrial production growth rates, while only slight increases in real activity follow positive stock returns.

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<sup>1</sup> Neftci (1984) found evidence that suggested that economic time series go through two different regimes during the business cycle.

Silvapulle and Silvapulle (1999) and Silvapulle, Silvapulle and Tan (1999) use threshold autoregressive (TAR) models to show that negative stock market returns have steeper effects on the business cycle than positive returns in the US and Malaysian respectively. Siklos (2002) uses a threshold cointegration model to show that share prices cointegrate asymmetrically with unemployment and that real share prices above the corresponding unemployment rate are a relatively stronger “attractor” than when the situation is reversed. His argument is based on the so-called “structural slump” invented by Phelps (1994) which asserts that a steep decline in share prices is followed by a gradual rise in unemployment.

In the latter category, Jensen, Mercer and Johnson (1996) argued that monetary variables will have an asymmetric influence on the stock market depending on the state of the business cycle. They found that after including a broad measure of monetary stringency, business conditions explain future stock returns only in expansive monetary policy periods. They also found that only the dividend yield and the default premium are significant while the term spread is insignificant. After controlling for monetary stringency, the term spread alone contributes significantly in explaining expected bond returns in restrictive monetary policy periods. In contrast, only the dividend yield is significant in expansive policy periods. Therefore, business conditions proxies play substantially different roles in explaining variation in expected stock and bond returns depending upon monetary stringency.

McQueen and Roley (1993) and Jarvinen (2000) studied the impact of macroeconomic news on the stock market (residuals from VAR models) conditioned on the state of the economy for the US and Finland respectively. They argue that it is possible that higher than expected economic growth during a depression might indicate the end of the recession and hence influence the stock market positively. On the other hand, higher than expected economic growth in an economic expansion might induce fears of an overheating economy which might prompt monetary authorities to rise interest rates and hence be bad news for the stock market. Their results were supportive of asymmetric relationships between the stock market and macroeconomic variables conditional on the state of the business cycle.

Most studies modeling stock prices or stock returns use data for developed countries. The study by Fifield, Power and Sinclair (2002) is an exception in which cross-sectional data for 13 emerging markets are used. They test the influence of domestic variables (inflation, exchange rate, short term interest rate, GDP, money supply and the trade balance) as well as global variables (world return, world inflation, commodity prices, world industrial production, oil price and US interest rates) in explaining the stock market. Their results indicate that domestic GDP, inflation, money supply, interest rates, as well as world production and world inflation is able to explain fluctuations in equity returns in emerging markets. The importance of the factors varies between countries.

The results of the study by Fifield, Power and Sinclair (2002) on emerging stock markets, which differs substantially from the results of studies for developed countries, highlights the importance of empirically modeling the South African stock market. The South African stock market, which functions in an emerging economy, will be determined by different factors than stock markets in developed countries. In addition, the results of Fifield, Power and Sinclair (2002) pertinently showed that the importance of the various determinants differs even among emerging stock markets.

### **4.3 SOUTH AFRICAN STUDIES**

#### **4.3.1 Studies on the Efficiency of the South African Stock Market**

There are several studies that tested the efficiency and the existence of anomalies on the Johannesburg Stock Exchange (JSE). Le Roux and Smit (2001) tested for the presence of several well-known stock market anomalies in the JSE, namely the day-of-the-week effect, the week-of-the-month effect, the month-of-the-year effect, the turn-of-the-month effect, the turn-of-the-year effect and a quarterly effect using the Anova F-test and the Kruskal-Wallis test. They found evidence of week-of-the-month and turn-of-the-month effects, while the day-of-the-week and turn-of-the-year effects that previously existed have disappeared. Bradfield (1990) also tested for the presence of anomalies in the JSE and found December as well as July effects.

## University of Pretoria – Moolman, HC (2004)

The evidence on all three forms of market efficiency are quite mixed for the JSE. Gilbertson (1976) tested 11 South African unit trusts for the period 1970-1976 and found evidence supporting strong-form efficiency. In contrast, Knight and Firer (1989) rejected strong-form efficiency based on their analysis of 11 South African unit trusts for the period 1977-1986. Knight and Affleck-Graves (1983) rejected semi-strong form efficiency while Knight, Affleck-Graves and Hamman (1985) found support of for semi-strong form efficiency. Jammie and Hawkins (1974) rejected weak-form efficiency based on the results of their analysis of JSE share prices for the period 1966 to 1973. Affleck-Graves and Money (1975) tested the random walk hypothesis for 50 industrial shares and found evidence supporting weak-form efficiency. Likewise, Hadassin (1976) rejected the random walk hypothesis using 30 shares traded on the JSE for the period 1971-1973. Gilbertson and Roux (1977, 1978) analyzed 24 industrial and mining shares and found dependencies which were too small and random to be profitable so that they did not reject weak form efficiency. Consistent with these results, Brummer and Jacobs (1981) found price change dependencies which were too small to be profitable in their study of 94 industrial shares for the period 1970-1971. Du Toit (1986) rejected the weak form efficiency using 180 highly trades shares.

Given the mixed evidence on efficiency of the JSE, the issue is whether there is sufficient abnormal price behavior to make it worthwhile for normal investors to seek superior returns. Thompson and Ward (1995) presented a thorough overview of the literature on the efficiency of the JSE and their conclusion from the literature is that there are some share price dependencies but too small to be profitably exploited. Given the mixed evidence on the efficiency of the JSE, the issue is whether there is sufficient abnormal price behaviour to make it worthwhile for the average investor to seek opportunities for abnormal returns, or whether the best option for most investors would simply be to buy and hold a well-diversified portfolio. They conclude that the JSE is “operationally efficient”, which is defined as a market that “provides a reward mechanism for those whose expertise and efforts sustain its efficiency” (Keane 1986:59). Such a market will enable a small group of investors to profit from market inefficiencies but will prevent the majority of investors from market inefficiencies by rapidly adjusting prices when the specialists communicate their knowledge to the

public. In other words, while a small group of investors will be able to outperform the market, most investors will not be able to do so.

#### **4.3.2 Structural Models of the South African Stock Market**

Similar to the case of international studies, few studies modeled the level of the South African stock market. Barr and Kantor (2002) developed and estimated a structural econometric model in which they attempt to capture the linkages between the South African real and financial markets and the global economy using cointegration techniques. Since their focus is on identifying and modeling the linkages between the different markets, their stock market equation reflects the main channels through which the South African stock market is influenced rather than the fundamental factors driving it. In addition to an autoregressive term, their results show that the JSE is also a positive function of foreign stock prices and commodity prices.

Van Rensburg (1995, 1998, 1999) made the largest contribution to the literature on modeling relationships between returns on the JSE and macroeconomic variables. Van Rensburg (1995) estimated linear relationships between the Johannesburg Stock Exchange and four economic factors, namely the unexpected changes in the term structure, unexpected returns on the New York Stock Exchange, unexpected changes in inflation expectations and unexpected changes in the gold price. His results indicated that all four factors significantly influences stock prices.

Van Rensburg (1998) used bivariate Granger causality tests and correlations to study relationships between stock market returns and macroeconomic variables. He does not attempt to estimate a model for the stock market, but only causal relationships between the stock market and macroeconomic variables. He tests three categories of variables, namely factors influencing the discount rate (such as various interest rates), factors influencing dividends (such as economic growth) and international factors.

In addition to returns on the Johannesburg Stock Exchange (JSE) overall index, Van Rensburg (1999) also analyzed relationships between the returns on the industrial index and gold index of the JSE and several macroeconomic variables. His results show that the long-run interest rate, the gold and foreign reserve balance and the

balance on the current account significantly influence the returns all three indexes. In addition, the industrial index is influenced significantly by the short-term interest rate and the Dow Jones industrial index while the gold index is influenced significantly by the rand-dollar exchange rate and the gold price.

Like Van Rensburg (1995, 1998, 1999), Barr (1990) tried to identify the macroeconomic factors that influence returns on the JSE. Unlike Van Rensburg, however, Barr follows a factor-analytic approach and identify the gold price, the short-term interest rate, foreign stock markets and local business confidence as factors that significantly influence returns on the JSE.

Jefferis and Okeahalam (2000) used cointegration and error correction techniques to model the stock markets of South Africa, Botswana and Zimbabwe. They followed an a-theoretical approach. They used quarterly data for the period 1985 to 1995 and modeled the JSE overall index as a function of domestic and foreign GDP, the real exchange rate and long-term domestic and foreign real interest rates. They hypothesized a positive relation between stock market and GDP, exchange rate and foreign interest rates and a negative relation between the stock market and domestic interest rates. Higher GDP increases profits and hence share prices should rise, while a depreciation boosts the profitability of domestic producers of tradables (exports and import substitutes) relative to foreign competitors. As a result the exchange rate should have a positive influence on their profits and hence on their stock prices. Higher interest rates are hypothesized to depress stock prices through the substitution effect (interest-bearing assets become more attractive relative to shares), an increase in the discount rate (and hence a reduced present value of future expected returns), or a depressing effect on investment and hence on expected future profits. Their empirical results for South Africa indicated that real stock prices are positively related to the real exchange rate and real GDP and negatively related to the long-term interest rate. In the short-run, real domestic long-term interest rates, US interest rates, the real exchange rate and domestic GDP influence the stock market.

#### 4.4 CONCLUSION

In this chapter studies modeling stock markets has been reviewed in order to analyze the empirical implications of the theoretical stock market models in chapter 3. The studies that have modeled stock markets have been divided into two categories. The first category includes studies that test whether stock markets are efficient, while studies in the second category analyze the relationship between the stock market and macroeconomic variables. Studies in this category either evaluate the bivariate relationship between stock prices and a macroeconomic variable, or try to build a model for stock prices

Studies analyzing the relationship between stock prices and macroeconomic variables or trying to build a stock price model use the present value model as theoretical foundation. According to this model stock prices are determined by dividends and the discount rate and are hence influenced by macroeconomic variables that influences or proxies dividends or the discount rate. It follows trivially that the systematic forces that influence stock prices and hence returns, are those that influence the discount factor or dividends. Variables identified in the literature as determinants of stock prices include short-term and long-term interest rates, (expected) inflation, economic growth, the state of the business cycle, the gold price, exchange rates, term premium, default premium, money supply and the trade balance. In addition, emerging stock markets are also influenced by global variables such as world return, world inflation, commodity prices, world industrial production, the oil price and US interest rates.

The literature on empirical models of the South African stock market is quite sparse. The evidence on the efficiency of the JSE is mixed, but the general conclusion seems to be that it is operationally efficient, so that stock price behavior cannot be successfully predicted on the basis of historical stock prices alone (Thompson and Ward 1995). This emphasizes the scope of developing a structural model that can be used with potentially more success than technical analysis in trading shares on the JSE. Variables that have been found significant in influencing the JSE can be divided into three categories, namely variables that influence dividends, variables that influence the discount rate and variables capturing the influence of global markets (Van Rensburg 1995, 1998, 1999).



The literature review in this chapter has confirmed that stock prices are in practice determined according to the dividend discount model explored in chapter three. In other words, stock prices are determined by future stock returns, which are usually proxied by an indicator of economic activity, and the discount rate, which is usually proxied by the long-term interest rate and a risk premium. However, consistent with the theoretical hypothesis in chapter three, the relationship between economic activity and stock prices is found to be asymmetric with respect to the state of the business cycle, in other words whether the economy is in a downswing or an upswing. Any empirical stock market model therefore has to capture this potential asymmetry. In the next chapter, a Markov switching regime model of the South African economy will be developed and estimated. This model generates a business cycle indicator that can be used to model business cycle asymmetry in the empirical stock market model in chapter six.

## CHAPTER 5

### A MARKOV SWITCHING REGIME MODEL OF THE SOUTH AFRICAN BUSINESS CYCLE

#### 5.1 INTRODUCTION

According to theory, the behavior of stock market investors and hence the behavior of stock prices is potentially asymmetric conditional on the business cycle (see chapter three). In order to empirically evaluate and estimate this asymmetry, an indicator of the business cycle has to be developed. This indicator should ideally reflect not only whether the economy is in a recession or an expansion, but also the degree of certainty with which investors can regard the economy as being in a recession or expansion. In this chapter, such an indicator will be developed by estimating a Markov switching regime model for the business cycle.

Hamilton (1989) first introduced the Markov switching regime model, a stochastic regime model, to business cycle modeling. He applied it to economic growth and his model has been increasingly used to assist in the dating and forecasting of turning points in the business cycle. The model is conceptually appealing in that over time the variable of interest, such as some appropriate measure of the business cycle, is regarded as having a certain probability of switching abruptly among a number of regimes. In the case of the business cycle, expansions and contractions might be considered as the two regimes, each with unique characteristics such as a unique mean and variance. In other words, the business cycle switches between a high-growth and a low-growth regime.

These discrete shifts have their own dynamics, specified as a Markov switching regime process. An attractive feature of the model is that no prior information regarding the dates when the economy was in each regime, or the size of the two growth rates is required. This is in contrast with models such as probit and logit models that require and depend

heavily upon the exact dates of all the regimes in the history of the series. Instead, the probability of being in a particular regime is inferred from the data.

In this chapter, the South African business cycle will be modeled with a Markov switching regime model. The purpose of the Markov switching regime (MS) model is two-fold. First, it estimates the data generating process (DGP) of the variable under consideration in this case economic growth. Second, it can be used to classify each observation into one of two regimes, which can in turn be used to predict turning points in the cycles when a number of observations in one regime is followed by a number of observations in the other regime. In the empirical analysis, the performance of the MS model in each of these two aspects will be compared against other models with the same purpose. Specifically, the performance of the MS model in terms of modeling the growth rate will be compared against an autoregressive model. Likewise, the accuracy of the turning points predicted by the MS model will be compared against the outcomes of a logit model.

It has become increasingly popular to use the yield spread as explanatory or information variable to model business cycle turning points (see e.g. Estrella and Hardouvelis (1991), Bernard and Gerlach (1996), Estrella and Mishkin (1998)). In this chapter, the yield spread will be used as explanatory or information variable in both the Markov switching regime and the logit models (see Appendix 1 for a comparison of the performance of the yield spread and other indicators in predicting business cycle turning points).

The outline of this chapter is as follows: The next section will summarize the theory of the lagged relationship between the yield spread and the business cycle. In section 5.3, the Markov switching regime and logit techniques are exposed. Section 5.4 provides an overview on the empirical literature of modeling the business cycle with the Markov switching regime technique, as well as empirical models of the relationship between the yield spread and the business cycle. The estimation results are presented in section 5.5.

## 5.2 THE RELATIONSHIP BETWEEN THE BUSINESS CYCLE AND THE YIELD SPREAD

There are two explanations for the relationship between the business cycle and the term structure of interest rates or the yield spread between similar long-term and short-term interest rates (the so-called “yield spread”). For the first explanation, assume that the country is currently enjoying high growth, so that there is a general agreement among investors that the country is heading for a slow-down or recession in the future. Consumers want to hedge against the recession and therefore purchase financial instruments (e.g. long-term bonds) that will deliver pay-offs during the economic slowdown. The increased demand for long-term bonds causes an increase in the price of long-term bonds, in other words a decrease in the yield on long-term bonds. In order to finance these purchases, investors sell their shorter-term assets, which results in a decline in the price of short-term assets and an increase in the yield on short-term assets. In other words, if a recession is expected, long-term interest rates will fall and short-term interest rates will rise. Consequently, prior to the recession, the slope of the term structure of interest rates will become flat (or even inverted), which means that the yield spread declines. Similarly, long-term interest rates rises while short-term interest rates falls when an expansion is expected, so that an upward-sloping yield curve predicts an expansion.

The second explanation is based on the expectations hypothesis of the term structure of interest rates. This hypothesis is based on the assumption that similar financial instruments with different maturities are perfect substitutes, so that an investor will be indifferent between investing in one long-term instrument or several similar consecutive short-term instruments, as long as their expected returns are equal (Mishkin 1998:156). This means that, for similar financial instruments, the long-term yield will be the average of current and future short-term yields. Assume that a central bank tightens monetary policy by raising short-term rates. Economic agents will view this as a temporary shock and therefore they expect future short-term rates to rise by less than the current change in short-term interest rates. Based on the expectations hypothesis of the term structure, long-term rates will rise by less than the current short rate. This will lead to a flatter or even an

inverted yield curve. Since monetary policy affects economic activity with a lag of one to two years, the tightening of policy will cause a reduction of future economic activity and an increase in the probability of a recession. Therefore, prior to a recession (expansion), the yield spread will decline (increase).

### 5.3 THE ECONOMETRIC TECHNIQUES

#### 5.3.1 The Markov Switching Regime Model

(i) *The Markov switching regime model with fixed transition probabilities*

Assume that there are two regimes, represented by an unobservable process denoted  $S_t$ . Let  $S_t$  take on the values 0 and 1, depending on the prevailing regime. Then the data generating process of the series being modeled,  $Y_t$ , will be different in each regime, for example

$$Y_t = \phi_{0,0} + \phi_{1,0} Y_{t-1} + \dots + \phi_{p,0} Y_{t-p} + \varepsilon_{t,0} \quad \text{if } S_t = 0 \quad (5.1)$$

$$Y_t = \phi_{0,1} + \phi_{1,1} Y_{t-1} + \dots + \phi_{p,1} Y_{t-p} + \varepsilon_{t,1} \quad \text{if } S_t = 1 \quad (5.2)$$

where  $\varepsilon_{t,j} \sim N(0, \sigma_j^2)$ .

Following Hamilton (1989), assume that  $S_t$  is a first-order Markov-process, which means that the current regime ( $S_t$ ) depends only on the regime in the preceding period ( $S_{t-1}$ ). The model is completed by defining the transition probabilities of moving from one regime to another, called the transition probabilities:

$$P(S_t=j|S_{t-1}=i) = p_{ij} \quad i, j = 0,1 \quad (5.3)$$

Notice that, since  $p_{01} = 1 - p_{00}$  and  $p_{10} = 1 - p_{11}$ , the transition probabilities are completely defined by  $p_{00}$  and  $p_{11}$ .

Let  $\Omega_{t-1}$  be the information matrix at time  $t-1$ :

$$\Omega_{t-1} = (Y_{t-1}, Y_{t-2}, \dots, Y_1). \quad (5.4)$$

Assuming that  $\varepsilon_t$  in equations 5.1 and 5.2 are Gaussian, the density of  $Y_t$  conditional upon the history  $\Omega_{t-1}$  and  $S_t$  is

$$f(Y_t | S_t = j, \Omega_{t-1}, \theta) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(Y_t - \phi'_j X_t)^2}{2\sigma^2}\right\} \quad (5.5)$$

where

$$X_t = (1, Y_{t-1}, Y_{t-2}, \dots, Y_{t-p})'$$

$$\phi_j = (\phi_{0,j}, \phi_{1,j}, \dots, \phi_{p,j})'$$

$$\theta = (\phi_1', \phi_2', p_{00}, p_{11}, \sigma^2)'$$

$$j = 0, 1$$

$$t = 1, \dots, n$$

$n$  is the sample size.

Since the regime  $S_t$  is unobservable, the conditional log likelihood for the  $t$ th observation  $l_t(\theta)$  is given by the log of the density of  $Y_t$  conditional only upon the history  $\Omega_{t-1}$ , that is:

$$l_t(\theta) = \ln f(Y_t | \Omega_{t-1}; \theta) \quad (5.6)$$

where

$$f(Y_t | \Omega_{t-1}; \theta) = f(y_t, S_t = 0 | \Omega_{t-1}; \theta) + f(y_t, S_t = 1 | \Omega_{t-1}; \theta)$$

$$= \sum_{j=0}^1 f(y_t | S_t = j, \Omega_{t-1}; \theta) \cdot P(S_t = j | \Omega_{t-1}; \theta) \quad (5.7)$$

In order to calculate this density, the conditional probability of being in a regime given the history of the process,  $P(S_t = j | \Omega_{t-1}; \theta)$ , has to be quantified. If the regime at time  $t-1$  were known, the optimal forecasts of the regime probabilities would be

$$\hat{\xi}_{t|t-1} = P \cdot \xi_{t-1} \quad (5.8)$$

where

$$\hat{\xi}_{t|t-1} = \begin{bmatrix} P(S_t = 0 | \Omega_{t-1}; \theta) \\ P(S_t = 1 | \Omega_{t-1}; \theta) \end{bmatrix} \text{ and } P = \begin{bmatrix} p_{00} & 1-p_{11} \\ 1-p_{00} & p_{11} \end{bmatrix}$$

$$\xi_{t-1} = (1,0)' \quad \text{if } S_{t-1} = 0$$

$$\xi_{t-1} = (0,1)' \quad \text{if } S_{t-1} = 1.$$

However,  $S_{t-1}$  is unobservable therefore  $\xi_{t-1}$  is replaced by an estimate of the probabilities of each regime occurring at time  $t-1$  conditional on all information up to and including observation  $t-1$ . Let  $\hat{\xi}_{t-1|t-1}$  be the optimal inference concerning the regime probabilities. Then

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t-1|t-1} \Theta f_t}{1' \hat{\xi}_{t-1|t-1} \Theta f_t}. \quad (5.9)$$

Given  $\hat{\xi}_{1|0}$  and  $\hat{\theta}$ , the optimal forecast and inference for the conditional regime probabilities can be calculated by iterating on the following two equations:

$$\hat{\xi}_{t|t} = \frac{\hat{\xi}_{t-1|t-1} \Theta f_t}{1' \hat{\xi}_{t-1|t-1} \Theta f_t} \quad (5.10)$$

$$\hat{\xi}_{t+1|t} = P \cdot \hat{\xi}_{t|t} \quad (5.11)$$

where  $f_t$  denotes the vector containing the conditional densities for the two regimes,  $\mathbf{1}$  is a 2x1 vector of ones and the symbol  $\odot$  indicates element-by-element multiplication. The necessary starting values  $\hat{\xi}_{1|0}$  can either be taken to be affixed vector of constants which sum to unity, or can be included as separate parameters that need to be estimated. Hamilton (1994:693) provides an intuitive explanation of why this algorithm works.

Finally, let  $\hat{\xi}_{t|n}$  denote the smoothed inference on the regime probabilities, in other words, the estimates of the probability that regime  $j$  occurs at time  $t$  given all available observations in the sample:

$$\hat{\xi}_{t|n} = P(s_t = j | \Omega_n; \theta). \quad (5.12)$$

Kim (1993) developed an algorithm to calculate the smoothed inference probabilities:

$$\hat{\xi}_{t|n} = \hat{\xi}_{t|t} \otimes \left( P \cdot \left[ \hat{\xi}_{t+1|n} \div \hat{\xi}_{t+1|t} \right] \right) \quad (5.13)$$

where  $\div$  indicates element-by-element division and  $\otimes$  indicates element-by-element multiplication. The algorithm runs backwards though the sample, that is, starting with  $\hat{\xi}_{n|n}$  from the inference regime probabilities up to  $\hat{\xi}_{1|n}$ .

It was shown by Hamilton (1990) that the maximum likelihood estimates of the transition probabilities are given by

$$\hat{p}_{ij} = \frac{\sum_{t=2}^n P(s_{t=j}, s_{t-1} = i | \Omega_n; \hat{\theta})}{\sum_{t=2}^n P(s_{t-1} = i | \Omega_n; \hat{\theta})}. \quad (5.14)$$

The maximum likelihood estimates of the transition probabilities satisfy the following first order conditions (Hamilton 1990):



$$\hat{\sigma}_j = \frac{1}{n} \sum_{t=1}^n \sum_{j=1}^2 (y_t - \hat{\phi}'_j x_t)^2 P(s_t = j | \Omega_n; \hat{\theta}) \quad (5.15)$$

and

$$\hat{\phi}_j = \left( \sum_{t=1}^n x_t(j) x_t(j)' \right)^{-1} \left( \sum_{t=1}^n x_t(j) y_t(j) \right). \quad (5.16)$$

In other words, the maximum likelihood estimates of  $\sigma^2$  and  $\phi_j$  can be obtained by estimating a weighted least squares regression of  $y_t$  on  $x_t$ , where the weights are given by the square root of the smoothed probability of regime  $j$  occurring. Therefore, the maximum likelihood estimate of  $\phi_j$  is the vector of coefficients in a regression of  $y_t(j)$  on  $x_t(j)$ , where

$$y_t(j) = y_t \sqrt{P(s_t = j | \Omega_n; \hat{\theta})} \quad (5.17)$$

$$x_t(j) = x_t \sqrt{P(s_t = j | \Omega_n; \hat{\theta})}. \quad (5.18)$$

Putting all the above elements together suggests the following iterative procedure to estimate the parameters of the Markov switching regime model. Start off with an arbitrary initial guess for the value of  $\hat{\theta}^{(0)}$ , where  $\hat{\theta} = (\hat{\phi}_1, \hat{\phi}_2, \hat{p}_{11}, \hat{p}_{22}, \hat{\sigma}^2)$ . This can be used with equations 5.10 to 5.12 to calculate the initial estimates of the smoothed regime probabilities ( $\hat{\xi}_{t|n}^{(0)}$ ). Next, the smoothed regime probabilities are combined with the initial estimates of the transition probabilities ( $\hat{p}_{ij}^{(0)}$ ) to calculate new estimates of the transition probabilities ( $\hat{p}_{ij}^{(1)}$ ). Finally, equations 5.15 and 5.16 can be used to obtain a new set of estimates of the autoregressive parameters ( $\hat{\phi}_j$ ) and the residual variance ( $\hat{\sigma}^2$ ). Combined with the new estimates of the transition probabilities, this gives a new set of estimates for all the parameters in the model,  $\hat{\theta}^{(1)}$ .

Iterating this process renders estimates for the parameters  $\hat{\theta}^{(2)}, \hat{\theta}^{(3)}, \dots$  until convergence occurs, in other words, until the estimates in subsequent iterations are the same. This procedure turns out to be an application of the Expectation Maximization (EM) algorithm developed by Dempster, Laird and Rubin (1977). It can be shown that each iteration of this procedure increases the value of the likelihood function, which guarantees that the final estimates are maximum likelihood estimates (Hamilton 1994: 689).

(ii) *The Markov switching regime model with time-varying transition probabilities*

The drawback of fixed transition probabilities model set out in the previous section is that it implies that the expected durations of expansions and recessions can differ but are forced to be constant over time. Intuitively, the expected duration of an expansion or contraction is generally thought to vary with the underlying strength of the economy. For example, as the economy exits a relatively deep recession and enters a relatively robust recovery period, the economy is less likely to fall back into the recession at that time (Filardo and Gordon 1998). The assumption that the transition probabilities are time invariant, may be costly from an empirical point of view. With fixed transition probabilities, the conditional expected durations do not vary over the cycle. This implies that exogenous shocks, macroeconomic policies and an economy's own internal propagation mechanisms do not affect the expectation of how long an expansion or recession will last (Filardo and Gordon 1998).

A solution to this problem is to incorporate time-varying transition probabilities (TVTP) into the model, by using a specification for the transition probabilities that reflects information about where the economy is heading. The variations in the transition probabilities will generate variations in the expected durations (Filardo and Gordon 1998).

The time-invariant transition probabilities were

$$P(S_t = s_t | S_{t-1} = s_{t-1}, z_t) = \begin{bmatrix} p_{00} & 1 - p_{11} \\ 1 - p_{00} & p_{11} \end{bmatrix} \quad (5.19)$$

where  $p_{ii} = P(S_t = i | S_{t-1} = i)$ .

Instead, the time-varying transition probabilities are

$$P(S_t = s_t | S_{t-1} = s_{t-1}, z_t) = \begin{bmatrix} p_{00}(z_t) & 1 - p_{11}(z_t) \\ 1 - p_{00}(z_t) & p_{11}(z_t) \end{bmatrix} \quad (5.20)$$

where  $z_t$  is the information variable(s) upon which the evolution of the unobserved regime will depend, such as the index of leading indicators, or individual leading indicators such as the term structure of interest rates.

There are three reasons why the time-varying transition probabilities (TVTP) model may be a significant extension of the fixed transition probabilities (FTP) model (Filardo 1994):

- The TVTP model allows the transition probabilities to rise just before a contraction or an expansion begins, while the FTP does not. In an FTP model, the transition probabilities are constant before, during and after turning points. On the other hand, TVTP models have the flexibility to identify systematic variations in the transition probabilities both before and after turning points.
- The TVTP model is able to capture more complex temporal persistence than an FTP model. Both the FTP and TVTP models can distinguish between two sources of business cycle persistence, namely through the autoregressive (AR) parameters and through the persistence of the phase over time that is reflected in the transition probability matrix. By allowing the transition probabilities to vary over time, the nature of the persistence that can be identified is expanded.

- TVTP are intrinsically linked to the notion of time-varying expected durations in the Markov switching regime framework. In the FTP model, expected duration is constant, while it can vary over time in the TVTP model. Several studies (see e.g. Diebold, Rudebusch and Sichel (1993) and Durland and McCurdy (1993)) have confirmed the intuition that the expected duration of a cycle is not necessarily constant over time and unlike the FTP model, the TVTP model is flexible enough to capture this.

A popular way to model time-varying transition probabilities is to incorporate a simple probit or logit function (see e.g. Filardo and Gordon (1998), Durland and McCurdy (1994) and Bodman (1998)). A probit or logit function can be estimated to measure the transition probability matrix at each time  $t$ . This way, the transition probabilities is a function of an economic indicator(s) such as the index of leading indicators (see e.g. Filardo and Gordon (1998)), or an individual leading indicator such as the term structure of interest rates (see e.g. Filardo (1994)). In particular, if a logit function is used the transition probabilities are

$$p_{11} = P(S_t=1 | S_{t-1}=1) = \exp(\alpha_1 + \beta_1 z_t) / (1 + \exp(\alpha_1 + \beta_1 z_t)) \quad (5.21)$$

$$p_{22} = P(S_t=2 | S_{t-1}=2) = \exp(\alpha_2 + \beta_2 z_t) / (1 + \exp(\alpha_2 + \beta_2 z_t)) \quad (5.22)$$

The expected duration of a phase is determined by the transition probabilities. This means that variation in  $z_t$  and  $S_{t-1}$  will affect the expectation of how long a phase will last.

### 5.3.2 The Logit Model

Several authors have used probit or logit models to model business cycle turning points (see e.g. Estrella and Hardouvelis 1991; Dueker 1997; Dotsey 1998; Estrella and Mishkin 1998; Bernard and Gerlach 1996). The probit or logit form is dictated by the fact that the variable being predicted takes on only two possible values – whether the economy is in a

recession or not. The model is defined in reference to a theoretical linear relationship of the form:

$$Y_{t+k}^* = \alpha + \beta * x_t + \varepsilon_t \quad (5.23)$$

where  $Y_t^*$  is an unobservable that determines the occurrence of a recession at time t, k is the length of the forecast horizon,  $\varepsilon_t$  is a normally distributed error term and  $x_t$  the value of the explanatory variable at time t. The parameters  $\alpha$  and  $\beta$  are estimated with maximum likelihood. The observable recession indicator  $R_t$  is related to this model by

$$R_t = 1 \text{ if } Y_t^* > 0 \text{ and } 0 \text{ otherwise} \quad (5.24)$$

The form of the estimated equation is

$$P(R_{t+k} = 1) = F(\alpha + \beta * x_t) \quad (5.25)$$

where F is the cumulative logistic distribution function.

The model is estimated by maximum likelihood. The recession indicator is obtained from the South African Reserve Bank, that is,  $R_t = 1$  if the economy is in a recession at time t and 0 otherwise.

#### **5.4 EXISTING MARKOV SWITCHING REGIME BUSINESS CYCLE MODELS**

Business cycles have been modeled with different techniques, such as autoregressive integrated moving average (ARIMA) models (e.g. Nelson and Plosser (1982), Beveridge and Nelson (1981) and Campbell and Mankiw (1987)); cointegration techniques (e.g. King, Plosser, Stock and Watson (1991)); and the Kalman filter whereby real gross

national product (GNP) is modeled as the sum of unobserved components (e.g. Harvey (1985), Watson (1986), Clark (1987)). These techniques share a potential shortcoming, namely the assumption that the growth rate of real GNP is a linear stationary process. Linear models are incompatible with the asymmetry between expansions and contractions that has been documented by, amongst others, Neftci (1984), Stock (1987), Diebold and Rudebusch (1990) and Sichel (1993).

Hamilton (1989) proposed a Markov switching regime model that models real GNP growth as an autoregressive model of order four (AR(4)), allowing for non-linearity by introducing discrete shifts in the mean between high-growth and low-growth regimes. These discrete shifts have their own dynamics, specified as a two-regime first-order Markov process. The most attractive feature of this model is that no prior information regarding the dates of the two growth periods or the size of the two growth rates is required. In addition, the low-growth rate need not be negative. In this section, a brief overview of the empirical literature on Markov switching regime models for business cycles and on the relationship between the yield spread and the business cycle will be given.

#### **5.4.1 Empirical Markov Switching Regime Business Cycle Models with Fixed Transition Probabilities**

Hamilton (1989) developed a Markov switching regime model for dating and forecasting business cycles. He applied this model to the quarterly real GNP of the US for the period 1951 to 1984. In particular, he modeled GNP growth as a AR(4) two regime Markov switching regime (MS) model. In other words, GNP growth switches between two regimes, which each have a unique intercept but he constrained the AR coefficients to be the same across regimes. The MS model calculates the probability that the economy is in a particular regime in a certain period and the econometrician has to devise a dating rule to actually decide from which regime this observation is. Hamilton used a very popular dating rule, which classifies a particular period as a recession (expansion) if the econometrician concludes that the economy is more likely than not to be in a recession

(expansion), in other words, when the probability of being in a recession (expansion) is higher than the probability of being in a expansion (recession). The dates of the turning points predicted by his MS model are usually within three months of the dates of the official dates set by the National Bureau for Economic Research (NBER).

Goodwin (1993) used Hamilton's (1989) Markov switching regime model to model the business cycles of eight developed countries. Real GNP growth was allowed to follow an AR(4) process. Hansen's (1992) likelihood ratio test rejected the null hypothesis that the Markov model performs better than linear autoregressive models. However, the filtered and smoothed conditional probabilities indicated business cycle turning points that closely correlate with official turning points. Implicit in much of the research on business cycles going back to Keynes and before, is the notion that business cycles can be characterized as exhibiting sharp drops during contractions followed by gradual movements during expansions. Goodwin tested a closely related idea, namely that contractions have shorter durations than expansions, by comparing the expected durations of expansion and recessions. He rejected the hypothesis of symmetry, in other words that the expected duration of expansion and recessions are equal.

Ivanova, Lahiri and Seitz (2000) used the same technique as Hamilton (1989) and Goodwin (1993), but instead of modeling GNP directly, they modeled a leading indicator and then consider a change in regime as a business cycle turning point signal. In particular, they compared the performance of a number of interest rate spreads as predictors of the German business cycle. They use a two regime, first order Markov switching regime model, in other words they allowed for two regimes where the regime probability in a particular period is only influenced by the regime in the preceding period. They allow the dynamic behavior of the economy to vary between expansions and recessions in terms of duration and volatility. They model the interest rate spread as a univariate Markov switching model with no autoregressive terms, allowing both the intercept and variance to differ across regimes. They define a regime change as the event that the probability of a recession (expansion) is greater than the probability of an expansion (recession). Since the interest rate spread is considered to be a leading

indicator of the business cycle, the change in regime is the turning point signal. Their results indicate that the market spreads does follow regimes. None of the bank spreads gave any false signals, but the spread between government and bank bonds of 1-2 years gave multiple false signals. The call rate spread performs slightly inferior to the other spreads, since its predictions lagged the predictions of the other spreads.

Instead of a univariate Markov switching regime model, Kontolemis (1999) used a vector Markov switching regime model to date and forecast US business cycle. In other words, they forced the different indicators to have simultaneous turning points. The four series used in the construction of the coincident index are the index of industrial production, non-agricultural employment, personal income (less transfer payments) and manufacturing and trade sales. Monthly data from 1948 to 1995 was used. Following Hamilton (1989), the rule for dating the business cycle is based on whether the economy is more likely than not to stay in one of the two phases. They imposed a requirement that each cycle is at least 6 months (i.e. two quarters) to eliminate spurious cycles in the monthly series. The estimated probabilities tracked the NBER downturns relatively well. They extended the model to include an autoregressive term, but this model failed to track the NBER reference cycle during the entire sample period. The vector Markov switching model produces more accurate forecasts than a simple univariate Markov switching model specification.

#### **5.4.2 Empirical Markov Switching Regime Business Cycle Models with Time-Varying Transition Probabilities**

The models reviewed in section 5.4.1 all assumed constant transition probabilities, which implies that the conditional expected durations are constant as well. Intuitively, however, the expected duration of an expansion or contraction is generally thought to vary with the underlying strength of the economy. For example, as the economy exits a relatively deep recession and enters a relatively robust recovery period, the economy is less likely to fall back into the recession at that time. The time-varying transition probabilities (TVTP) model offers a solution to this problem, by using a specification for the transition



probabilities that reflects information about where the economy is heading. The variations in the transition probabilities will generate variations in the expected durations.

Filardo (1994) extended the Markov switching regime model to allow for time-varying transition probabilities. He used a logit function to generate the transition probabilities. He compared different information variables, namely the composite index of leading indicators, the interest rate spread, the Standard and Poor stock index and the short-term interest rate. There was statistically significant evidence that the model supports the two-phase view of the US business cycles, in other words that economic growth switches between a positive growth rate (expansion) and a negative growth rate (recession). In addition, it has been shown that expansions have higher persistence and that of both phases are time-varying. The different leading indicators used contain different information and gave different turning points. His results showed that the business cycle dynamics of this model stem mainly from the variation in the transition probabilities, rather than from a shift in the means.

Durland and McCurdy (1994) also modeled time-varying transition probabilities with a logit function. They modeled the transition probabilities as functions of both the inferred current regime and the associated number of periods the system has been in the current regime. In other words, they allowed the transition probabilities to be duration dependent, so that the probability of staying in, say, a recession, declines the longer the economy is in a recession. They are able to reject the linear model in favor of a duration-dependent parameterization of the regime transition probabilities in a regime-switching model.

Filardo and Gordon (1998) generated the time-varying transition probabilities with a probit function. Specifically, they use the information contained in leading indicator data to forecast the transition probabilities. Their results indicate that the US business cycle can indeed be classified as a two-state model and the turning points predicted by their model are similar to the official turning points.

Probit and logit functions are flexible and have a sensible economic interpretation. However, some studies have reported estimation problems when these functions are applied. In context of smooth transition autoregressive (STAR<sup>1</sup>) modeling, Ocal and Osborn (2000) found exponential STAR (ESTAR) more robust to outlier observations than logistic STAR (LSTAR). Therefore Simpson, Osborn and Sensier (2001) tried to model the time-varying transition probabilities with an exponential function instead of the popular probit or logit functions. The problem with the logistic form is that the interpretation is not as economically intuitive as the logit or probit form and it may not lead to sensible probabilities for certain values of the leading indicator because of its shape. Their results indicate that a constant transition probability Markov switching regime model captures the major recessions of the sample, but the use of leading indicators through the time-varying transition probabilities framework improve this regime recognition. On average, contractions are shorter than expansions.

Layton and Katsuura (2001) compared different techniques to date and forecast US business cycles, using three different composite business cycle indexes. Specifically, they estimated binomial and multinomial probit models, binomial and multinomial logit models and a two-regime Markov switching regime model where the transition probabilities are modeled as logistic functions. All these models estimate the probabilities that the economy is in contraction or expansion. When these probabilities are more than 0.5, the economy are regarded to be in contraction or expansions and, in this way, they date the turning points as derived from the models. They used the  $R^2$ , the log likelihood and also the official dates of US business cycles as determined by the NBER as a benchmark for comparison. Their results showed that the MS model performed relatively better than the other models. The MS model overcomes a very real practical and fundamental limitation of the logit and probit specifications as far as their use in real time business cycle phase shift forecasting is concerned. Their estimation requires exact knowledge of the regime of the economy for every observation in the estimation period so as to assign values to the dependent variable in the model.

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<sup>1</sup> Like the Markov switching regime model, the STAR model is also a regime switching modeling technique. However, in the STAR model the regime is determined by an observable variable, in contrast with the Markov switching regime model where the regime is determined by an unobservable variable.

### 5.4.3 The Yield Spread as Predictor of Business Cycles

Estrella and Hardouvelis (1991) were the first to empirically analyze the term structure as a predictor of real economic activity. Their study was based on quarterly data of US GNP growth for the period 1955 to 1988. They used the slope of the yield curve, defined as the difference between the 10-year government bond rate and the 3-month T-bill rate, as explanatory variable. Regressions of future GNP growth on the slope of the yield curve and other information variables showed that a steeper (flatter) slope implies faster (slower) future growth in real output. The estimated constant and coefficient of the yield spread for GNP one to five quarters ahead are approximately 1.70 and 1.30 respectively. The positive constant term implies that a negative slope does not necessarily predict negative future real GNP growth. The forecasting accuracy is the highest five to seven quarters ahead. In addition, they also used a probit model to analyze the predictive power of the term structure on a binary variable that simply indicates the presence or absence of a recession. Their probit model relates the probability of a recession as dated by the NBER during the current quarter to the slope of the yield curve lagged four quarters. The results showed that an increase in the spread between the long- and short-term interest rates implies a decrease in the probability of a recession 4 quarters later.

In addition to the domestic term structure, Bernard and Gerlach (1996) also tested the ability of foreign term structures to predict business cycle turning points in eight industrial countries for the period 1972:1 to 1993:4. Using probit models, they showed that the domestic term spreads are statistically significant in explaining business cycle turning points in all eight countries. The period over which the domestic term spread successfully forecast the turning points vary across countries, but the optimal forecast period range from two to five quarters. In general, downward-sloping (upward-sloping) yield curves have historically been associated with subsequent recessions (expansions).

Estrella and Mishkin (1998) compared the performance of various financial variables, including four term structures of interest rates, stock prices, monetary aggregates, indexes

of leading indicators and other economic variables such as GDP, CPI and exchange rates, as predictors of US recessions. They estimated probit models with quarterly data for the period 1959 to 1995. Their results indicated that the yield curve outperforms the other indicators for forecasting beyond one quarter ahead.

The only study on the relationship between the term structure of interest rates and the business cycle in the South Africa economy was done by Nel (1996). Unlike the other studies, he analyzed the contemporaneous relationship with cointegration techniques, instead of the lead-lag relationship dictated by theory. He showed that quarterly real GDP is a positive function of the yield spread between 10-year government bonds and the three month banker's acceptance rate. He found real GDP and the yield spread to be cointegrated and showed that the yield spread is statistically significant in explaining GDP, despite a poor overall fit. While Nel (1996) modeled the level or course of the business cycle, this chapter will focus on predicting only turning points.

## **5.5 EMPIRICAL ANALYSIS OF THE SOUTH AFRICAN BUSINESS CYCLE**

### **5.5.1 Methodology**

The South African business cycle is modeled with linear and non-linear models with data for the period 1978 to 2001. Specifically, the performance of a Markov switching regime model of the South African business cycle will be compared with the performance of an autoregressive model and a logit model. In all the models the leading indicator used as explanatory variable was the yield spread. Like most similar studies (see e.g. Durland and McCurdy (1994), Goodwin (1993) and Simpson, Osborn and Sensier (2001)), the empirical estimation was done on a quarterly basis to avoid the excessive random noise prevalent in monthly data.

**Table 5.1 Business Cycle Phases According to SARB Since 1978**

Upward phase		Downward phase	
January 1978	August 1981	September 1981	March 1983
April 1983	June 1984	July 1984	March 1986
April 1986	February 1989	March 1989	May 1993
June 1993	November 1996	December 1996	August 1999

Source: South African Reserve Bank, Quarterly Bulletin, various issues.

### 5.5.2 The Estimated Linear Model

Following the most popular Markov switching regime specification for business cycles, real GDP growth is modeled as an AR(4) process with different intercepts in the two different regimes (see e.g. Hamilton (1989), McCurdy and Durland (1994), Goodwin (1993) and Bodman (1998)). Therefore, in the linear model real GDP growth ( $Y_t$ ) will be modeled as an AR(4) process.

**Table 5.2 Linear Autoregressive Model**

<b>Dependent Variable: <math>Y_t</math></b>				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>Prob.</i>
$Y_{t-1}$	0.421611	0.108621	3.881486	0.0002
$Y_{t-2}$	0.080301	0.118026	0.680367	0.4981
$Y_{t-3}$	-0.021405	0.117935	-0.181498	0.8564
$Y_{t-4}$	-0.043410	0.107054	-0.405500	0.6861
C	1.136723	0.445845	2.549594	0.0125
R-squared	0.208481	F-statistic	5.728825	
Adjusted R-squared	0.172090	Prob(F-statistic)	0.000386	

Source: Own calculations

In the linear model, only the first autoregressive term is significant. The performance of this model is evaluated in section 6, when it is also compared with the performance of the MS model.

### 5.5.3 The Estimated Logit Model

**Table 5.3 Logit model**

<b>Dependent Variable: Rec<sub>t</sub>*</b>				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>z-Statistic</i>	<i>Prob.</i>
Spread <sub>t-2</sub>	-0.994626	0.204696	-4.859029	0.0000
C	0.514365	0.348941	1.474072	0.1405
S.E. of regression		0.299932	Akaike criterion	0.671411
Sum squared resid		8.096318	Schwarz criterion	0.726232

\* Rec<sub>t</sub> is a dummy variable that takes on the value 1 if the economy is officially in a recession in period t and 0 if not.

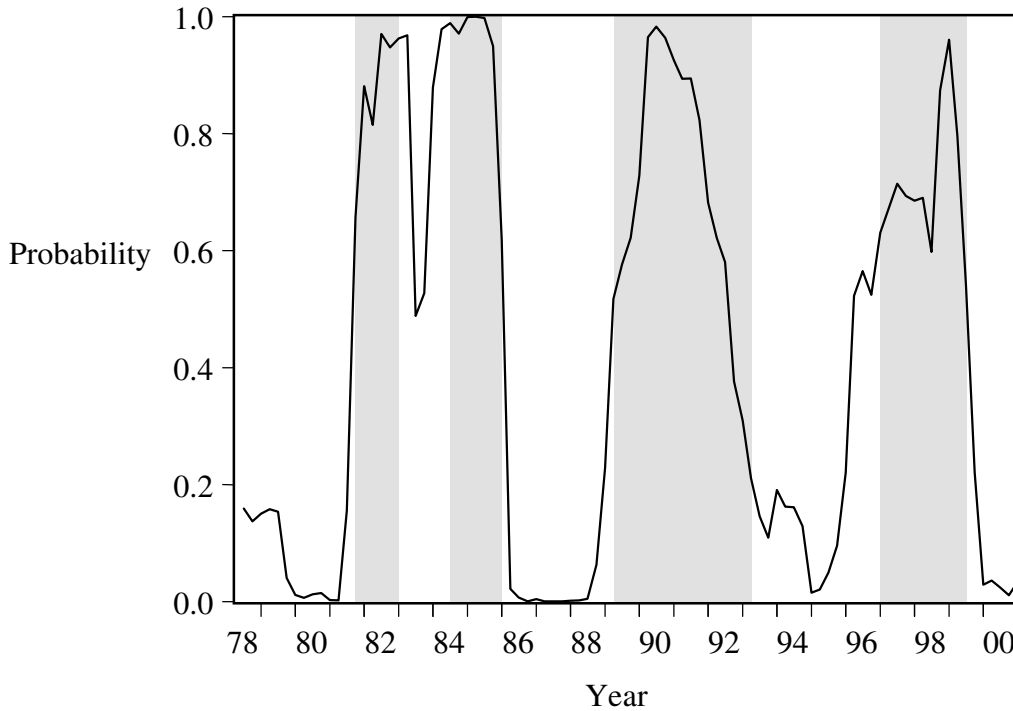
Source: Own calculations

The results in table 5.3 indicate that the probability of a recession in a specific quarter is a negative function of the yield spread lagged two quarters (spread<sub>t-2</sub>). Expressed algebraically

$$P(R_{t+2} = 1) = F(0.514 - 0.995 * x_t) \tag{5.26}$$

where F is the cumulative logistic distribution, x<sub>t</sub> is the yield spread in period t and R<sub>t</sub> is a dummy variable that takes on the values one if the economy is in a recession in period 1. In other words, an increase in the spread between the long-term and short-term interest rates implies a decrease in the probability of a recession two quarters later. According to the results in table 5.3, the relationship between the probability of a recession and the yield spread is statistically significant.

**Figure 5.1 Recession Probabilities of the Logit Model**



Source: Own calculations

Figure 5.1 plots the estimated probability of a recession derived from the historical data on the yield spread lagged two quarters, the parameter estimated in table 5.3 and the cumulative logistic distribution. The shaded areas denote periods of actual recessions as classified by the South African Reserve Bank.

In seven of the eight turning points, the peak of the estimated probability of a turning point preceded the actual turning point by zero to two quarters, in other words the yield spread predicted turning points two to four quarters ahead. The only exception was the upswing in April 1983, when the estimated probability of a recession declined but was higher than with the other upswings. This means that, based on a dating rule that classifies recessions (expansions) as estimated probabilities above (below) 50 percent, the model missed only the upswing in 1983. (However, if the dating rule classifies recessions (expansions) as estimated probabilities above (below) 0.7, the model predicted all the turning points.) If the upswing of 1983 is excluded, the peak of the estimated probability

coincided with all the turning points, except for the expansion from June 1993 to November 1996 when it preceded the turning point by two quarters. However, this imperfection should be seen in perspective. For most market participants, the cost of expecting the turning point too early is lower than the cost of expecting the turning point too late. A crucial characteristic of this model is that it did not give any false signals.

#### 5.5.4 The Estimated Markov Switching Regime Model

A first-order, two-regime Markov switching regime model was estimated for the South African business cycle. The model was specified as follows:

$$Y_t = \mu_0(1 - S_t) + \mu_1 S_t + \phi_1(Y_{t-1} - (\mu_0(1 - S_{t-1}) + \mu_1 S_{t-1})) + \phi_2(Y_{t-2} - (\mu_0(1 - S_{t-2}) + \mu_1 S_{t-2})) + \phi_3(Y_{t-3} - (\mu_0(1 - S_{t-3}) + \mu_1 S_{t-3})) + \phi_4(Y_{t-4} - (\mu_0(1 - S_{t-4}) + \mu_1 S_{t-4})) + \varepsilon_t \quad (5.27)$$

where  $\varepsilon_t \sim N(0, \sigma^2)$

$S_t = 1$  if low-growth regime, 0 otherwise

$P(S_t=j|S_{t-1}=i) = p_{ij,t} \quad i, j = 0, 1.$

Notice that, since  $p_{10,t} = 1 - p_{11,t}$  and  $p_{01,t} = 1 - p_{00,t}$ , the transition probabilities are completely defined by  $p_{11,t}$  and  $p_{00,t}$ .

Following Filardo (1994), Durland and McCurdy (1994), amongst others, the transition probabilities were modeled with a logit function:

$$p_{11,t} = p(S_t = 1 | S_{t-1} = 1) = \exp(\alpha_1 + \beta_1 z_{t-k}) / (1 + \exp(\alpha_1 + \beta_1 z_{t-k})) \quad (5.28)$$

$$p_{00,t} = p(S_t = 0 | S_{t-1} = 0) = \exp(\alpha_0 + \beta_0 z_{t-k}) / (1 + \exp(\alpha_0 + \beta_0 z_{t-k})) \quad (5.29)$$

where  $z_t$  is the yield spread and  $\alpha$  and  $\beta$  the coefficients estimated with maximum likelihood.



Table 5.4 presents significant evidence to support the assumption that two distinct growth-rate phases characterize the business cycle. The point estimates of the regime-dependent means,  $\mu_1$  and  $\mu_0$ , are statistically different. More important, their magnitudes differ significantly and economically. The mean growth rate in the high-growth regime,  $\mu_0$ , is significantly positive, while the mean growth rate in the low-growth regime,  $\mu_1$ , is significantly negative. Because the sample dichotomizes into phases that exhibit declining aggregate output and growing aggregate output, each can be labeled as low-growth and high-growth regimes of the economy.

**Table 5.4 Parameters of Growth Equation in Markov Switching Regime Model**

**Growth Model:**

$$Y_t = \mu_0(1 - S_t) + \mu_1 S_t + \phi_1(Y_{t-1} - (\mu_0(1 - S_{t-1}) + \mu_1 S_{t-1})) + \phi_2(Y_{t-2} - (\mu_0(1 - S_{t-2}) + \mu_1 S_{t-2})) + \phi_3(Y_{t-3} - (\mu_0(1 - S_{t-3}) + \mu_1 S_{t-3})) + \phi_4(Y_{t-4} - (\mu_0(1 - S_{t-4}) + \mu_1 S_{t-4})) + \varepsilon_t$$

<i>Parameter</i>	<i>Coefficient</i>	<i>Std. Error</i>
$\mu_1$	-1.061275	0.287213
$\mu_0$	3.741749	0.313490
$\phi_1$	0.332210	0.064285
$\phi_2$	0.035363	0.067236
$\phi_3$	-0.032597	0.068706
$\phi_4$	0.001868	0.067109
$\sigma^2$	2.693322	0.293941

Source: Own calculations

According to the results in table 5.5, all the estimated coefficients in the generation process of the transition probabilities are significant. The parameters that govern the time-variation of the transition probabilities,  $\beta_1$  and  $\beta_0$ , have different signs. This is consistent with the intuition that an increase in the yield spread decreases the probability of remaining in an expansion and increases the probability of remaining in a recession

(see section 5.4.3). The parameters  $\alpha_0$  and  $\alpha_1$  determine the unconditional mean duration of recessions and expansions. The estimates capture the potential asymmetry in duration across expansions and recessions.

**Table 5.5 Parameters of Transition Probability Equation in Markov Switching Regime Model**

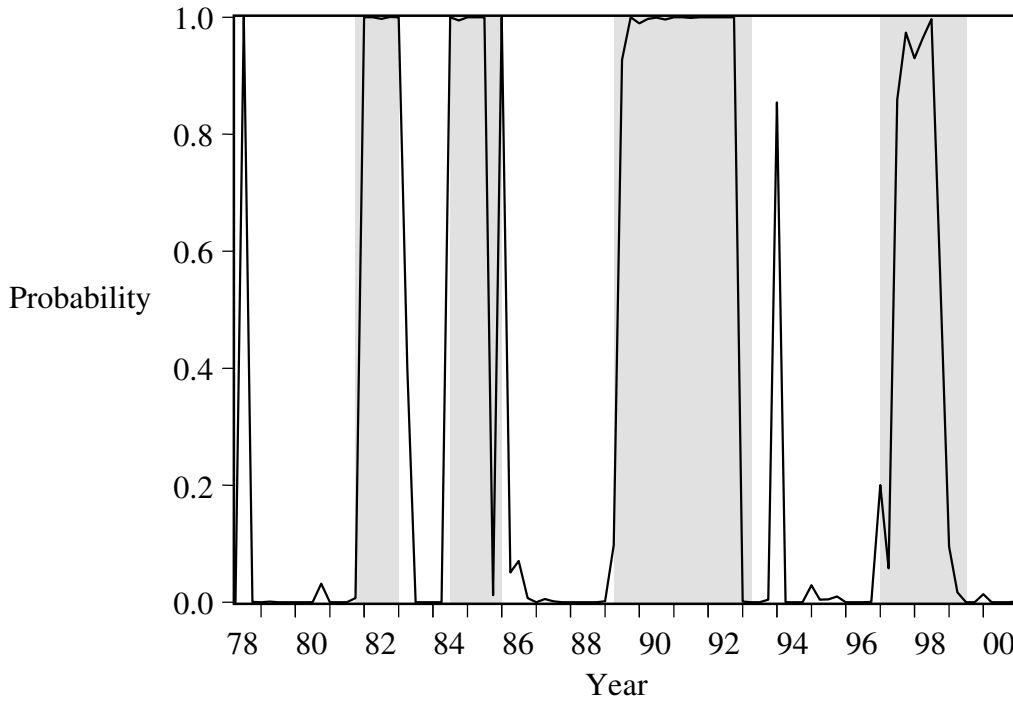
<b>TVTP model:</b> $p_{ii,t} = p(S_t = i   S_{t-1} = i) = \exp(\alpha_i + \beta_i z_{t-k}) / (1 + \exp(\alpha_i + \beta_i z_{t-k}))$			
<i>Parameter</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>T-value</i>
$\alpha_1$	-0.880836	0.536753	1.64
$\beta_1$	-0.784035	0.418566	1.87
$\alpha_0$	1.250595	0.555241	2.25
$\beta_0$	0.388441	0.184527	2.11

Source: Own calculations

Figure 5.2 plots the inferred probability of a low-growth-rate regime given the available data. When above (below) 0.5, the economy is more likely to be in a recession (expansion). The inferred regimes of the FTP model correspond to the official cycles of the SARB. The shaded areas represent the official recessions.

The turning points predicted by the Markov switching regime model are highly correlated with the dates of the official turning points and the regime probabilities are generally very close to 0 or 1, so it is always explicitly indicating one of the regimes. The Markov switching regime model gave “false” signals of an expansion in 1985 and a recession in 1994, but both these signals only lasts for 1 quarter and can therefore be eliminated by applying the common dating rule that a cycle should last for at least 2 quarters. However, instead of regarding these signals as “false” simply because they do not correspond to the official dates, a careful analysis of the periods during which they occurred might show that they were not truly false in the sense of incorrectly indicating the general state of the economy.

**Figure 5.2 Markov Switching Regime Model: Time-Varying Transition Probabilities**



Source: Own calculations

The definition used by the Reserve Bank is to classify a recession as at least two consecutive quarters of negative economic growth. In other words, if only a single quarter of negative growth is experienced it will not be reflected by the official recessions. For example, during the first quarter of 1994, the economy was contracting by 0.6 percent but since the previous and following quarters both had positive economic growth this was not defined as a recession. The high recession probability in the first quarter of 1994 therefore are reflecting this drop in economic growth rather than giving a false signal. Likewise, the low recession probability in the last quarter of 1985 corresponds to a positive economic growth rate, but since growth was negative during the following quarter the economy was officially still in a recession. This was also the case with the third quarter of 1978. This means that the differences between the Markov switching regime model and the official classification should not be viewed as “false” signals, but should rather be viewed as additional information given by the Markov

switching regime model regarding the true state of the economy which are not influenced by an asymmetric classification definition.

## 5.6 MODEL SELECTION

As stated earlier, the purpose of Markov switching regime model is two-fold, namely to model economic growth, as well as to model the dating of the two regimes. In this section, the two types of results of the Markov switching regime model will be compared with two corresponding types of models. First, the Markov switching regime model's accuracy in modeling economic growth will be compared with two linear models. Second, the Markov switching regime model's accuracy in predicting business cycle turning points will be compared with the turning points predicted by a logit model.

### 5.6.1 Comparing Linear and Markov Switching Regime Models

**Table 5.6 Model Selection Criteria for the Linear and Markov Models**

Criteria	Linear model	Markov model
MAPE	1.13	1.48
RMSE	3.31	2.99
MAE	2.46	2.20
Theil's U	0.48	0.36

Source: Own calculations

The mean absolute percentage error (MAPE), the square root of the mean squared error (RMSE), the mean absolute error (MAE) and Theil's inequality coefficient (U) were used to compare the linear and MS models. The Markov switching regime model was preferred to the AR(4) models by all the criteria.

**5.6.2 Comparing the Estimated Logit and Markov Switching Regime Models**

Criteria:

- (i) Number of wrong predictions:  $\sum_{i=1}^n (y_i - \hat{y}_i)^2$
- (ii) Sum of Squared Residuals (SSR):  $\sum_{i=1}^n (y_i - F(x_i, \hat{\beta}))^2$
- (iii) Sum of Absolute Value of Residuals:  $\sum_{i=1}^n |y_i - F(x_i, \hat{\beta})|$
- (iv) Efron's (1978)<sup>2</sup> R<sup>2</sup>:  $R^2_{Efron} = \frac{\sum (y_i - F(x_i, \hat{\beta}))^2}{\sum (y_i - \hat{y}_i)^2}$

where  $\hat{y}_i = 1$  if  $F(x_i, \hat{\beta}) \geq 0.5$  and  $\hat{y}_i = 0$  if  $F(x_i, \hat{\beta}) < 0.5$ .

The model selection criteria for the logit and Markov switching regime models are given in table 5.7. The preferred model according each criterion is indicated in bold print.

**Table 5.7 Model Selection Criteria for Logit and MS Models**

Criteria	MS model	Logit model
Number of wrong predictions	12	<b>11</b>
Sum of squared errors	9.58	<b>8.03</b>
Efron's R <sup>2</sup>	<b>0.57</b>	0.50
Sum of absolute errors	<b>14.58</b>	16.67

Source: Own calculations

<sup>2</sup> The usual R<sup>2</sup> is calculated as  $\sum \hat{y}_i^2 / \sum y_i^2$ .

The results in table 5.7 indicate that the Markov model made fewer wrong predictions than the logit model with regards to the inferred regime or regime of the economy. However, this criterion penalizes a model only for the number of times that it is wrong, without taking into account the size of the wrong probability. According to the sum of squared errors, the logit model is preferred to the Markov model. However, since the errors will always lie between zero and one, the larger the error the smaller its square will be. When the sum of the absolute values of the errors is used instead, the Markov model is preferred to the logit model.

It should be kept in mind that the logit model is designed to try to get the best fit for the official turning points. The Markov model, on the other hand, does not use the official turning points in its estimation at all. Against this background, the Markov model actually compares extremely well with the logit model and did make the fewest mistakes.

## **5.7 CONCLUSION**

According to theory, the behavior of stock market investors and hence the behavior of stock prices is potentially asymmetric conditional on the business cycle (see chapter three). In order to empirically evaluate and estimate this asymmetry, an indicator of the business cycle has to be developed. This indicator should ideally reflect not only whether the economy is in a recession or an expansion, but also the degree of certainty with which investors can regard the economy as being in a recession or expansion. In this chapter, such an indicator has been developed by estimating a Markov switching regime model for the business cycle.

The South African business cycle has been modeled with a two-state first-order Markov switching regime with time-varying transition probabilities, with the logit technique and with a autoregressive model. The transition probabilities and the logit model were estimated with the yield spread as explanatory variable. The results indicated that two distinct growth rate phases, a low and a high growth rate phase, characterize the business

## University of Pretoria – Moolman, HC (2004)

cycle. It was showed that the Markov switching regime model outperformed both the linear and logit models and even provided more information regarding the state of the business cycle than the official classification of the Reserve Bank. Therefore this indicator is ideal for capturing the state of the business cycle as well as the (un-)certainty regarding this state and can therefore be used in the stock market model to test the influence of these factors.

## CHAPTER 6

### EMPIRICAL ESTIMATION OF THE SOUTH AFRICAN STOCK MARKET

#### 6.1 INTRODUCTION

In this chapter, a structural model for the South African stock market is developed and estimated based on the theory presented in chapter three. The long run and short-run behaviour of the stock market is modelled separately with the cointegration equation and the error correction model respectively. However, standard cointegration techniques assume that stock market behaviour is symmetric, while theory suggests that there are several potential causes for asymmetry (see chapter three). Therefore, the Enders and Siklos (2001) test for asymmetric cointegration will be used to evaluate the potential asymmetry where appropriate. Three different cases of asymmetry will be evaluated, namely asymmetry conditional on (i) the state of the business cycle, (ii) whether the stock market is over-valued or under-valued and (iii) the direction of the error terms, thus allowing for the possibility that the errors exhibit more “momentum” in one direction than the other<sup>1</sup>.

Once cointegration has been established and the cointegration vector estimated, the error correction model (ECM) will be estimated taking into account the asymmetric adjustment if it is found to be significant in the cointegration analysis. Since investors in the stock market is forward-looking, the error-correction model will also be specified in such a way that this is captured.

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<sup>1</sup> It is debatable whether the asymmetry exists in the conditional mean or variance of stock prices, and proponents of both can be found in the literature. Studies that analyze asymmetry in the conditional variance of stock prices usually employ GARCH models. However, these studies are typically based on daily or high frequency data (e.g. De Santis 1991, Kitazawa 2000, Masulis and Ng 1995, Koutmos and Booth 1995, Brooks *et al* 1997), in contrast with this study in which quarterly data will be used. In this study, asymmetry in the conditional mean of stock prices will be evaluated, although a test for omitted GARCH non-linearity will be done to show that there are no remaining non-linearity in the conditional variance.



## 6.2 DATA

The data for the South African gross domestic product (GDP), JSE all-share index (JSE), long-term ( $R_L$ ) and short-term interest rates ( $R_S$ ) and the gold price (Gold) were obtained from the South African Reserve Bank ([www.reservebank.co.za](http://www.reservebank.co.za)). Data for the US long-term interest rate ( $R_L^{US}$ ) and the Standard and Poor 500 Index (SP500) were obtained from the Federal Reserve Bank of St. Louis ([www.stlouisfed.org](http://www.stlouisfed.org)). Quarterly data were used from the third quarter of 1978 to the end of 2000. The construction of the discount rate (Discount), risk premium (Risk) and state of the business cycle indicator (S) is described below.

The discount rate comprises the real risk-free long-term interest rate, an inflation premium and a risk premium (see chapter three). The nominal yield on 10-year government bonds captures both the real interest rate and the inflation premium. However, this yield also includes a risk premium that awards investors for taking on the additional risk of investing in South African bonds instead of US government bonds which are considered truly risk-free. Since this yield already includes a premium for the country risk, the additional risk premium included in the discount rate only has to capture the risk of investing in South African stocks rather than bonds, in other words the equity premium. Jagannathan *et al* (2000) showed that the equity premium can be proxied by the sum of the dividend yield and expected dividend growth, less the real bond yield. According to the IMF (2001), the expected dividend growth can be proxied by the growth in potential output. Following Barrel and Davis (2003), the growth in potential output was constructed by using a Hodrick Prescott filter on real economic growth to proxy dividend growth. Hence the discount rate in this study was constructed as the sum of the nominal yield on 10-year government bonds and the equity premium<sup>2</sup>.

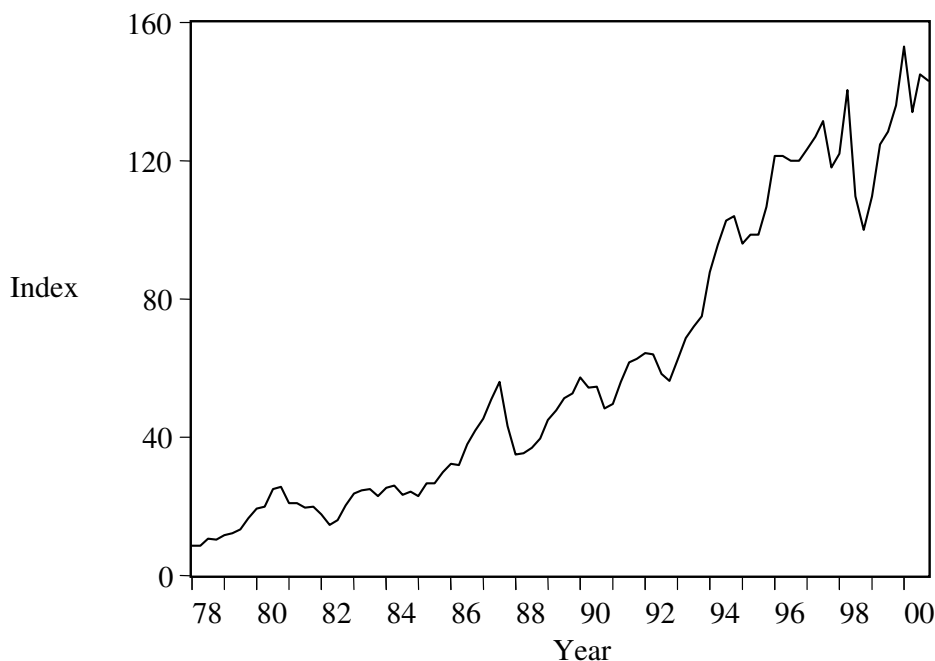
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<sup>2</sup> In many studies the risk premium is assumed to be constant (see e.g. Harasty and Roulet 2000). However, Firer and Bradfield (2002) have shown that South Africa's risk premium has declined over time. Barrel and Davis (2003) have shown that the risk premiums of six developed countries have also been time-varying. It would therefore be inappropriate to follow Harasty and Roulet (2000) in omitting the risk premium based on the assumption that it is constant.

The risk premium (risk) attempts to capture the country risk of investing in South Africa and is therefore constructed as the excess returns on long-term South African government bonds relative to long-term US government bonds.

The state of the business cycle variable was constructed in chapter five with the Markov switching regime model (see section 5.5.4). This variable takes on the value one if the economy is in a recession according to the Markov switching regime model and zero otherwise.

**Figure 6.1 The JSE All-share Index**



Source: South African Reserve Bank, Quarterly Bulletin, various issues.

Models that contain potentially non-stationary variables can result in a spurious regression, indicating statistically significant relationships where there are none. The statistical significance obtained from standard regression techniques with non-stationary variables is picking up the existence of contemporaneous correlation in the variables due to their trending over time, rather than a meaningful causal relationship between them. It is therefore vital to determine the order of integration of all the variables used in the econometric analysis, since this will determine the correct estimation technique to use.

**Table 6.1 List of Variables**

<b>Variable</b>	<b>Explanation</b>
JSE	JSE all-share index
GDP	Gross domestic product
Discount	Constructed discount rate
Gold	Gold price
SP500	Standard and Poor's 500 Index (S&P500)
S	State of the business cycle dummy variable constructed in chapter five
R\$	Rand-\$US exchange rate
R <sub>s</sub>	Short-term interest rate (three-month bankers' acceptance rate)
Risk	Risk premium, defined as difference between long-term interest rates of South Africa and the US (the yields on 10-year government bonds)
Residual	Residual from estimated long-run stock market equation (see table 6.9)

In this study, the augmented Dickey Fuller (ADF) and Phillips-Perron (PP) tests were used in conjunction with data plots to establish the order of integration of the variables. The ADF test assumes that the errors are statistically independent and have a constant variance, while the PP test allows the disturbances to be weakly dependent and heterogeneously distributed (Enders 1995:239). The PP test also has greater power to reject the false null hypothesis of a unit root, except when the errors have a moving average (MA) structure, in which case this test tends to reject the null hypothesis whether it is true or false. Since the structure of the error terms is usually unknown, it is preferable to use both tests. Hence both the augmented Dickey Fuller (ADF) and the Phillips-Perron (PP) tests were used in this study to establish the order of integration of the variables.

According to the results in tables 6.2 and 6.3, the stock price index, GDP, the gold price, the Standard Poor 500 index, the short-term interest rate, the Rand-US\$ exchange rate and the risk premium is integrated of order one and therefore has to be differenced once before being included in the ECM.

**Table 6.2 Augmented Dickey-Fuller and Phillips-Perron Tests for Non-Stationarity, Levels**

Series	Model	Lags	$\tau_\tau, \tau_\mu, \tau$	$\phi_3, \phi_1$	PP (3 lags)
Log(JSE)	Trend	1	-4.356***	7.84	-3.88**
	Constant	1	-1.720	2.98	*1.729
	None	1	1.911		2.24
Log(GDP)	Trend	4	-1.26	4.44	-0.48
	Constant	3	-4.31***	6.33	-4.14***
	None	4	2.23		12.13
Log(Gold)	Trend	0	-2.59**	7.81	-3.62**
	Constant	0	-2.60	6.78	-2.56
	None	0	-2.74*		2.47
Log(SP500)	Trend	1	-2.45	2.70	-2.47
	Constant	0	0.52	0.72	0.43
	None	0	5.01		4.64
R <sub>S</sub>	Trend	1	-2.82	9.83	-2.26
	Constant	1	-2.92	14.91	-2.39
	None	1	-0.71		-0.61
Log(R\$)	Trend	3	-2.76	3.09	-2.32
	Constant	3	-0.35	1.83	0.012
	None	3	1.86		2.87
Risk	Trend	0	-2.087	2.21	-2.20
	Constant	0	-1.35	1.81	-1.34
	None	0	-0.21		-0.19

\*/\*\*/\*\*\* Significant at a 10%/5%/1% level.

Source: Own calculations

**Table 6.3 Augmented Dickey-Fuller and Phillips-Perron Tests for Non-Stationarity, First Differenced**

Series	Model	Lags	$\tau_\tau, \tau_\mu, \tau$	$\phi_3, \phi_1$	PP (3 lags)
$\Delta\log(\text{JSE})$	Trend	0	-7.86***	30.90	-7.81
	Constant	0	-7.81***	61.07	-7.77
	None	0	-7.28***		-7.28
$\Delta\log(\text{GDP})$	Trend	2	-6.56***	23.99	-9.72***
	Constant	3	-2.95**	17.38	-8.29***
	None	3	-1.101		-2.61***
$\Delta\log(\text{Gold})$	Trend	0	-8.44***	35.6	-8.43***
	Constant	0	-8.30***	68.8	-8.29***
	None	0	-7.69***		-7.73***
$\Delta\log(\text{SP500})$	Trend	0	-7.88***	31.25	-7.86***
	Constant	0	-7.93***	62.83	-7.91***
	None	0	-6.45***		-6.55***
$\Delta R_S$	Trend	0	-5.98***	17.89	-5.94***
	Constant	0	-5.96***	35.54	-5.93***
	None	0	-5.99***		-5.97***
$\Delta\log(\text{R\$})$	Trend	2	-4.12***	19.86	-8.366***
	Constant	2	-4.14***	26.77	-8.39***
	None	2	-3.21***		-7.48***
$\Delta\text{Risk}$	Trend	0	-8.46***	35.83	-8.41***
	Constant	0	-8.51***	72.31	-8.46***
	None	0	-8.53***		-8.48***

\*/\*\*/\*\*\* Significant at a 10%/5%/1% level.

Source: Own calculations

### 6.3 EFFICIENCY OF THE SOUTH AFRICAN STOCK MARKET

Stock market efficiency has fundamental implications for stock market analysis and trading. If stock markets are not efficient, stock prices are forecastable from past price behavior alone (see section 3.2.1). The Random Walk theory, which assumes that consecutive price changes are independent and identically distributed over time, is central to the testing of the ability of past returns to predict future returns. If prices follow a random walk, it means that yesterday's price change should not be related to the price change of today, or any other day, since it should be independent (Fifield, Lonie and Power 1998). The implication for trading is that future price movements cannot be predicted successfully on the basis of historic price movements and technical analysis will therefore not yield abnormal profits. However, a fundamental analyst capable of making a better than average estimate of the intrinsic value of shares will be able to make above average profits.

Several tests including the runs test, the Durbin-Watson test and the Breusch-Godfrey test have been performed to test whether the South African stock market is weak-form efficient. Although share prices are seldom perfectly independent, stock market investors are mostly concerned with whether the dependence is sufficient to allow the history of the series of price changes to be used to predict the future in such a way that the expected returns would be greater than under a simple buy-and-hold model (Thompson and Ward 1995).

The runs test was performed on the share returns to test the null hypothesis that successive outcomes are independent, in other words that no serial correlation are present and hence that historical price information and trends cannot be used to predict future share prices. The number of runs ( $k$ ) is distributed asymptotically normally with

$$m: \quad E(k) = \frac{2n_1n_2}{n_1 + n_2} + 1 \quad (6.1)$$

and

$$\text{variance: } \sigma_k^2 = \frac{2n_1n_2(2n_1n_2 - n_1 - n_2)}{(n_1 + n_2)^2(n_1 + n_2 - 1)} \quad (6.2)$$

where  $n_1$  is the number of positive observations and  $n_2$  the number of negative observations. From the total of 90 share return observations, 61 are positive and the remaining 29 are negative returns. The number of runs ( $k$ ) was 53. Using the standard normal test statistic of 29.11, the null hypothesis of randomness was rejected, which is evidence against stock market efficiency.

As a second test for efficiency, the level of share prices was modeled with a random walk. According to the results of the Durbin-Watson test for serial correlation, the null hypothesis of no serial correlation was not rejected (the calculated value of the Durbin-Watson test statistic was 2.08). Therefore the residuals of the random walk are not autocorrelated, which is supporting market efficiency since prior observations of share prices do not significantly influence current share prices. Furthermore, an integrated autoregressive moving average (ARIMA) model was also estimated for the share returns to confirm the results of the share price ARIMA model. According to the Akaike and Schwartz-Bayesian model selection criteria, the best ARIMA model had no autoregressive or moving average terms and the order of integration was zero, so that share returns are randomly distributed. According to the results of the Durbin-Watson test for serial correlation (a calculated test statistic of 2.08), the null hypothesis of no serial correlation was not rejected. The Breusch-Godfrey test for no serial correlation were applied to the residuals of this equation and the null hypothesis of no autocorrelation up to order two (LM=3.74) or four (LM=5.27) were not rejected at a five percent level of significance. This also supports weak-form efficiency.

The results of the runs and serial correlation tests are inconclusive regarding the efficiency of the JSE and a structural model therefore might outperform trading rules based on technical analysis. Although primary focus of study is on developing and estimating a structural model of the stock market not on developing a trading strategy, the profitability and forecasting ability of the structural model will be compared to other models in chapter seven.

#### 6.4 THE COINTEGRATION EQUATION

According to the expected present value model reviewed in chapter three, stock prices are a function of (a proxy for) dividends and the discount rate. However, it has to be tested empirically whether this model holds for South Africa. If these variables are cointegrated, the cointegration vector will reflect the magnitudes of the impact of each variable on the long-run level of the stock market. In addition to the long-run cointegration equation an error-correction model will be estimated to capture the short-run fluctuations of the stock market. This will evaluate whether and to what extent factors such as exchange rates, interest rates, contagion, foreign stock markets and the gold price influences the stock market in the short-term.

According to the theories reviewed in chapter three, there are several potential asymmetries in these relationships. Theoretically, risk-averse investors might react asymmetrically to good or bad conditions or news, since they will react promptly on receiving bad news or during adverse conditions, while it prevents them from acting quickly when receiving good news or during positive conditions (Chalkley and Lee 1998). There are two potential forces driving this asymmetry. First, since real economic activity is one of the main determinants of dividends an economic upswing (downswing) will cause higher (lower) dividends and can therefore be considered as good (bad) news or conditions. In other words, the speed of adjustment during downswings should be faster than during upswings. This necessitates the use of a variable that reflect the state of the economy. Since the official indicator of the South African business cycle published by the South African Reserve Bank is only available with a considerable lag, the Markov-switching state variable developed in chapter five will be used instead. This variable also has the advantage that it is not biased by the asymmetric recession definition and can therefore indicate the true state of the economy in each period.

Second, if the stock market is undervalued it means that the market prices of shares are below their intrinsic value, so that a profit opportunity created since investors can buy shares at the low current market price and eventually resell it at a higher price once the market has corrected the discrepancy between the market and intrinsic value. In contrast, when the stock market is overvalued market prices of shares are above the



intrinsic values. Eventually the market will correct this discrepancy so that share prices fall, in which case investors will lose money. Investors are risk averse which means that when they are not absolutely certain whether the market is under- or over-valued, they would rather choose the least risky option. In other words, they will react quickly when the stock market is overvalued in order to avoid a potential loss, but they will react much slower when the stock market is undervalued. In addition, Siklos (2002) has suggested that the asymmetry might be caused not only by whether the stock market is over- or undervalued, but also by the direction of the error terms so that the momentum depends on whether the errors are increasing or decreasing. Therefore, the possibility of asymmetric cointegration caused by the under- or over-evaluation or by the direction of the error have to be explored.

It has been shown by Pippenger and Goering (1993), Balke and Fomby (1997) and Enders and Granger (1998) that the Johansen and Engle-Granger tests assuming linear adjustment have low power in the presence of asymmetric adjustment. In other words, there is a high probability of not rejecting the null hypothesis of no cointegration when in fact the series are cointegrated. However, this means that the conclusion is reliable if the null hypothesis of no cointegration is rejected and problems only arise when the null hypothesis is not rejected. In order to avoid this problem, the Enders and Siklos (2001) test for threshold cointegration will be employed to evaluate the potential asymmetry introduced by the sign or momentum of the error terms. The asymmetric behavior conditional on the state of the business cycle will be dealt with individually since no test has yet been developed for this case.

#### **6.4.1 Stock Market Asymmetry Conditional on Characteristics of the Error Terms**

The test of Enders and Siklos (2001) to determine whether the deviations from the long-run equilibrium are asymmetric in nature is a generalization of the Enders and Granger (1998) threshold autoregressive (TAR) and momentum-TAR (M-TAR) tests for unit roots to a multivariate context. These are, in turn, based on the basic TAR and M-TAR models, which respectively allows the degree of autoregressive decay to depend on state of variable at interest and different degrees of autoregressive decay to depend on whether the series is increasing or decreasing.

In the Enders and Siklos (2001) test, the error term,  $u_t$ , is modified to allow for two types of asymmetric error corrections based on the cointegration relationship. First the long-run cointegration equation is estimated in order to calculate the estimated results, which are used to estimate the following equation

$$\Delta \hat{u}_t = I_{t-1} \rho_1 \hat{u}_{t-1} + (1 - I_{t-1}) \rho_2 \hat{u}_{t-1} + \sum_{i=1}^p \gamma_i \Delta \hat{u}_{t-i} + \varepsilon_t \quad (6.3)$$

where  $I_t$  is the Heaviside indicator function which takes on one of the following specifications depending on the source of the asymmetry:

$$(i) I_{t-1} = 1 \text{ if } \hat{u}_{t-1} \geq \tau, 0 \text{ otherwise} \quad (6.4)$$

$$(ii) I_{t-1} = 1 \text{ if } \Delta \hat{u}_{t-1} \geq \tau, 0 \text{ otherwise} \quad (6.5)$$

where  $\tau$  is the threshold.

In general, the value of  $\tau$  is unknown and it has to be estimated along with the values of  $\rho_1$  and  $\rho_2$ . However, in most economic applications it makes sense to set  $\tau=0$  so that the cointegrating vector coincides with the attractor (Enders and Siklos 2001). In such circumstances, adjustment with specification (i) is  $\rho_1 u_t$  if the stock market is above the long-run equilibrium and  $\rho_2 u_t$  if the stock market is below long-run equilibrium. In other words, the speed of adjustment is different depending on whether the stock market is over- or under-valued.

Specification (ii), the momentum-threshold autoregressive (M-TAR) model, was suggested as an alternative to specification (i) by Enders and Granger (1998) and Caner and Hansen (1998) such that the threshold depends on the previous period's change in the error correction term. The M-TAR model allows for the possibility that the errors ( $u_t$ ) exhibit more "momentum" in one direction than the other. This type of adjustment is especially relevant in situation where policy makers are attempting to smooth out any large changes in the series. For example, the central bank might take strong measures to counteract shocks to the term structure relationship if these shocks are deemed to indicate increases, but not decreases, in inflationary expectations.

Similarly, with a managed float exchange rate regime, the central bank may want to mitigate large changes in the exchange rate without attempting to influence the long-run level of the rate.

This specification is consistent with a wide variety of error-correcting models. Given the existence of a single cointegrating vector with stationary residuals  $\{u_t\}$  the error-correcting model for any variable  $y_{it}$  can be written in the form

$$\Delta y_{it} = \rho_{1,i} I_{t-1} \mu_{t-1} + \rho_{2,i} (1 - I_{t-1}) \mu_{t-1} + \dots + v_{it} \quad (6.6)$$

where  $\rho_{1,i}$  and  $\rho_{2,i}$  are the speed of adjustment coefficients of  $\Delta y_{it}$ . In other words, once cointegration has been established and the cointegrating vector has been estimated, the error correction model can be estimated as usual as long as the speed of adjustment is allowed to differ conditional on the indicator variable ( $I_t$ ).

The procedure for using the Engle and Siklos (2001) test is as follows. Equation 6.3 is estimated and the two t-statistics for the null hypothesis  $\rho_1=0$  and  $\rho_2=0$  along with the F-statistic for the joint hypothesis  $\rho_1 = \rho_2 = 0$  (called the  $\phi$  test statistic) are recorded. The smallest of the two t-statistics is called t-Min and the largest t-statistic is called t-Max. The t-Min statistic has been shown to have very low power and therefore only the t-Max and  $\phi$  tests are used. The distribution of t-Max depends on number of variables included in the cointegration equation and the sample size as well as the dynamic structure of the data generating process (similar to Engle-Granger ADF critical values). The t-Max and  $\phi$  tests are used to test the null hypothesis of no cointegration using the critical values given by Enders and Siklos (2001). If the variables are cointegrated, the null hypothesis of symmetric adjustment  $H_0: \rho_1=\rho_2$  can be tested.

Similar to the case of the Engle-Granger test for symmetric cointegration, the error terms have to be white noise. Serial correlation is eliminated by the lagged changes in the first difference of the long-run residual ( $u_t$ ) in equation 6.3. Following the recommendation of Said and Dickey (1984), serial correlation was tested from a maximum of  $\text{int}(T^{1/3}) = \text{int}(4.48) = 4$  lags. In both cases only the first lag of the

differenced residual were significant. The results of the cointegration test for TAR and M-TAR adjustment are presented in tables 6.4 and 6.5. The cointegration equation underlying the results in tables 6.4 and 6.5 is based on the discounted dividend model, in other words between share prices, GDP and the discount rate. The estimation results of this equation are presented in table 6.9.

**Table 6.4 Cointegration Results, Case (I) TAR-Adjustment**

Dependent Variable: $\Delta \text{Log}(\text{Residual})$			
<i>Variable</i>	<i>Coefficient</i>	<i>t-statistic</i>	<i>Probability</i>
Residual(-1)*I(-1)	-0.25	-2.29	0.025
Residual(-1)*(1-I(-1))	-0.35	-2.65	0.010
$\Delta \text{Residual}(-1)$	-0.25	-2.29	0.025
t-Max	-2.29*	F-test ( $\rho_1 = \rho_2$ )	0.226
$\phi$ -statistic	8.31*		

Source: Own calculations

According to the results in table 6.4, the  $\phi$ -statistic of 8.31 is greater than the 10 percent critical value of 5.08, while the t-Max statistic of  $-2.29$  is less than the 10 percent critical value of  $-1.92$ , so that the null hypothesis of no cointegration is rejected by both tests at the 10 percent level. According to the results for testing the null hypothesis of symmetric adjustment (F-statistic is 0.226), the null hypothesis is not rejected and therefore the adjustment is symmetric. This means that the adjustment is symmetric regardless whether the stock market is over- or undervalued.

According to the results in table 6.5, the  $\phi$ -statistic of 8.31 is greater than the five percent critical value of 6.01 and the t-Max statistic of  $-2.885$  is less than the 10 percent critical value of  $-1.92$  so that the null hypothesis of no cointegration is rejected at least at the 10 percent level by both tests. According to the results for testing the null hypothesis of symmetric cointegration/adjustment (F-statistic is

0.003), the null hypothesis is not rejected and therefore the adjustment is symmetric. In other words, the adjustment is symmetric regardless of the direction of the stock market.

**Table 6.5 Cointegration Results, Case (II) MTAR-Adjustment**

Dependent Variable: $\Delta \text{Log}(\text{Residual})$			
<i>Variable</i>	<i>Coefficient</i>	<i>t-statistic</i>	<i>Probability</i>
Residual(-1)*I(-1)	-0.29	-3.51	0.000
Residual(-1)*(1-I(-1))	-0.30	-2.88	0.005
$\Delta \text{Residual}(-1)$	0.32	3.25	0.002
t-Max	-2.88*	F-test ( $\rho_1 = \rho_2$ )	0.003
$\phi$ -statistic	8.31*		

Source: Own calculations

#### 6.4.2 Stock Market Asymmetry Conditional on the State of the Business Cycle

It has been established that no asymmetry of the first two types, i.e. based on the sign or momentum of the error terms, are present in the stock market. However, the possibility of asymmetry conditions on the state of the business cycle remains to be tested. No test equivalent to that of Enders and Siklos (2001) is available for testing asymmetry conditional on the state of the business cycle. However, since the problem with applying the Johansen and Enders and Granger tests for symmetric cointegration in the presence of asymmetric adjustment is low power (Pippenger and Goering (1993), Balke and Fomby (1997) and Enders and Granger (1998)), the problem is a high probability of not rejecting the null hypothesis of no cointegration when in fact the series are cointegrated. However, this means that the conclusion is reliable if the null hypothesis of no cointegration is rejected and problems only arise when the null hypothesis is not rejected. The results of the Johansen cointegration tests are presented in tables 6.7 and 6.8.

The order of the VAR was determined on the basis of the Likelihood and the Akaike and Schwartz-Bayesian criteria (see table 6.6). Tables 6.7 and 6.8 give the results of the trace and eigenvalue tests, which indicate that the equation is cointegrated at a five percent level of significance and that there is only one cointegration vector. The cointegration results are reported in table 6.9.

**Table 6.6 Test Statistics and Choice Criteria for Selecting the Order of the VAR Model**

Order	Log Likelihood	Akaike	Schwarz Bayesian
4	<b>229.5090</b>	193.5090	149.3308
3	223.0076	<b>196.0076</b>	<b>162.8739</b>
2	175.5390	157.5390	135.4499
1	117.4193	108.4193	97.37490
0	-597.2638	-597.2638	-597.2638

Source: Own calculations

**Table 6.7 Trace Test For Cointegration**

Cointegration LR Test Based on Trace of the Stochastic Matrix

Order of VAR = 3

<i>Null</i>	<i>Alternative</i>	<i>Statistic</i>	<i>95% critical value</i>	<i>90% critical value</i>
r=0	r>=1	39.3256*	31.54	28.78
r<=1	r>=2	14.7101	17.86	15.75
r<=2	r=3	4.79810	8.070	6.500

\* Reject null hypothesis on 5% level of significance

Source: Own calculations

**Table 6.8** Eigenvalue Test For Cointegration

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Cointegration LR Test Based on Maximal Eigenvalue of the Stochastic Matrix  
Order of VAR = 3

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<i>Null</i>	<i>Alternative</i>	<i>Statistic</i>	<i>95% critical value</i>	<i>90% critical value</i>
r=0	r=1	24.6155*	21.12	19.02
r<=1	r=2	9.91200	14.88	12.98
r<=2	r=3	4.79810	8.070	6.500

---

\* Reject null hypothesis on 5% level of significance

Source: Own calculations

The trace and eigenvalue tests rejected the null hypothesis of no cointegration and confirmed the presence of a single cointegrating vector. The Engle and Granger test statistic of  $-4.85$  is smaller than the relevant critical value, so that the null hypothesis of no cointegration is rejected, which confirms that the variables are cointegrated. This means that there is a cointegrated relationship between these variables and that the long-run relationship can be estimated using cointegration techniques.

In the presence of non-stationary variables, ordinary least squares (OLS) is super-consistent if the variables are cointegrated. However, in the presence of non-stationary series the OLS coefficients are biased and the t-statistics have a non-standard distribution. Therefore the Fully-Modified OLS (FM-OLS) estimator and t-statistic of Phillips and Hansen (1990), which correct the bias of the OLS estimator and t-statistic, will be used instead. This FM-OLS estimator is super-consistent, asymptotically unbiased and asymptotically normally distributed. The adjusted t-statistic is asymptotically distributed standard normal.

**Table 6.9** Cointegration Equation

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 Dependent Variable:  $\text{Log}(JSE)$ 

Method: FM-OLS

Order of VAR: 3

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<i>Variable</i>	<i>Coefficient</i>
Log(GDP)	0.866
Discount rate	-0.012
Constant	-6.585

---

Source: Own calculations

The results in table 6.9 confirm that the long-run level of the South African stock market is determined according to the present value model. According to these results, a one percent increase in gross domestic product (GDP) will cause a 0.866 percent increase in the stock market, while a one unit increase in the discount rate will cause a decline of 0.012 percent in the stock market. Since cointegration has been established and the cointegration vector estimated, an ECM can be estimated. In the estimation of the ECM the speed of adjustment will be allowed to differ across business cycle states. Statistically significant differences between the speed of adjustment in the two states would support cyclical asymmetry in stock market adjustment. This will be evaluated in section 6.5.

## 6.5 THE SHORT-RUN DYNAMICS: AN ERROR CORRECTION MODEL

In addition to the long-run cointegration equation, an error correction mechanism (ECM) can be estimated in order to capture the short-run or dynamic adjustment process to the long-run equilibrium. It incorporates the equilibrium error (residual terms) estimated from the long-run equilibrium relationship. According to theory, stock prices are determined as the sum of all the future income stream discounted at the discount rate, which means that rational stock market investors will be forward-



looking. This error correction model has to be consistent with the forward-looking behaviour of stock market investors.

Nickell (1985) derived an ECM from a forward-looking model with quadratic costs of adjustment. He assumes that agents have an infinite horizon and that they minimize the present value of the one period losses given by

$$L_t = \sum_{i=t}^{\infty} \delta^i \left[ \frac{1}{2} (y_i - y_i^*)^2 + \frac{\theta}{2} \Delta y_i^2 \right] \quad (6.7)$$

where  $\delta$  is the discount factor. This function captures the cost to deviate from some desired level ( $y^*$ ) with the first term  $(y_i - y_i^*)^2$  and the cost of adjustment with the second term  $\Delta y_i^2$ . By letting the desired level ( $y^*$ ) be the predicted level of stock prices, the first term captures the cost of incorrectly predicting the level of stock prices and the cost of making an error is proportional to the size of the error. The appropriate Euler condition for this problem may then be stated as

$$\delta y_{t+1} - (1 + \delta + \theta^{-1})y_t + y_{t-1} = -y_t^*/\theta. \quad (6.8)$$

Re-arranging equation 6.8 yields the following

$$\Delta y_t = \frac{1}{\delta} \Delta y_{t-1} + \frac{1}{\theta \delta} (y_{t-1} - y_{t-1}^*). \quad (6.9)$$

Equation 6.9 is in the standard ECM form, with an added lagged first difference of the dependent variable, stock prices. In addition to the terms on the right-hand side of equation 6.9, additional stationary variables influencing the stock market in the short-run will be added when estimating the ECM.

It has been shown in section 6.4.1 that neither the over- or under-valuation or the direction of the stock market are causing asymmetry in stock prices<sup>3</sup>. However, no equivalent test for testing the possibility of different speeds of adjustment based on the state of the business cycle is available. Different speeds of adjustment across business cycle states can be conducted by allowing different coefficients for the error correction term in the ECM. Statistically significant differences between the speeds of adjustment in the two states would support cyclical asymmetry in stock market adjustment.

The state of the business cycle indicator has been developed in chapter five with the Markov-switching regime model. The Markov-switching regime model constructs the probability of being in a particular state, say a recession and when the economy is more likely to be in a recession than an expansion (i.e. the recession probability is greater than 0.5) the state variable takes on the value 1 and 0 otherwise.

In order to test for asymmetry conditional on the state of the business cycle, only the state variable (S) is needed from the Markov-switching regime model. However, an additional output of the Markov model is a probability of being in a particular regime for each period and it can be readily assumed that a higher probability reflect more certainty regarding the predicted state (variable). Therefore, in addition to testing whether the speed of adjustment differs between economic upswings and downswings, the influence of the uncertainty regarding the state of the economy can also be evaluated. For example, it can be tested whether investors react faster (slower) when they are very sure (uncertain) about the state of the economy by adding an interaction term between the error correction term and the Markov state probability variable. This can be combined with the (potential) business cycle asymmetry by

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<sup>3</sup> Kia (2003) argues that the magnitude of the error term may also influence the speed of adjustment if speculators ignore small deviations from the equilibrium price while reacting drastically to large deviations. He tested this with various kinds of non-linear specifications in which the squared, cubed and fourth powered equilibrium errors as well as products of the significant errors were added as regressors in the error correction model. He found that some evidence of non-linearity in the Canadian stock market, such that investors don't react to small equilibrium errors (bubbles) but very drastic to big errors (bubbles). These specifications were tested for the South African stock market by including squared, cubed and fourth powered equilibrium errors in the error correction model, but they were all insignificant.

interacting the state variable and the certainty variable with the error correction term. The estimation results of the ECM are reported in table 6.10.

**Table 6.10 Error Correction Model**

Dependent Variable: $\Delta\log(\text{JSE})$				
Method: Least Squares				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>p-value</i>
Residual(-1)	-0.186	0.048	-3.889	0.000
Residual (-1)*S	-0.129	0.095	-1.357	0.179
$\Delta\text{Log}(\text{Gold})$	0.177	0.085	2.075	0.042
$\Delta\text{Log}(\text{SP500})$	0.869	0.108	8.027	0.000
Risk	-0.044	0.008	-5.681	0.000
Risk(-1)	0.042	0.009	4.889	0.000
$\Delta\text{Log}(\text{R}\$(-1))$	0.350	0.090	3.876	0.000
Constant	0.020	0.016	1.228	0.223
$\Delta\text{Log}(\text{R}_S(-1))$	-0.025	0.006	-4.119	0.000
S	-0.045	0.015	-3.089	0.003
Dum98	-0.041	0.020	-2.120	0.037
Dum00	-0.146	0.015	-9.725	0.000
Dum94	0.055	0.016	3.419	0.001
$\Delta\text{Log}(\text{JSE}(-1))$	0.309	0.056	5.473	0.000
R-squared	0.708	F-statistic	13.78	
Adjusted R-squared	0.656	Prob(F-statistic)	0.0000	
S.E. of regression	0.058			

Source: Own calculations

According to the results of the ECM in table 6.10, the interaction term between the state variable<sup>4</sup> (S) and the error-correction term (Residual) is statistically significant<sup>5</sup>.

<sup>4</sup> S takes on the value one (zero) when the economy is more likely to be in a recession (expansion) than not.

Since the coefficient of the error-correction term measures the speed of adjustment to equilibrium, this means that the speed of adjustment is significantly different in expansions than recessions. Specifically, since the estimated coefficient of the interaction term between the state variable and error-correction term is negative, the speed of adjustment is significantly slower in expansions than recessions<sup>6</sup>. This is consistent with the theory of Chalkley and Lee (1998) that investors react slower on good news than on bad news<sup>7</sup>.

However, the variable (S) reflecting the state of the business cycle was *generated* by the Markov switching regime model in chapter five and the consequences introduced by using generated regressors have been established in the seminal work by Pagan (1984). According to Pagan (1984), the estimator of the generated regressor's coefficient is perfectly efficient as long as the null hypothesis being tested is that this coefficient equals zero. For any other hypothesis, it is necessary to use an instrumental variable or 2-stage least squares (2SLS) program to obtain a consistent estimate of the variance of this coefficient. Therefore, the ECM is also estimated using instrumental variables. The generated state of the business cycle indicator, S, was instrumented with a dummy variable reflecting the actual periods of negative real economic growth. The results are presented in table 6.11.

The results in table 6.11 confirm the different speeds of adjustment between recessions and expansions. Specifically, the speed of adjustment coefficient for expansions is  $-0.147$  and  $(-0.147-0.243=) -0.39$  for recessions. Interactive terms

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<sup>5</sup> The associated p-value of 0.17 is calculated for the two-sided null hypothesis that the coefficient is equal to zero (i.e. insignificant) against the alternative hypothesis that the coefficient is not equal to zero (i.e. significant). However, since it is *a priori* known that the coefficient should be negative, the one-sided hypothesis that the coefficient is smaller than zero should be tested against the alternative that the coefficient is not smaller than zero. The p-value for testing a one-sided hypothesis is half the value of a two-sided hypothesis, and therefore the relevant p-value that should be used for this particular coefficient is actually 0.085, which is smaller than 0.1 and hence this coefficient is significant on a 10 percent level of significance.

<sup>6</sup> The speed of adjustment coefficient for expansions is  $-0.186$  and  $(-0.186-0.129=) -0.315$  for recessions. The speed of adjustment coefficient always has to be negative since that ensures that the adjustment is in the opposite direction than the error and hence *towards* equilibrium. The speed of adjustment is indicated by the *magnitude* of the error correction coefficient – the bigger the coefficient the faster the speed of adjustment.

<sup>7</sup> Marshall and Walker (2002) also found stock market asymmetry with respect to good and bad news. They argue that, since investors are overconfident they will under react to any new information, but that their reluctance to realize losses implies more under reaction (and hence more persistence) in the case of bad news than good news. Their results of their study of the Chilean stock market supported this hypothesis.

between the state variable and each of the explanatory variables have also been tested to detect any additional asymmetries, but all these interaction terms were insignificant. It is also interesting to note that an interaction term between the variable measuring uncertainty and the error correction term was insignificant (regardless of whether the state variable was added), which means that the degree of uncertainty does not influence the speed of adjustment of the stock market<sup>8</sup>.

**Table 6.11 Error Correction Model with Instrumental Variables**

Dependent Variable: $\Delta\log(\text{JSE})$				
Method: Instrumental variables				
<i>Variable</i>	<i>Coefficient</i>	<i>Std. Error</i>	<i>t-Statistic</i>	<i>p-value</i>
Residual(-1)	-0.147	0.061	-2.420	0.018
Residual (-1)*S	-0.243	0.121	-2.005	0.049
$\Delta\text{Log}(\text{Gold})$	0.154	0.079	1.958	0.054
$\Delta\text{Log}(\text{SP500})$	0.906	0.133	6.815	0.000
Risk	-0.042	0.007	-5.845	0.000
Risk(-1)	0.040	0.008	5.062	0.000
$\Delta\text{Log}(\text{R}\$(-1))$	0.387	0.099	3.896	0.000
Constant	0.020	0.019	1.027	0.308
$\Delta\text{Log}(\text{R}_s(-1))$	-0.024	0.006	-4.070	0.000
S	-0.064	0.022	-2.952	0.004
Dum98	-0.047	0.022	-2.157	0.034
Dum00	-0.155	0.016	-9.520	0.000
Dum94	0.054	0.013	4.073	0.000
$\Delta\text{Log}(\text{JSE}(-1))$	0.285	0.066	4.315	0.000
R-squared	0.666	F-statistic	11.687	
Adjusted R-squared	0.609	Prob(F-statistic)	0.0000	
S.E. of regression	0.062			

Source: Own calculations

<sup>8</sup> As discussed earlier (see footnote three) the speed of adjustment was also allowed to be non-linear with respect to the magnitude of the error terms, but this was found to be insignificant.

The short-run dynamics of the stock market can be explained by the short term interest rate, the Rand-US\$ exchange rate, the Standard and Poor 500-index, the gold price, forward-looking expectations of investors and a risk premium. In many the cases the estimated coefficients of the ECM are not interpreted (see e.g. Du Toit (1999), Koekemoer (1999) and Du Toit and Moolman (2003)) since many of the variables enter the model in differenced form, which makes it difficult to sensibly interpret the relationships. In some sense theory is differenced away – very little is known about the relationship between the growth rates of any variables. However, in this study, the dependent variable of the ECM, the change in the log of the JSE, is equivalent to stock market returns. Following Kia (2003), it is therefore possible to interpret the estimated coefficients in the ECM. Kia (2003) interprets all the coefficients in the ECM. However, the coefficient of, for example,  $\Delta \log(R\$)$  should be interpreted as follows: a one unit increase in the growth of the exchange rate causes a 0.387 units increase in stock market returns (the percentage change in the JSE). Even though we expect that a depreciation in the exchange rate will improve stock prices and returns<sup>9</sup>, it is difficult to reason about the exact relationship between the growth rate of the exchange rate and stock market returns. Therefore, unlike Kia (2003), only some of the coefficients in the ECM will be interpreted<sup>10</sup>.

The stock market of a small, open and financially integrated economy is expected to follow stock markets in the rest of the world (Kia 2003). Lower returns on world stock markets are therefore expected to have a negative influence on returns on the South African stock market. The positive coefficient of foreign stock prices (measured by the Standard and Poor 500-index) is consistent with this *a priori* expectation. This result is also consistent with the results of Kia (2003), Ammer and Mei (1996), Koutmos and Booth (1995), Kearney (1998), Francis and Leachman (1998) and Ramchand and Susmel (1998).

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<sup>9</sup> As discussed in chapter two, most of the biggest firms listed on the JSE are mining-related companies who export a substantial part of their production. A depreciation of the rand lowers the relative price of South African exports and hence causes an increase in the demand for exports. This in turn improves the profits and share prices of these companies. For example, the earnings of Anglo American, the biggest company listed on the JSE, falls by US\$124 million if the rand appreciates 10 percent against the US dollar (McKay 2003). The income of Impala Platinum, the thirteenth largest share on the JSE, falls by R300 million for every 40 cents improvement in the rand against the US dollar (McKay 2003).

<sup>10</sup> Specifically, all the coefficients except those of the growth in the gold price, the growth in the short-term interest rate and the growth in the exchange rate are interpreted.

According to the results, the risk premium has a negative impact on returns. Risk averse investors require a higher discount rate for higher risk premiums. The discount rate is inversely related to share prices (see chapter three), and therefore the risk premium is expected to have a negative influence on stock market returns (Kia 2003)<sup>11</sup>.

The dummy variable Dum98, which takes on the value one during the year 1998 and zero otherwise, is reflecting the lower returns on emerging stock markets following the Asian crisis. Dum00, the dummy variable that takes on the value one in the last quarter of 1999 and zero otherwise, is capturing the lower returns at the end of the previous millennium when investors were selling their shares in anticipation of the so-called Y2K-problems. The third dummy variable, Dum94, takes on the value one during the year 1994 and zero otherwise, which captures the euphoria of South Africa's first democratic election during which the country experienced a significant increase in capital inflows<sup>12</sup> and the volume and value of shares traded<sup>13</sup> on the JSE<sup>14</sup>.

### 6.5.1 Evaluation and Diagnostic Testing of the ECM

The estimated model was subjected to rigorous diagnostic testing. Since all the variables in the ECM are stationary, the assumptions of classical regression analysis

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<sup>11</sup> The risk premium was constructed as the interest rate differential between South African and US long-term government bonds. An alternative explanation for the negative relationship between the risk premium and stock market returns can therefore be based on the relationship between the interest rate differential and stock market returns. A lower domestic interest rate relative to the foreign interest rate should have a negative impact on investors' subjective discount rate and a lower interest rate is also associated with higher expectations of corporate profits (Kia 2003). Higher expected corporate profits as well as a lower subjective discount rate will result in a rise of share prices. The relationship between the interest rate differential (used as a proxy for the risk premium) and stock market returns should therefore be negative.

<sup>12</sup> South Africa had net capital inflow in 1994 of R4 359 million compared with a net capital outflow of R5 669 in 1993 ([www.reservebank.co.za](http://www.reservebank.co.za)).

<sup>13</sup> The volume of shares traded on the JSE increased from 303.8 million in 1993 to 444.25 million in 1994 ([www.reservebank.co.za](http://www.reservebank.co.za)). The value of shares traded on the JSE almost doubled from R2843.92 million in 1993 to R5204.33 million in 1994 ([www.reservebank.co.za](http://www.reservebank.co.za)).

<sup>14</sup> The Japan Securities Dealers Association gave the JSE "designation status" in December 1994, which means that the JSE was then considered an "appropriate" market for Japanese investors (Brooks *et al* 1997). The JSE was included in the Morgan Stanley Index from March 1995, while it was included in the IFC Emerging Markets Global and Investable Indices from March 1995 (Brooks *et al* 1997).

are fulfilled. The  $R^2$  value of 66.6 indicates that 66.6 percent of the variation in the dependent variable is explained by the variation in the dependent variables, which is evidence of a very good fit. The F-statistic of 11.687 indicates that the explanatory variables are jointly significant in explaining the stock market index. The t-statistics testing the significance of the individual coefficients indicate that all the coefficients are significantly different from zero and should therefore be included in the model.

Standard diagnostic tests can therefore be used to determine which variables should be included in the final specification of the ECM (Harris 1995: 24). The diagnostic test results reported in table 6.12 indicate that the function passes all the relevant diagnostic tests. The errors are normally distributed, homoscedastic, not serially correlated and the model is not misspecified.

**Table 6.12 Diagnostic Tests**

Null hypothesis	Test	Test statistic	Probability
Normality	Jarque-Bera	0.12	0.94
Homoscedasticity	ARCH LM (1)	0.05	0.83
	ARCH LM (2)	0.83	0.66
	ARCH LM (3)	0.96	0.81
Homoscedasticity	White	19.5	0.62
No serial correlation	Breusch-Godfrey (1)	4.30	0.16
	Breusch-Godfrey (2)	4.65	0.20
	Breusch-Godfrey (3)	5.51	0.24
No serial correlation	Durbin-Watson	2.07	
No misspecification	Ramsey Reset	3.84	0.15

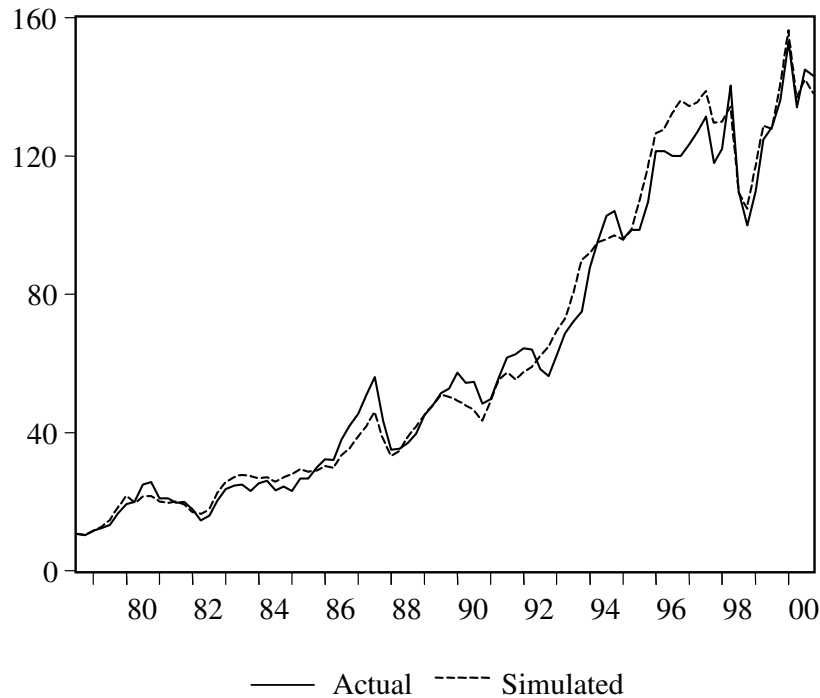
Source: Own calculations

### 6.5.2 Dynamic Simulation



To obtain an indication of the goodness of fit of the model, an initial dynamic simulation was performed (see figure 6.2). From figure 6.2 it is clear that the model is a good representation of the true data generating process. It picks up all the turning points in the stock market and closely tracks the level of the stock market as well.

**Figure 6.2 Actual and Fitted Values of the Stock Market**



## 6.6 POLICY IMPLICATIONS

In analyzing the impact of different variables on the stock market, the variables can be classified according to two criteria. First, from a policy perspective, the distinction between variables that policy-makers can influence and those variables that are completely beyond their control is crucial. Second, it is important to distinguish between variables that influence the stock market in the long run and those that only have an influence on the short-term fluctuations of the stock market.

The only variables that have an influence on the long run equilibrium level of the stock market are expected dividends (which can be proxied with economic activity) and the variables that influence the discount rate (i.e. the domestic long term interest

rate, the growth rate of dividends and the equity premium). Variables that influence the short term fluctuations of the stock market includes the gold price, foreign stock markets, the exchange rate, the short-term interest rate and the state of the business cycle.

The variables that are truly exogenous to the stock market from a policy-maker's perspective are the gold price and foreign stock prices. The gold price is determined on international markets by the global demand for and supply of gold. As explained in chapter two, South Africa, one of the world's largest gold producers, was traditionally heavily influenced by the gold mining industry. Gold exports used to be one of the major earners of foreign currency for South Africa and the mining sector is traditionally one of the biggest employers, an important source of tax revenue and an important stimulant of industries that provide products or services to the mines. Since the gold mining industry played such an important role in the economy, the gold price, which has an important influence on the profits of mining-related companies and hence their share prices, also has an important influence on the general stock market. This situation may change gradually as the role of the primary sector in the economy diminishes<sup>15</sup>. However, from the estimated model in this chapter the gold price seems to have only an influence on the short-term fluctuations of the stock market and not its long-run level.

Exchange controls on South African residents to invest abroad imply at least mild segmentation of the South African financial markets from the international financial markets (Brooks, Davidson and Faff 1997). However, the significant influence of the Standard & Poor 500 index confirms that even though there might be some degree of market segmentation, the South African financial markets do not operate in isolation and are influenced by the international financial markets. This is expected in the case of a small, open economy such as South Africa. However, although international financial markets influence the domestic stock market, domestic factors play bigger role in determining the stock market<sup>16</sup>. This means that the JSE is vulnerable to

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<sup>15</sup> In 1960, the primary sector produced 23 percent of South Africa's total GDP. By 1970 this proportion has declined to 18.7 percent and by 1980 the proportion was only 13.5 percent. This declined even further to 12.2 percent in 1990 and 10 percent in 2000 ([www.reservebank.co.za](http://www.reservebank.co.za)).

<sup>16</sup> This is consistent with the results of Harvey (1995a,b), who found that domestic information variables accounts for more than half of the predictable variance in the returns of emerging markets.

changes in the rest of the world, but that these markets are not the sole factor driving the South African stock market. This also implies that the JSE will be susceptible to contagion from the rest of the world, but that should only have a short-term impact and it should not change the long run equilibrium level of the stock market.

The stock price determinants other than the gold price and foreign stock prices can be influenced either directly or indirectly by policy-makers. These variables are not necessarily controlled by policy authorities, but they can to varying extents be influenced by policy-makers. The short-term interest rate, which is controlled by the South African Reserve Bank, influences the stock market through two channels that both impacts only on the short-run behavior of the stock market. First, it directly influences the returns on the stock market in the short-run. Second, it indirectly influences the speed of adjustment by influencing the state of the business cycle. An increase in the short-term interest rate increases the probability of a recession, which in turn increases the stock market's speed of adjustment towards equilibrium while lowering stock market returns.

Changes in the long term interest rate channels through to the stock market via three mechanisms. First, it influences the stock market indirectly through its influence on the state of business cycle. An increase in the long-term interest rate lowers the likelihood of a recession, which in turn lowers the stock market's speed of adjustment towards equilibrium. Second, an increase in the long-term interest rate increases the discount rate, which lowers the level of the JSE in the long-run. Finally, increases in the long-term interest rate causes increases in the excess returns of South Africa relative to the US, in other words it increases the risk premium, and this lowers returns. While the short-term interest rate can be influenced directly by monetary policy authorities, the long-term interest rate can be influenced indirectly through the expectations of inflation and future short-term interest rates (see Pretorius 2000). Pretorius and Du Toit (2001) showed that in South Africa the influence of inflation expectations on the long-term interest rate is greater than that of the short-term interest rate. This means that the recently introduced inflation-targeting<sup>17</sup> framework

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<sup>17</sup> In 2000 the Reserve Bank adopted an inflation-targeting regime, with a target range for average CPIX inflation, in other words headline consumer inflation excluding mortgage cost. The initial target

can have a significant impact on the long-term interest rate through its influence on inflation expectations.

The exchange rate only influences the stock market in the short-run. This means that any once off change in any direction (i.e. depreciations as well as appreciations) only influence the stock market in the subsequent period. However, every change in the exchange rate will be reflected by the stock market and hence a volatile exchange rate will cause a volatile stock market. The exchange rate is determined not only by economic fundamentals, but also by market sentiment towards South Africa (BEPA 2002). Policy authorities can therefore influence the exchange rate by maintaining sound economic fundamentals and economic policies. However, it is equally important that they manage market psychology, which includes generally responsible politics and good public governance, perceptions of political and other types of risk and the total cost of doing business in South Africa.

Economic activity, measured by gross domestic product (GDP), has a positive influence on the long-run level of share prices. Since GDP influences the long-run level of the stock market, an increase in domestic activity leads to a permanent increase in the JSE, in contrast with variables such as the exchange rate that only has a temporary impact on the stock market. GDP also influences the short-run behavior of the stock market since the state of the business cycle determines the speed of adjustment towards equilibrium.

## **6.7 CONCLUSION**

In this chapter, a structural model for the South African stock market was developed and estimated based on the theory presented in chapter three. Theoretically, several reasons exist that may cause asymmetric stock market behaviour. Three different cases of asymmetry has been evaluated, namely asymmetry conditional on (i) whether the stock market is over-valued or under-valued, (ii) the momentum of the stock market (thus allowing for the possibility that the errors exhibit more “momentum” in

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was between three and six per cent for 2002 and 2003 and between three and five per cent for 2004 and 2005. The target for 2004 was subsequently amended to between three and six percent.

one direction than the other) and (iii) the state of the business cycle. The results have shown that neither the over- or under-valuation nor the direction of the error terms cause stock market asymmetry. However, it has been shown that the speed of adjustment differs based on the state of the business cycle. Investors are loss-averse, in other words more sensitive to declines in their well being (losses) than increases (profits), and hence they react faster on bad news (recessions) than good news (expansions).

The results confirmed that the long-run level of the South African stock market is determined according to the present value model. Therefore, the long-run level of share prices are determined by discounted future dividends. In addition, the short-run fluctuations are caused by the short term interest rate, the rand-\$US exchange rate, the S&P500 index, the gold price, forward-looking expectations of investors and a risk premium.

In the next chapter this model will be used for forecasting the stock market. The model's in-sample and forecasting accuracy as well as its profitability will be compared with that of other models, such as the ones used by technical analysts. This should give an indication of the model's usefulness for forecasting purposes.

## CHAPTER 7

### COMPARING MODELS AND FORECASTS OF THE LEVEL AND TURNING POINTS OF THE SOUTH AFRICAN STOCK MARKET

#### 7.1 INTRODUCTION

The cointegration model of the South African stock market developed and estimated in chapter six made a contribution to the literature by establishing the factors that determine the level of the stock market in both the long-run and the short run. However, this model can also be used to forecast the stock market. This will enable investors and policy makers to simulate the impact of changes in macroeconomic indicators on the future course of the stock market and accurate forecasts of the stock market could be used by economists to forecast other macroeconomic indicators that lag the stock market such as consumption and investment<sup>1</sup>. In addition, forecasts of the stock market will predict the future direction of share prices and can hence be used by investors to construct profitable trading rules.

In this chapter the accuracy of the cointegration model in chapter six will be compared to other stock market models. This comparison will be done separately for the in-sample and forecast periods<sup>2</sup>. First the models' accuracy in modeling the level of the stock market will be compared. Then the models will be used to develop trading rules in order to compare their profitability and accuracy in modeling the direction of the stock market.

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<sup>1</sup> Gallinger (1994) gives three reasons why share prices are leading consumption and investment. First, changes in share prices are synonymous with changes in wealth, which influence the future demand for investment goods and consumption (Barro 1990). Second, the stock market is a leading indicator of the economy and reflects information about real activity before it occurs. Finally, an increase in real economic activity increases the demand on the existing production capacity, which increases the return on assets and therefore induces increases in future capital investment.

<sup>2</sup> Granger (1992) points out that only the out-of-sample evaluation of stock price models is relevant for several reasons including the possibility of small sample in-sample biases of coefficients that give overly encouraging results. This was also shown by Nelson and Kim (1990).

## 7.2 MODELING THE LEVEL OF THE STOCK MARKET

### 7.2.1 The Stock Market Models

The modeling and forecasting accuracy of three stock market models, namely the cointegration model from chapter six, a random walk and a Fully Modified vector autoregressive (FM-VAR) model, will be compared. The specifications of the cointegration and error-correction models are presented in equations 7.1 and 7.2 respectively (see sections 6.4 and 6.5):

$$\log(\text{JSE}_t) = -6.584897 + 0.865694955 * \text{Log}(\text{GDP}_t) - 0.0119161469 * \text{Discount}_t \quad (7.1)$$

$$\begin{aligned} \Delta \text{Log}(\text{JSE}_t) = & 0.3089012926 * \Delta \log(\text{JSE}_{t-1}) - 0.1864008165 * \text{Residual}_{t-1} - \\ & 0.1290787154 * (\text{Residual}_{t-1} * S_t) + 0.1768269797 * \Delta(\text{Log}(\text{Gold}_t)) + 0.8690841507 \\ & * \Delta(\text{Log}(\text{SP500}_t)) - 0.04438600119 * \text{Risk}_t + 0.04178532045 * \text{Risk}_{t-1} + \\ & 0.3497508004 * \Delta \log(\text{R}\$_{t-1}) + 0.0198328801 - 0.02534437603 * \Delta(\text{Log}(\text{R}_{S, t-1})) - \\ & 0.04484239067 * S_t - 0.041370202 * \text{DUM98}_t - 0.1455592312 * \text{DUM00}_t + \\ & 0.05524827626 * \text{DUM94}_t. \end{aligned} \quad (7.2)$$

The explanations of the variables are given in table 7.1. Equations 7.1 and 7.2 can be combined as follows:

$$\begin{aligned} \Delta \text{Log}(\text{JSE}_t) = & 0.3089012926 * \Delta \log(\text{JSE}_{t-1}) - 0.1864008165 * (\log(\text{JSE}_{t-1}) - (- \\ & 6.584897 + 0.865694955 * \text{Log}(\text{GDP}_{t-1}) - 0.0119161469 * \text{Discount}_{t-1})) - 0.1290787154 \\ & * ((\log(\text{JSE}_{t-1}) - 6.584897 + 0.865694955 * \text{Log}(\text{GDP}_{t-1}) - 0.0119161469 * \text{Discount}_{t-1}) * \\ & S_t) + 0.1768269797 * \Delta(\text{Log}(\text{Gold}_t)) + 0.8690841507 * \Delta(\text{Log}(\text{SP500}_t)) - \\ & 0.04438600119 * \text{Risk}_t + 0.04178532045 * \text{Risk}_{t-1} + 0.3497508004 * \Delta \log(\text{R}\$_{t-1}) + \\ & 0.0198328801 - 0.02534437603 * \Delta(\text{Log}(\text{R}_{S, t-1})) - 0.04484239067 * S_t - \\ & 0.041370202 * \text{DUM98}_t - 0.1455592312 * \text{DUM00}_t + 0.05524827626 * \text{DUM94}_t. \end{aligned} \quad (7.3)$$

**Table 7.1 List of Variables**

<b>Variable</b>	<b>Explanation</b>
JSE	JSE allshare index
GDP	Gross domestic product
Discount	Constructed discount rate
Gold	Gold price
SP500	Standard and Poor's 500 Index (S&P500)
S	State of the business cycle dummy variable constructed in chapter five
R\$	Rand-\$US exchange rate
R <sub>s</sub>	Short-term interest rate (three-month bankers' acceptance rate)
Risk	Risk premium, defined as difference between long-term interest rates of South Africa and the US (the yields on 10-year government bonds)
Residual	Residual from estimated long-run equation (see equation 7.1)

If the actual values of the explanatory variables during the forecasting period are used it gives the economic model an unrealistic benefit. Therefore, a very conservative approach will be followed with respect to the economic model whereby only observations that are available at the time of the forecast will be used. Instead of using the actual values of the explanatory variables during the forecasting period, the latest available values at the time of the forecast will be used. This implies that the explanatory variables are forecasted with a random walk where necessary. In other words, if only lagged values of a particular variable enters the stock market model in equation 7.3, then the actual value of this variable will be used in the forecast since it is available to the forecaster at the time of the forecast. For example, the rand-US\$ exchange rate only enters the model in the transformation  $\Delta \log(R\$_{t-1})$  which is available at the end of period t-1 to make a forecast of period t, the actual value will be used in the forecast. However, variables such as the first difference of the logarithmic transformation of the gold price enter the model contemporaneously, so that a forecast of this variable in period t is necessary for the forecast of the stock market in period t. The change in the logarithmic value of the gold price is forecasted



with a random walk, in other words the first difference of the logarithmic value of the gold price in period t-1 is used as forecast for the variable in period t. This is a very conservative approach and any improvement in the forecasts of the explanatory variables should obviously improve the forecasting ability of the cointegration model for the stock market.

The second model, the random walk, is specified as follows:

$$JSE_t = JSE_{t-1} + \varepsilon_t \quad (7.4)$$

where  $\varepsilon_t$  is a random error term. This model essentially forecasts no change from the previous period's observation. This naïve model may seem like a weak challenge, but McNees (1992) has showed that it performs very well in predicting many economic variables. One of the advantages of this model is that only lagged variables is used to explain the stock market, which means that actual values are available for a one-period ahead forecast.

The third model is an FM-VAR. The vector autoregression (VAR) modeling technique is an effective means of characterizing the dynamic interactions among economic variables by reducing dependence on the potentially inappropriate theoretical restrictions of structural models. The general VAR specification can be written as follows:

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + \dots + A_k X_{t-k} + e_t \quad (7.5)$$

where  $X_t$  is a  $(n \times 1)$  vector containing each of the  $n$  variables included in the VAR,  $A_0$  is a  $(n \times 1)$  vector of intercept terms,  $A_i$  is a  $(n \times n)$  matrix of coefficients and  $e_t$  is a  $(n \times 1)$  vector of error terms. As described by Phillips (1995), fully modified (FM) estimation of the VAR model should improve the OLS results in the presence of non-stationary regressors,  $I(1)$  processes and even cointegrating relationships. In addition, the FM-estimation procedure is valid without pre-testing for the exact cointegrating relationships or even the number of unit roots in the system. The FM-procedure specifically takes into account the possible serial correlation and endogeneities of the

system. The variables of the cointegration equation (see equation 7.1<sup>3</sup>) were included in the FM-VAR.

Individual autoregressive (AR) models are estimated for each variable included in the VAR and the maximum order of the individual AR models is used as the order of the FM-VAR. The Akaike (AIC) and Schwartz model selection criteria were used to determine the order of the VAR. The results are presented in table 7.2 and the preferred AR model according to each model selection criteria is printed in bold. A VAR of order one was estimated since autoregressive models of order one were preferred by both criteria for all three individual models.

**Table 7.2 Model Selection Criteria for Individual AR Models**

<b>Variable:</b>	<b>JSE</b>		<b>Discount rate</b>		<b>GDP</b>	
<b>Criteria:</b>	<b>AIC</b>	<b>Schwartz</b>	<b>AIC</b>	<b>Schwartz</b>	<b>AIC</b>	<b>Schwartz</b>
VAR order						
0	7.49	7.52	3.42	3.45	24.96	24.99
1	<b>3.89</b>	<b>3.94</b>	<b>1.13</b>	<b>1.18</b>	<b>16.86</b>	<b>16.91</b>
2	3.93	4.01	1.14	1.23	16.89	16.97
3	3.94	4.05	1.14	1.26	16.92	17.03
4	3.99	4.13	1.18	1.32	16.95	17.10

The results of the FM-VAR model are given in table 7.3, with standard errors reported below in parenthesis. T-statistics constructed with these standard errors are asymptotically valid. Significant variables (based on the cut-off value of 1.96) are indicated in bold print. The Parzen kernel is used for the non-parametric estimation required by the FM-VAR.

<sup>3</sup> The variables in the ECM were not included in the FM-VAR due to insufficient degrees of freedom.

**Table 7.3 Results of the FM-VAR Estimation**

	<b>JSE</b>	<b>Discount rate</b>	<b>GDP</b>
$\Delta JSE_{t-1}$	<b>-0.10</b> (0.02)	<b>0.09</b> (0.00)	-86 (7650)
$\Delta \text{Discount rate}_{t-1}$	<b>-0.83</b> (0.20)	<b>0.26</b> (0.01)	-339 (98295)
$\Delta \text{GDP}_{t-1}$	<b>0.00</b> (0.00)	<b>0.00</b> (1.63)	<b>0.21</b> (0.01)
$JSE_{t-1}$	<b>0.86</b> (0.01)	<b>0.01</b> (0.00)	84.6 (3927)
$\text{Discount rate}_{t-1}$	0.03 (0.02)	<b>0.97</b> (0.00)	160 (12167)
$\text{GDP}_{t-1}$	<b>0.0002</b> (2.14)	<b>0.00</b> (1.35)	<b>0.99</b> (0.00)
Constant	1.43 (8.28)	0.67 (0.52)	-240 (4090997)

According to the results in table 7.3, the JSE can be presented by the following equation:

$$JSE_t = -0.10*\Delta JSE_{t-1} - 0.83*\Delta \text{Discount}_{t-1} + 0.0002*\Delta \text{GDP}_{t-1} + 0.86*JSE_{t-1} + 0.03*\text{Discount}_{t-1} + 0.00*\text{GDP}_{t-1}. \quad (7.6)$$

The results of the FM-VAR estimation presented in table 7.3 differs from the standard output of a VAR, since it includes not only lagged variables but also the first differences of the lagged variables<sup>4</sup>. However, these results can easily be rewritten to

<sup>4</sup> Like in the case of the random walk, this model has the advantage that only lagged variables is used to explain the stock market, which means that actual values are available for a one-period ahead forecast.

be in the same format as the standard VAR, which is easier to interpret. Table 7.4 represents the results of the FM-VAR in the format as a standard VAR<sup>5</sup>.

**Table 7.4 Reparameterized Results of the FM-VAR**

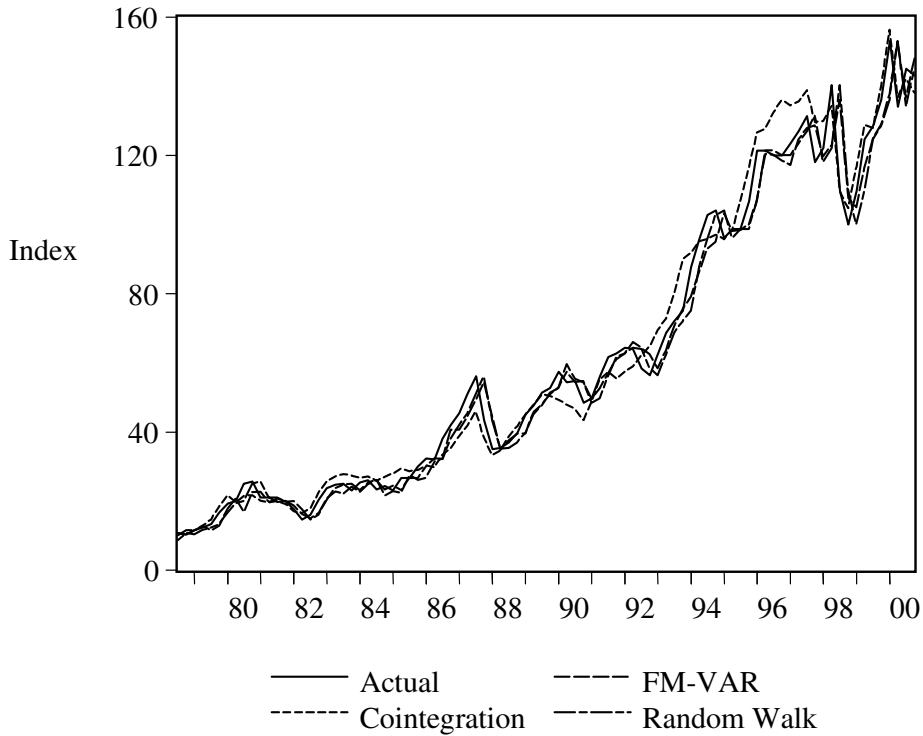
	<b>JSE</b>	<b>Discount rate</b>	<b>GDP</b>
JSE <sub>t-1</sub>	0.76	0.19	-1.79
JSE <sub>t-2</sub>	-0.10	0.09	-86
Discount rate <sub>t-1</sub>	-0.8	0.27	-179
Discount rate <sub>t-2</sub>	-0.83	0.26	-339
GDP <sub>t-1</sub>	0.00	0.00	1.64
GDP <sub>t-2</sub>	0.00	0.00	0.21
Constant	1.43	0.67	-240

Figures 7.1 to 7.4 present the three stock market models graphically. These graphs highlights several differences between the different models. The FM-VAR and random walk both includes the lagged dependent variable (JSE<sub>t-1</sub>) in the specification. Consequently, both these models closely follow the movements and trends in the stock market but this happens with a lag. In other words, these models pick up all the turning points in the stock market but always with a lag and never contemporaneously. For example, the stock market turning point in the third quarter of 1986 is only reflected by the FM-VAR and moving average in the fourth quarter of 1986. The cointegration model, on the other hand, sometimes deviates more than the FM-VAR and random walk from the actual stock price index, but there is no significant lag between the cointegration model and the actual stockmarket. For example, the cointegration model deviates quite substantially from the actual stock market index during 1996, while the deviations between FM-VAR and random walk models and the actual stock market are much smaller. The cointegration model and actual index peaked simultaneously in the third quarter of 1986, while the FM-VAR and random walk only peaked in the fourth quarter of 1986. Similarly, both the

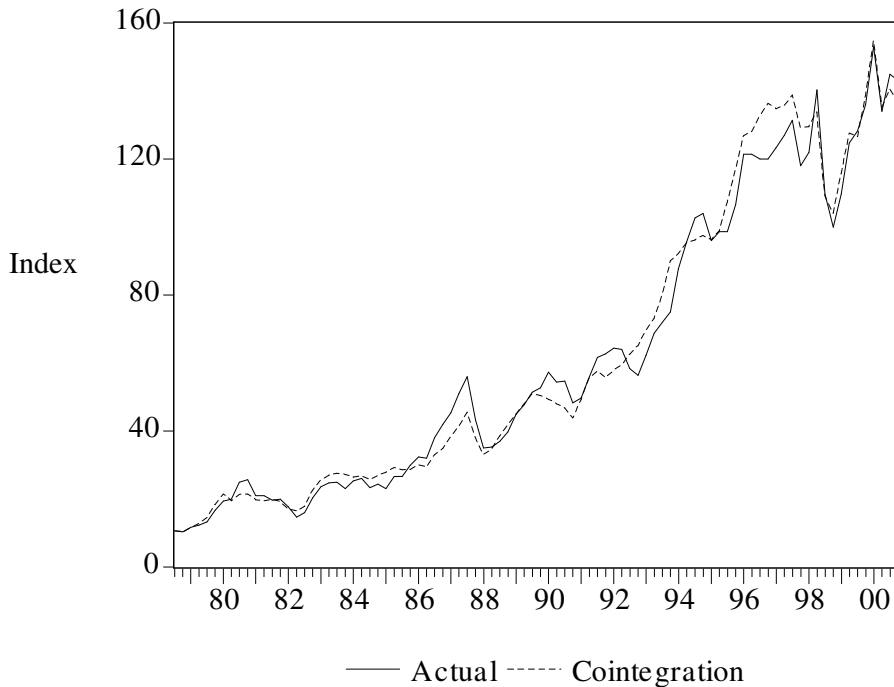
<sup>5</sup> The FM-VAR specification is  $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 \Delta y_{t-1}$ . This can be written as  $y_t = \beta_0 + \beta_1 y_{t-1} + \beta_2 (y_{t-1} - y_{t-2}) = \beta_0 + (\beta_1 + \beta_2) y_{t-1} + \beta_2 y_{t-2}$  which is the same format as the standard VAR.

cointegration model and the actual stock price index have a trough in the third quarter of 1998, while the FM-VAR and random walk models only start their upswings in the fourth quarter of 1998.

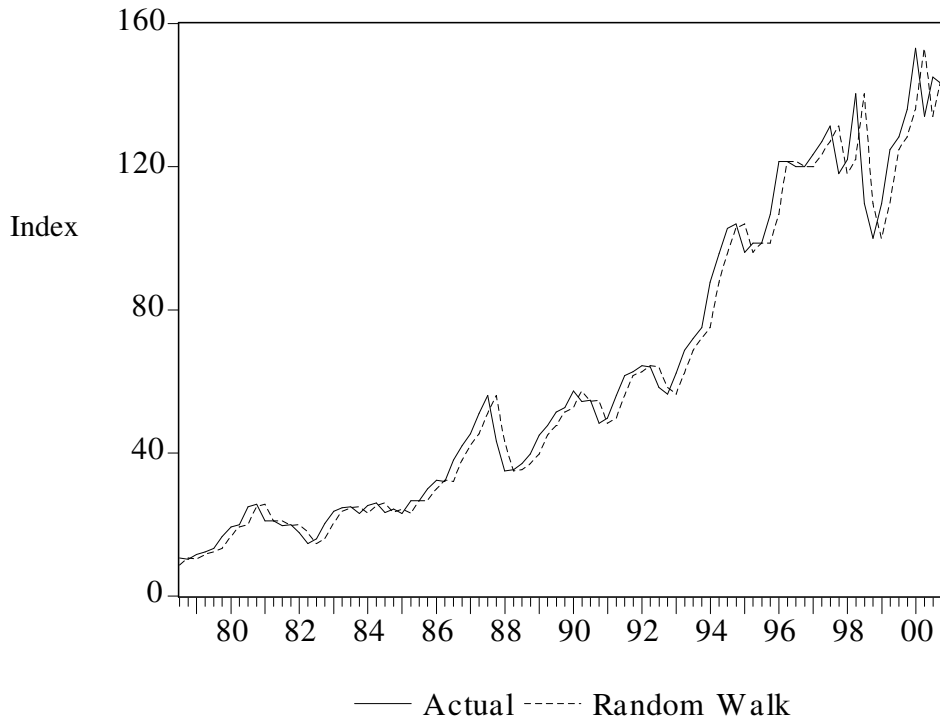
**Figure 7.1 Stock Market Models**



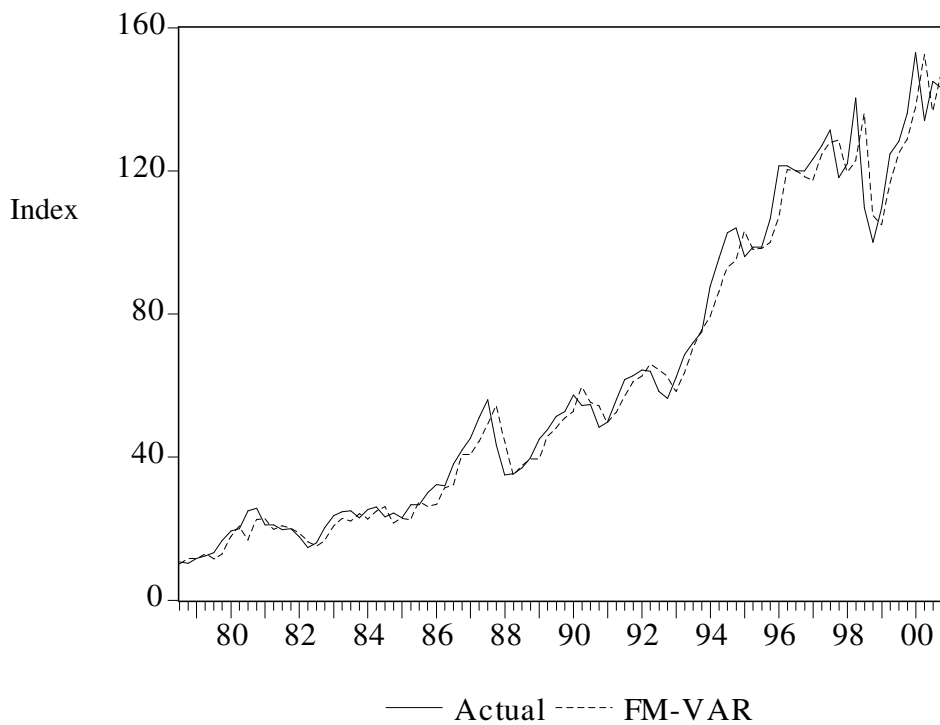
**Figure 7.2 The Cointegration Stock Market Model**



**Figure 7.3 The Random Walk Stock Market Model**



**Figure 7.4 FM-VAR Stock Market Model**



### 7.2.2 Evaluating the Stock Market Models

(i) *Evaluation criteria*

The performance of the three models for the sample and forecast periods will be evaluated and compared on the basis of the root mean squared error (RMSE), the root mean square percentage error (RMSPE) and Theil's inequality coefficient (U) across the observations for every period. These are defined as follows:

$$\text{RMSE} = \sqrt{\frac{1}{T} \sum_{t=1}^T (Y_t^s - Y_t^a)^2} \quad (7.7)$$

$$\text{RMSPE} = \sqrt{\frac{1}{T} \sum_{t=1}^T \left( \frac{Y_t^s - Y_t^a}{Y_t^a} \right)^2} \quad (7.8)$$

$$U = \frac{\sqrt{\frac{1}{T} \sum_{t=1}^T (Y_t^s - Y_t^a)^2}}{\sqrt{\frac{1}{T} \sum_{t=1}^T (Y_t^s)^2 + \frac{1}{T} \sum_{t=1}^T (Y_t^a)^2}} \quad (7.9)$$

where  $Y_t^s$  is the simulated value of  $Y_t$ ,  $Y_t^a$  is the actual value and  $T$  is the number of periods in the simulation (Pindyck and Rubinfeld 1991:338, 340). The RMSE is the criterion most frequently used to evaluate forecast performance, but the other two criteria have certain advantages over the RMSE. The RMSPE is similar to the RMSE, but compares each error with the magnitude of the actual value. Theil's inequality coefficient (U) is based on the RMSE, but it is scaled in such a way that U will always fall between 0 and 1. If  $U = 0$ , then  $Y_t^s = Y_t^a$  for all  $t$ , and the model is a perfect fit. On the other hand, if  $U = 1$ , then the forecasting ability of the model is as bad as it possibly could be. In other words, the best forecasting model will be the one with the minimum RMSE, RMSPE and U.

Theil's inequality coefficient (U) can be decomposed into three parts as follows:

$$U^M = \frac{(Y^s - Y^a)^2}{\frac{1}{T} \sum (Y_t^s - Y_t^a)^2} \quad (7.10)$$

$$U^S = \frac{(\sigma_s - \sigma_a)^2}{\frac{1}{T} \sum (Y_t^s - Y_t^a)^2} \quad (7.11)$$

$$U^C = \frac{2(1-\rho)\sigma_s\sigma_a}{\frac{1}{T} \sum (Y_t^s - Y_t^a)^2} \quad (7.12)$$

where  $\sigma_a$  and  $\sigma_s$  are the standard deviations of the actual and simulated series respectively and  $\rho$  is their correlation coefficient. The proportions  $U^M$ ,  $U^S$  and  $U^C$  are called the bias, variance and covariance proportions respectively. The bias proportion,  $U^M$ , is an indication of systematic error since it measures the extent to which the average values of the simulated and actual series deviate from each other. The variance proportion,  $U^S$ , indicates the ability of the model to replicate the degree of variability in the variable of interest. A large value of  $U^S$  means that the actual series has fluctuated considerably while the simulated series showed little fluctuation, or vice versa. The covariance proportion measure unsystematic error, in other words it represents the remaining error after deviations from average values have been accounted for. The ideal distribution over the three sources is therefore  $U^M = U^S = 0$  and  $U^C = 1$  (Pindyck and Rubinfeld 1991:341).

The abovementioned model selection criteria can be used to rank the performance of the different models, but it does not test whether the differences between the models' performances are statistically significant. Diebold and Mariano (1995) have suggested two tests<sup>6</sup> for the null hypothesis of equal accuracy of two competing forecasts<sup>7</sup>. Let the two rival forecasts of the time series  $\{y_t\}_{t=1}^T$  be  $\{\hat{y}_{it}\}_{t=1}^T$  and  $\{\hat{y}_{jt}\}_{t=1}^T$ , with

<sup>6</sup> They have also suggested an asymptotic test for the null of no difference in the accuracy of two rival forecasts, but the exact finite sample tests are preferred in the small sample context.

<sup>7</sup> Other tests such as an F-test for equal forecast error variances, the Morgan-Granger-Newbold test and the Meese-Rogoff test for testing the null of equal accuracy of two forecasts also exist. However, these tests are only strictly valid if several strong assumptions hold. The most important virtues of the Diebold and Mariano (1995) tests are that they are valid for a very wide class of loss functions, which need not be symmetric or continuous. In addition, the forecast errors do not have to be Gaussian or have a zero mean, and they can even be contemporaneously correlated. See Diebold and Mariano (1995) for a detailed discussion of the advantages of their tests over the other existing tests.



associated forecast errors  $\{e_{it}\}_{t=1}^T$  and  $\{e_{jt}\}_{t=1}^T$ . The null hypothesis of equal accuracy of  $\{\hat{y}_{it}\}_{t=1}^T$  and  $\{\hat{y}_{jt}\}_{t=1}^T$  is:

$$H_0: E[d_t]=0 \tag{7.13}$$

where  $d_t \equiv [g(e_{it}) - g(e_{jt})]$  and  $g()$  is the loss function applicable to the forecast. In general, the loss function,  $g$ , does not have to be a direct function of the forecast error, but can be a function of the actual and predicted values. In this case,  $d_t \equiv [g(y_t, \hat{y}_{it}) - g(y_t, \hat{y}_{jt})]$ .

The first test suggested by Diebold and Mariano (1995) is the sign test, which tests the null hypothesis of a zero median loss differential between the two forecasts:

$$H_0: \text{med}(g(e_{it}) - g(e_{jt})) = 0. \tag{7.14}$$

The test statistic is

$$S_1 = \sum_{t=1}^T I_+(d_t) \tag{7.15}$$

where

$$I_+(d_t) = \begin{cases} 1 & \text{if } d_t > 0 \\ 0 & \text{otherwise.} \end{cases} \tag{7.16}$$

The test statistic,  $S_1$ , is distributed binomial with parameters  $T$  (the sample size) and 0.5 under the null hypothesis. The studentized version of the test statistic is distributed standard normal in large samples:

$$S_{1a} = \frac{S_1 - 0.5T}{\sqrt{0.25T}} \sim N(0,1). \tag{7.17}$$

The second test for the null of equal forecast accuracy is Wilcoxon’s signed-rank test. Unlike the sign test, this test requires symmetry of the loss differential. However, this test is more powerful than the sign test in the case of a symmetric loss differential (Diebold and Mariano 1995). The test statistic is:

$$S_2 = \sum_{t=1}^T I_+(d_t) \text{rank}(|d_t|) \quad (7.18)$$

where  $\text{rank}(|d_t|)$  is the rank of the  $|d_t|$  when  $|d_t|$  is ordered from small to large. Like in the case of the sign test, the studentized version of the test is asymptotically distributed standard normal:

$$S_{2a} = \frac{S_2 - \frac{T(T+1)}{4}}{\sqrt{\frac{T(T+1)(2T+1)}{24}}} \stackrel{a}{\sim} N(0,1). \quad (7.19)$$

(ii) *In-sample performance*

Table 7.5 presents the calculated values of the RMSE, RMSPE and Theil’s inequality U as well as the decomposition of Theil’s U for each of the three stock market models for the sample period.

**Table 7.5 Evaluation of the In-Sample Performance of the Models**

<b>Criterion</b>	<b>Random Walk</b>	<b>Cointegration</b>	<b>FM-VAR</b>
RMSE	6.883	<b>5.492</b>	6.322
RMSPE	0.977	<b>0.751</b>	0.937
U	0.046	<b>0.036</b>	0.043
U <sup>M</sup>	0.047	<b>0.020</b>	0.048
U <sup>S</sup>	0.006	0.104	<b>0.003</b>
U <sup>C</sup>	0.958	0.887	<b>0.959</b>

According to the results in table 7.5, the cointegration model performs relatively well in modeling the stock market. It has the lowest root mean squared error (RMSE), root mean squared percentage error (RMSPE) and Theil's inequality coefficient (U). The cointegration model therefore outperforms the other two models in terms of these three criteria. However, when Theil's inequality coefficient is decomposed, the cointegration model has the lowest bias proportion ( $U^M$ ) but the FM-VAR has the lowest variance proportion ( $U^S$ ) as well as the highest covariance proportion ( $U^C$ ) and is therefore preferred to the cointegration model according to these two criteria. This comparison should be seen in perspective. The cointegration model has a lower inequality coefficient with a less desirable decomposition. On the other hand, the FM-VAR has a higher inequality coefficient with a more desirable decomposition. Therefore the cointegration model is still preferred to the FM-VAR model since it has the *lowest* inequality coefficient, which is arguably more important than the *composition* of the inequality coefficient.

Although the RMSE, RMSPE and U can be used to rank the performances of the models, it cannot be used to test whether the differences between the models are statistically significant. Therefore Diebold and Mariano's (1995) sign ( $S_{1a}$ ) and Wilcoxon signed-rank ( $S_{2a}$ ) tests will be used to test whether the models' accuracy is statistically different. These tests require the specification of a loss function. The following loss functions were used:

$$L1: g(e_t) = e_t \quad (7.20)$$

$$L2: g(e_t) = e_t^2 \quad (7.21)$$

$$L3: g(e_t) = \frac{\beta}{\alpha^2} \{ \exp(\alpha e_t) + \alpha e_t - 1 \} \text{ where } \alpha=-1, \beta=1 \quad (7.22)$$

$$L4: g(e_t) = \frac{\beta}{\alpha^2} \{ \exp(\alpha e_t) + \alpha e_t - 1 \} \text{ where } \alpha=-0.5, \beta=1 \quad (7.23)$$

$$L5: g(e_t) = \frac{\beta}{\alpha^2} \{ \exp(\alpha e_t) + \alpha e_t - 1 \} \text{ where } \alpha=-2, \beta=1 \quad (7.24)$$

$$L6: g(e_t) = \frac{\beta}{\alpha^2} \{\exp(\alpha e_t) + \alpha e_t - 1\} \text{ where } \alpha=-3, \beta=1 \quad (7.25)$$

$$L7: g(e_t) = \frac{\beta}{\alpha^2} \{\exp(\alpha e_t) + \alpha e_t - 1\} \text{ where } \alpha=-4, \beta=1. \quad (7.26)$$

Loss functions L1 and L2 are standard, symmetric loss function that minimizes the errors and squared errors respectively. Loss functions L3 to L7 are linex loss functions<sup>8</sup> which are asymmetric. In these loss functions the parameter  $\alpha$  determines the degree of asymmetry<sup>9</sup>. If  $\alpha > 0$ , then the losses are approximately linear for  $e < 0$  and approximately exponential for  $e > 0$ . By defining the error ( $e$ ) as the actual value less the simulated value, positive values of  $\alpha$  corresponds to the case in which underpredictions are more costly than overpredictions. Negative values, on the other hand, corresponds to the case where the function is exponential to the left of the origin and linear to the right. Furthermore, the closer  $\alpha$  is to zero, the closer the function approximates the standard quadratic case. As explained in chapter six, overpredictions are more dangerous to investors than underpredictions, and therefore negative values of  $\alpha$  are used in this study so that overpredictions are more costly than underpredictions<sup>10</sup>.

In table 7.6,  $\{e_{Rt}\}$ ,  $\{e_{Ct}\}$  and  $\{e_{Vt}\}$  are the error series of the random walk model, the cointegration model and the FM-VAR model respectively. The signed-rank test requires a symmetric loss function and is therefore not applied to the asymmetric loss functions L3 to L7 (see section 7.2.2). According to the results in table 7.6 all the models' accuracy are statistically different for loss function L1 according to both the sign and signed-rank tests. However, using any of the other loss functions there are no statistically significant differences in the accuracy of the models.

<sup>8</sup> The linex loss function was introduced by Varian (1974) and Zellner (1992).

<sup>9</sup> The parameter  $\beta$  in the linex loss function is a scaling factor, which does not influence the results. This is illustrated in Appendix 2 where the results of the test of equal accuracy are presented for different values of  $\beta$ . The results show that different values of  $\beta$  do not influence the results.

<sup>10</sup> See Appendix 2 for the results in the counterintuitive case of positive values of  $\alpha$ , in other words when underpredictions are more costly than overpredictions. The results show that none of the models' accuracy is significantly different for loss functions with positive values of  $\alpha$ .

**Table 7.6 Equal Accuracy Tests for In-Sample Performance**

<b>Loss function:</b>	<b>L1</b>		<b>L2</b>		<b>L3</b>	<b>L4</b>	<b>L5</b>	<b>L6</b>	<b>L7</b>
<b>Test statistic:</b>	<b>S<sub>1a</sub></b>	<b>S<sub>2a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>2a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>
H <sub>0</sub> : med(g(e <sub>Rt</sub> )-g(e <sub>Ct</sub> ))=0	-3*	-3*	-1.1	0.48	-1.5	-0.6	-1.5	-1.9	-1.9
H <sub>A</sub> : med(g(e <sub>Rt</sub> )-g(e <sub>Ct</sub> ))≠0									
H <sub>0</sub> : med(g(e <sub>Rt</sub> )-g(e <sub>Vt</sub> ))=0	2.5*	2.9*	1.1	1.87	1.05	1.05	0.84	0.84	0.63
H <sub>A</sub> : med(g(e <sub>Rt</sub> )-g(e <sub>Vt</sub> )) ≠0									
H <sub>0</sub> : med(g(e <sub>Ct</sub> )-g(e <sub>Vt</sub> ))=0	9.5*	8.2*	-0.6	-0.1	1.26	0.21	1.90	1.90	1.90
H <sub>A</sub> : med(g(e <sub>Ct</sub> )-g(e <sub>Vt</sub> )) ≠0									

\* Significant on a 1% level of significance.

(iii) *Forecasting performance*

The forecasting accuracy of the three stock market models are compared using the RMSE, RMSPE and Theil's inequality coefficient (U) from the first quarter of 2001 quarter until the first quarter of 2003. The results are presented in table 7.7. The preferred model according to each of the criteria is printed in bold.

**Table 7.7 Evaluation of the Forecasting Performance of the Models**

<b>Criterion</b>	<b>Random Walk</b>	<b>Cointegration</b>	<b>FM-VAR</b>
RMSE	14.577	<b>8.423</b>	14.690
RMSPE	0.086	<b>0.051</b>	0.088
U	0.044	<b>0.026</b>	0.044
U <sup>M</sup>	0.007	0.136	<b>0.005</b>
U <sup>S</sup>	0.009	<b>0.032</b>	0.000
U <sup>C</sup>	0.984	0.832	<b>0.995</b>

According to the results in table 7.7, the cointegration model performs relatively well in forecasting the stock market. It has the lowest root mean squared error (RMSE), root mean squared percentage error (RMSPE) and Theil's inequality coefficient (U). The cointegration model therefore outperforms the other two models in terms of these three criteria. However, when Theil's inequality coefficient is decomposed, the cointegration model has the lowest variance proportion ( $U^S$ ) but the FM-VAR has the lowest bias proportion ( $U^M$ ) as well as the highest covariance proportion ( $U^C$ ) and is therefore preferred to the cointegration model according to these two criteria.

In addition to the RMSE, RMSPE and U criteria, Diebold and Mariano's (1995) sign ( $S_{1a}$ ) and Wilcoxon signed rank ( $S_{2a}$ ) tests are used to test whether the models' forecasting accuracy is statistically different. The results are presented in table 7.8.

**Table 7.8 Equal Accuracy Tests for Forecasting Performance**

<b>Loss function:</b>	<b>L1</b>		<b>L2</b>		<b>L3</b>	<b>L4</b>	<b>L5</b>	<b>L6</b>	<b>L7</b>
<b>Test statistic:</b>	<b>S<sub>1a</sub></b>	<b>S<sub>2a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>2a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>	<b>S<sub>1a</sub></b>
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	4	16*	6	32*	6	6	6	6	6
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$									
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	2	9*	4	23*	4	4	4	4	4
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt})) \neq 0$									
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	4	17*	2	7*	1*	1*	0*	0*	0*
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt})) \neq 0$									

\* Significant on a 10% level of significance.

According to the results in table 7.8, the null hypothesis that the random walk and cointegration model are equally accurate in forecasting the stock market is rejected against the alternative that they are not equally accurate if the loss function is symmetric<sup>11</sup>. Likewise, the forecasting accuracy of the random walk and FM-VAR

<sup>11</sup> The results of the sign ( $S_{1a}$ ) and signed-rank ( $S_{2a}$ ) are contradictory for loss functions L1 and L2. However, the signed-rank test is more powerful in the case of symmetric loss functions such as L1 and

differs significantly in the case of symmetric loss functions but not in the case of asymmetric loss functions. The null hypothesis of equal forecasting accuracy of the cointegration and FM-VAR models is rejected for the symmetric as well as the asymmetric loss functions. To summarize, the forecasting accuracy of any pair of models is statistically different for symmetric loss functions, in other words when over- and under-predictions are equally costly to investors. However, in the case of asymmetric loss functions in which over-predictions are more costly than under-predictions, only the cointegration and FM-VAR models differ significantly in terms of forecasting accuracy.

### **7.3 MODELLING TURNING POINTS IN THE STOCK MARKET**

#### **7.3.1 The Turning Point Models**

The modelling and forecasting accuracy of the models in the previous section, namely the cointegration, FM-VAR and random walk models, are compared in modelling the direction of the stock market. The simulated values of these models are used to calculate the implied predicted direction of the stock market. In addition, they are compared to one of the most popular models used by technical analysts, a moving average<sup>12</sup>.

One of the most popular averages used to identify major stock market trends is the 200-day (or 30-week) moving average (Jones 1991:438). The moving average line is used to create a basic trend line of stock prices. A general sell (buy) signal is created when the actual stock price index fall below (rise through) the moving average line. The following are specific signals of a sell signal (i.e. an upper turning point) (Jones 1991:438):

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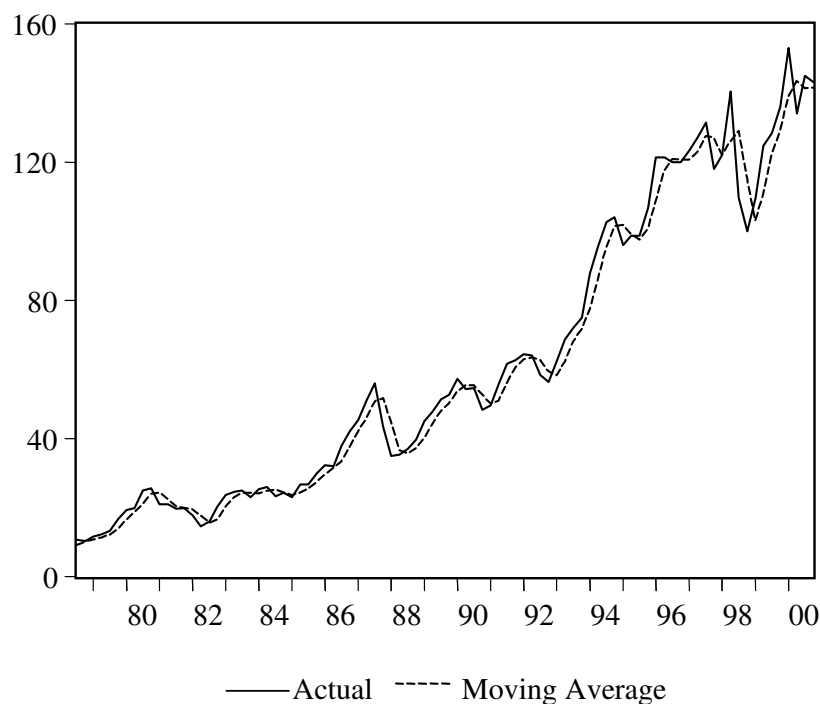
L2 and therefore the results of the signed-rank test are interpreted rather than that of the sign test (Diebold and Mariano 1995).

<sup>12</sup> Technical trading rules are designed to signal when to buy or sell shares and not to model the level of share prices. Therefore the moving average was only used to model the direction and not the level of the stock market, since this is consistent with its general purpose.

- The actual share price index is approaching the moving average from below, but does not cross the moving average line before it starts to fall again.
- The moving average declines after a rise and the actual share price index crosses it from above.
- The actual share price index rises above the moving average line when the average is still falling.

In this study a 30-week (or equivalently 7-month) moving average is constructed as technical trading rule. The moving average is calculated using monthly data and is then converted to quarterly data before the implied turning points are calculated. The calculated 7-month moving average of the JSE is presented in figure 7.5. The graph highlights the lag between movements of the moving average and the actual stock price index. For example, the stock market had a peak in the fourth quarter of 1980, while the turning point predicted by the moving average (i.e. when the actual index intersects with the moving average) only follows in the first quarter of 1981. Likewise, the stock market troughs in the second quarter of 1982 and the first quarter of 1988 are followed by turning point signals that are lagged by one quarter. However, the moving average seems to pick up all the peaks and troughs in the stock price index.

**Figure 7.5 A Moving Average Model of the JSE**





### 7.3.2 Evaluating the Turning Point Models

Investors are investing in the stock market to maximize their profits following a basic strategy of buying when share prices are low and selling when they are high. In order to evaluate the usefulness of the cointegration model for investors, the profitability of the different stock market models will be compared following this strategy of selling when share prices reach their predicted upper turning point and selling when share prices reach their predicted lower turning point. It is assumed that investors receive the short-term interest rate on their money while they do not hold the all-share index and that the returns are reinvested according to the same strategy as the original investment<sup>13</sup>. This will be compared to the returns of a buy-and-hold strategy over the sample period as well as receiving the short-term interest rate<sup>14</sup> on their money over the sample period. Following Heathcotte and Apilado (1974), a commission of 0,5 percent was charged on each trade<sup>15</sup>. Dividends were excluded from the analysis and any taxes were ignored.

(i) *The in-sample profitability of the stock market models*

Table 7.9 contains the results of these strategies for an initial investment of R100 at the beginning of the sample period. The second column presents the quarterly rate of return of the investment at an annual rate. The third and fourth columns contain the number and percentage of times that the specific model predicted a different direction than the actual realization of the stock market.

According to the results in table 7.9, trading according to the cointegration model would have yielded a return of 24.39 percent, which is higher than the return on the buy-and-hold strategy. In fact, the return yielded by the cointegration model is higher than that of all the other models except the moving average model which would have yielded a return of 26.71 percent. The cointegration model also outperforms all the models except the moving average in terms of the number or percentage of times that it correctly predicts the direction of the stock market.

---

<sup>13</sup> Dividends are not included.

<sup>14</sup> The yield on three-month bankers' acceptances was used throughout the study.

<sup>15</sup> This is consistent with the rate charged by PSG, an investment services firm in South Africa ([www.psg-online.co.za](http://www.psg-online.co.za)).

**Table 7.9 In-sample Profitability of Different Trading Strategies**

Model	Final value of investment <sup>16</sup>	Annualized rate of return <sup>17</sup>	Wrong predictions	% Wrong predictions
Buy-and-hold	835.380	9.89%		
Interest rate	1702.90	13.43%		
Cointegration	13564.6	24.39%	12	13.33%
FM-VAR	1268.60	11.95%	35	38.89%
Random Walk	1251.00	11.88%	35	38.89%
Moving Average	20584.7	<b>26.71%</b>	<b>11</b>	<b>12.22%</b>

(ii) *The forecasting profitability of the stock market models*

Table 7.10 contains the results of these strategies for an initial investment of R100 at the beginning of the forecast period. The forecast period was from the first quarter of 2001 until the second quarter of 2003.

According to the results in table 7.10, the cointegration model outperformed all the stock market models in terms of return on investment. However, it was as accurate as the moving average in terms of the number of times that it predicted the wrong direction for the stock market. Despite the good performance of the cointegration model in predicting the stock market, an investor would have been better off by simply investing in interest-bearing instruments during this particular period. However, it has to be kept in mind that dividends were not included in the calculation of these returns

<sup>16</sup> The final value of the investment refers to the value at the end of sample period of the R100 invested at the beginning of the sample period if the investment strategy was to invest the money in share if the model predicted that share prices will increase while the money was invested in short-term bearing instruments when the relevant model predicted that share prices would decline. With the buy-and-hold and interest rate strategies, it is assumed that the money was kept in share or interest-bearing instruments respectively for the full sample period.

<sup>17</sup> The annualized rate of return is calculated as the percentage increase in the original R100 investment expressed at an annual rate.

and that any taxes on the returns were ignored. Table 7.11 replicates the results in table 7.10 but includes the dividends.

**Table 7.10 Forecasting Profitability of Different Trading Strategies**

<b>Model</b>	<b>Final value of investment</b>	<b>Annualized rate of return</b>	<b>Wrong predictions</b>	<b>% Wrong predictions</b>
Buy-and-hold	84.01	-6.73%		
Interest rate	127.12	10.07%		
Cointegration	121.99	8.27%	3	30%
FM-VAR	102.02	0.81%	4	40%
Random Walk	106.41	2.51%	4	40%
Moving Average	106.94	2.72%	3	30%

**Table 7.11 Forecasting Profitability Including Dividends**

<b>Model</b>	<b>Final value of investment</b>	<b>Annualized rate of return</b>	<b>Wrong predictions</b>	<b>% Wrong predictions</b>
Buy-and-hold	91.08	-3.67%		
Interest rate	127.12	10.07%		
Cointegration	124.87	9.29%	3	30%
FM-VAR	106.46	2.53%	4	40%
Random Walk	110.75	4.17%	4	40%
Moving Average	111.30	4.38%	3	30%

The ranking of the models remain the same when dividends are included in the calculation of the rates of return. However, the difference in the returns of the stock market models and the interest-bearing scenario shrinks when dividends are included

in the analysis. The yield on the cointegration model increases from 8.27 percent to 9.29 percent, while the yield on the FM-VAR model increases from 0.81 percent to 2.53 percent when dividends are added to the analysis. The returns on the moving average model increases from 2.72 percent to 4.38 percent, while the returns on the buy-and-hold scenario increases from -6.73 percent to -3.67 percent.

#### 7.4 CONCLUSION

In this chapter the accuracy of the cointegration model developed and estimated in chapter six was compared to other stock market models. The comparison was done separately for the in-sample and forecast periods. First the models' accuracy in modeling and forecasting the level of the stock market were compared. Then the models were used to develop trading rules in order to compare their profitability and accuracy in modeling and forecasting the direction of the stock market.

The accuracy of the cointegration model developed in chapter six was compared to that of a random walk and a Fully Modified Vector Autoregressive (FM-VAR) model. The performance of these models for both the sample and forecast periods was evaluated and compared on the basis of the root mean squared error (RMSE), the root mean square percentage error (RMSPE) and Theil's inequality coefficient (U) across the observations for every period.

According to the results, the cointegration model performed relatively well in modeling the stock market within the sample period. The cointegration model outperforms the other two models in terms of the RMSE, RMSPE and U. Diebold and Mariano's (1995) sign and Wilcoxon sign rank tests are used to test whether the models' accuracy is statistically different. According to the results the accuracy of all the models differ significantly if the minimized loss function is simply the errors. However, using any of the other symmetric or asymmetric loss functions there are no statistically significant differences in the accuracy of the models.

The cointegration model also performs relatively well in forecasting the stock market, as it is preferred to the other models according to the RMSE, RMSPE and U.

According to the results, the null hypothesis that the random walk and cointegration model are equally accurate in forecasting the stock market is rejected against the alternative that they are not equally accurate if the loss function is symmetric. Likewise, the forecasting accuracy of the random walk and FM-VAR differs significantly in the case of symmetric loss functions but not in the case of asymmetric loss functions. The null hypothesis of equal forecasting accuracy of the cointegration and FM-VAR models is rejected for the symmetric as well as the asymmetric loss functions. To summarize, the forecasting accuracy of any pair of models is statistically different for symmetric loss functions, in other words when over- and under-predictions are equally costly to investors. However, in the case of asymmetric loss functions in which over-predictions are more costly than under-predictions, only the cointegration and FM-VAR models differ significantly in terms of forecasting accuracy.

The models used to model and forecast the level of the stock market is also used to model and forecast the direction of the stock market. The simulated values of these models are used to calculate the implied predicted direction of the stock market. In addition, they are compared to one of the most popular models used by technical analysts, a 30-week moving average. According to the results, trading according to the cointegration model would have yielded a higher return than the returns yielded by a buy-and-hold strategy. In fact, the return yielded by the cointegration model is higher than that of all the other models except the moving average model. The cointegration model also outperforms all the models except the moving average in terms of the number or percentage of times that it correctly predicts the direction of the stock market.

To summarize, in terms of both accuracy and profitability the cointegration model is preferred to other stock market models in modelling and forecasting the level as well as the turning points of the stock market.

## CHAPTER 8

### SUMMARY AND CONCLUSION

#### 8.1 INTRODUCTION

The primary objective of this study was to develop and estimate a structural econometric model of the South African stock market, the Johannesburg Stock Exchange (JSE). The main purpose of the model is structural analysis, in other words to understand the impact of macroeconomic and other variables on the stock market and to evaluate the role of phenomena such as globalization, policy shifts and contagion. Finally, the model's forecasting ability was evaluated and compared to other stock market models.

#### 8.2 MODELLING APPROACH

There are two alternative approaches that can be followed in modeling stock markets, namely technical analysis and fundamental analysis. Technical analysis builds on the belief that stock prices move in trends that persist. It believes that the patterns in financial markets repeat themselves and therefore their stock market models and analyses are aimed at capturing historical patterns which they then use to forecast the stock market. Technical analysts believe that when new information comes to the market, it is not immediately available to everybody but rather disseminated from professional investors to the aggressively investing public and then to the great bulk of investors. Therefore it is possible to outperform a buy-and-hold strategy with a trading rule based on historical price data.

This is in direct contrast to even the weak form of the efficient market hypothesis, according to which security prices adjust rapidly to reflect all new information (Reilly 1989:244). This means that if stock markets are efficient, share prices fully reflect all the relevant information, so that trading based only upon past data cannot be profitable since by the time information is publicly available it is already reflected by

the share prices. It has been shown in this study that the South African stock market is operationally efficient<sup>1</sup>, which means that share prices cannot be predicted on the basis of historical share prices alone and hence technical analysis is not the relevant approach to model the South African stock market.

In contrast with technical analysis, fundamental analysis focuses on determining the fundamental factors that drive the stock market and base any modeling on the structural and theoretically justifiable relationships between the stock market and economic variables. However, while economic theory should be able to explain the long-run trend of the stock market, the short-run movements are potentially driven not only by the variables dictated by theory but also by variables reflecting market sentiment as well as other factors such as political instability, emerging market crises, exchange rates etcetera (Jefferis and Okeahalam 2000). The influence of these short-run determinants can only be determined empirically (Harasty and Roulet 2000). The long-run behavior of stock prices are usually modeled based on the expected present value model and then the short-run fluctuations of the market around this long-run trend are determined empirically.

The technique of cointegration makes it possible to distinguish between the long-run equilibrium level or intrinsic value of the stock market and the short-run fluctuations around the equilibrium level by estimating both a cointegration equation and an error correction model (ECM). In the long-run or cointegration equation, the intrinsic value or long-run level of the stock market is modeled based on the relationship between the stock market and economic variables dictated by theory. According to the expected present value model, the most popular theory for modeling stock markets, stock prices are a function of future dividends discounted by a discount rate. In the error-correction model, short-run fluctuations around the long run equilibrium level and the speed of adjustment towards equilibrium are modeled. In the short-run, not only the economic variables dictated by theory but also variables reflecting market sentiment, important socio-political changes and other non-fundamental factors play a role. However, none of these relationships necessarily have to be symmetric. This study

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<sup>1</sup> This is consistent with the conclusion of Thompson and Ward (1995) based on a survey of the literature on the efficiency of the JSE.

has described the potential causes of asymmetry and also tested empirically whether stock market behavior is asymmetric.

### 8.3 CONTRIBUTIONS OF THIS STUDY

This study has made three important contributions to the literature, namely to estimate a structural model for the South African stock market, to capture the asymmetric behavior of investors in this model and to estimate a Markov switching regime model of the South African business cycle which is used in the stock market model to capture the stock market asymmetry caused by investment behavior. First, it developed and estimated a structural model of the South African stock market. There is a wealth of literature modeling stock markets and examining the relationship between share prices and various economic factors, both theoretically and empirically. However, most studies use data for developed countries in their analyses and very little literature exists for the South African stock market. The main contribution of this study to the literature is the development of a structural model of South African stock market that was estimated econometrically using cointegration techniques and error correction modeling.

The second contribution of this study is to incorporate the potential asymmetric effects introduced by the risk and loss aversion of investors. Risk aversion refers to the tendency of rational investors to prefer certainty to risk *ceteris paribus* (Reilly 1989:10,255; Renwick 1971:400). Loss aversion, on the other hand, refers to the inclination of economic agents to be more sensitive to reductions in their levels of well-being than to increases (Bernartzi and Thaler 1995). Two explanations have been given in the literature on why investors' risk and/or loss aversion induces stock market asymmetry. First, Chalkley and Lee (1998) argues that risk aversion encourages economic agents to react promptly on receiving bad news, while it prevents them from acting quickly when receiving good news. A downturn in the relevant economic data (which influences the particular stock price negatively) may be indicative of other economic agents receiving bad news or it might be a random change, but in either case the cautious (i.e. risk averse) response is to act immediately as if the bad data is truly reflecting adverse conditions. In this case "bad" news (i.e.



adverse economic data), risk aversion and uncertainty about the information value of aggregate data work together, leading informed agents to quickly respond to the downturn in economic data and other agents to quickly respond to that response. Of course, there is also uncertainty about the interpretation of an upturn in economic data, but in this case risk (and loss) aversion works against reacting to such a signal since investors will wait until the “good” news is confirmed before they act on it.

It can therefore be expected that investors will react more reluctantly to an upturn in economic data and vice versa. When the behavior of these individual investors are aggregated it implies that the stock market will react quicker during good conditions or on good news or expectations, or put differently, that its adjustment to equilibrium will be slower during adverse economic conditions and faster during positive economic conditions. The “upturn” and “downturn” of data in the Chalkley and Lee (1998) framework originally referred to good or bad conditions as reflected in the state of the business cycle. Since stock prices are discounted future dividends and since real economic activity is one of the main determinants of dividends, an economic upswing (downswing) will cause higher (lower) dividends and an indicator of the state of the business cycle can therefore be used to measure the upturn or downturn in economic data.

The second explanation for asymmetric investor (and hence stock market) behavior is driven by the potential loss (profit) in and overvalued (undervalued) stock market. Following the same line of reasoning as Chalkley and Lee (1998), Phelps and Zoega (2001) and Siklos (2002) also hypothesized different speeds of adjustment but they introduced a different driving force for the asymmetry by redefining the good and bad news or conditions that prompts the asymmetric behavior of investors. Their theory on stock market asymmetry is based on the paradigm of the structural slump developed by Phelps (1967). A structural slump is characterized by a steep decline in share prices followed by a gradual rise in unemployment. A structural boom, on the other hand, entails a steep rise in share prices followed by a decline in unemployment. In the case of a structural boom, investors calculate that this signals a jump in future asset returns and, consequently, the valuation of these assets as reflected in the stock market. The resulting rise in the profitability of investment signals a falling

unemployment rate. The boom ends when the productivity rise increases investment costs.

Theoretically, this scenario works symmetrically, but Phelps and Zoega (2001) argued that it might in practice work asymmetrically since other factors may influence the progress of the business cycle. The potential asymmetry was first evaluated empirically by Siklos (2002). His results showed that the relationships between the economy and the stock markets of the UK and the US were indeed asymmetric.

Although Siklos (2002) tested the stock market asymmetry based on the relationship between the stock market and unemployment, the asymmetry also holds for any other stock market model. If the stock market is undervalued it means that the market prices of shares are below their intrinsic value, so that a profit opportunity is created since investors can buy shares at the low current market price and eventually resell it at a higher price once the market has corrected the discrepancy between the market and intrinsic value. In contrast, when the stock market is overvalued market prices of shares are above the intrinsic values. Eventually the market will correct this discrepancy so that share prices fall, in which case investors will lose money. Since investors are loss averse it is more important to avoid the potential loss if the market is overvalued than to make the profit if the market is undervalued. Therefore, if investors are uncertain, they will react faster to an overvaluation that poses a potential loss than to an undervaluation that poses a potential profit.

The techniques of cointegration and error correction modeling are ideally suited for modeling different speeds of reaction of investors. In the error correction model, the adjustment to equilibrium is modeled and the speed of adjustment is estimated. Usually the coefficient measuring the speed of adjustment is assumed to be constant, but the model can easily be adapted to capture different speeds of adjustment in different circumstances. Econometrically, the two potential causes of asymmetric investor (and stock market) behavior have to be modeled differently. Siklos and Enders (2001) developed a threshold cointegration technique with which different speeds of adjustment can be modeled for overvalued and undervalued series. This test can be applied directly to under- or overvaluation of the stock market. However, this test is not applicable when the asymmetry is caused by different states of the business

cycle and this type of asymmetry therefore has to be evaluated differently. In the case of asymmetry with respect to the state of the business cycle, a variable is needed that reflects the different states of the business cycle. In this study, the state variable was constructed using a Markov switching regime model of the South African business cycle. The Markov switching regime model can be used to simultaneously estimate the probability of the economy being in an expansion or recession and the expected economic growth rate.

The third contribution of this study is the estimation of the Markov switching regime model, which is in itself a significant contribution to the literature since no Markov switching regime model has been estimated for the South African business cycle yet. Apart from its use in the stock market model to capture the potential asymmetry, the Markov model can be used for two additional purposes. First, it estimates the data generating process (DGP) of the variable under consideration, which is real economic growth in this study. Second, it estimates a probability of the economy or business cycle being in either of two possible states, for example being in a recession or an expansion, for each period. Since this time series of probabilities reflects the likelihood of a recession or expansion, it can therefore be used to classify each observation into one of two regimes. For example, the economy is regarded as being in a low-growth (high-growth) or recession (expansion) regime or state if the probability of being in recession (expansion) is higher than the probability of being in an expansion (recession). In addition, the probabilities may be used to reflect the degree of certainty of economic agents regarding the state of the business cycle, if it is assumed that a recession probability of one (zero) indicates that the economic agent is absolutely certain that the economy will (not) be in a recession, while a probability of 0.5 indicates that a recession or expansion is equally likely and therefore there are no certainty regarding the state of the business cycle. In other words, the closer the recession probability is to zero or one, the higher the certainty regarding the state of the business cycle. On the other hand, the closer the recession probability is to 0.5, the higher the uncertainty regarding the state of the business cycle.

The estimated Markov-switching regime business cycle model can therefore be used not only to forecast economic growth, one of the most important macroeconomic indicators, but also to forecast the occurrence of recessions and expansions. The only

indicator currently available to reflect recessions and expansions is that of the South African Reserve Bank, but their indicator is only available with a considerable time lag. It is therefore not useful for forecasting purposes at all. The Markov-switching regime indicator can fill this gap and will consequently be extremely useful for policy-makers, investors and producers that want to plan their economic decisions or actions.

To summarize, in this study a structural model of South African stock market incorporating both the fundamental factors driving stock prices as well as the influence of the risk aversion of investors were estimated. Cointegration techniques has been used to distinguish between the long-run behavior and short-run fluctuations of the stock market, allowing for the possibility that fundamental factors might drive the long-run behavior but that additional factors comes into play in the short-run. Two potential causes of asymmetric investor (and hence stock market) behavior have been evaluated. First, the Siklos and Enders (2001) threshold cointegration test has been used to evaluate asymmetric adjustment in under- and overvalued stock markets. Second, asymmetry with respect to the state of the economy has been evaluated, which necessitates the construction of a state variable. A Markov switching regime model has been developed to estimate the probability of the state of the economy, reflecting both the expected direction of the business cycle as well as the certainty regarding this expectation.

## **8.4 RESULTS**

### **8.4.1 Structural Model**

In this study, a structural model for the South African stock market was developed and estimated based on the expected present value model. Theoretically, several reasons exist that may cause asymmetric stock market behaviour. Two different cases of asymmetry has been evaluated, namely asymmetry conditional on (i) whether the stock market is over-valued or under-valued and (ii) the state of the business cycle.

The results have shown that neither the over- or under-valuation nor the direction of stock market movement causes stock market asymmetry. However, it has been shown that the speed of adjustment differs based on the state of the business cycle. Consistent with *a priori* expectations, the adjustment is significantly faster in recessions than expansions.

The results confirmed that the long-run level of the South African stock market is determined according to the expected present value model. Therefore, the long-run level of share prices are determined by discounted future dividends. In addition, the short-run fluctuations are caused by the short term interest rate, the rand-\$US exchange rate, the S&P500 index, the gold price, forward-looking expectations of investors and a risk premium.

#### **8.4.2 Comparative Performance**

The cointegration model's performance in modeling and forecasting the level of the stock market was compared to that of the FM-VAR and random walk. Both the FM-VAR and random walk includes the lagged stock market index as explanatory variable. Consequently, both models closely follow the movements and trends in the stock market but with a lag. In other words, these models pick up all the turning points in the stock market but always with a lag and never contemporaneously. The cointegration model, on the other hand, sometimes deviates more than the FM-VAR and random walk from the actual stock price index. For example, the cointegration model deviates quite substantially from the actual stock market index during 1996, while the gaps between the FM-VAR and random walk models and the actual stock market are much smaller. However, unlike the FM-VAR and the random walk there seems to be no lag between the cointegration model and the actual stock market.

The cointegration model performs relatively well in *modeling* the stock market. It has the lowest root mean squared error (RMSE), root mean squared percentage error (RMSPE) and Theil's inequality coefficient (U). The cointegration model therefore outperforms the other two models in terms of these three criteria. Although the RMSE, RMSPE and U can be used to rank the performances of the models, it cannot be used to test whether the differences between the models are statistically significant.

Therefore Diebold and Mariano's (1995) sign ( $S_{1a}$ ) and Wilcoxon signed-rank ( $S_{2a}$ ) tests were also used to test whether the models' accuracy is statistically different. These tests require the specification of a loss function. In this study two symmetric loss functions, based on the errors and squared errors, and asymmetric linex loss functions with varying degrees of asymmetry have been used. According to the results all the models' accuracy are statistically different for a loss function based on the untransformed error terms according to both the sign and signed-rank tests. However, using any of the other loss functions there are no statistically significant differences in the accuracy of the models.

The *forecasting* accuracy of the three stock market models are compared using the RMSE, RMSPE and Theil's inequality coefficient (U) for the period from the first quarter of 2001 until the first quarter of 2003. According to the results, the cointegration model performs relatively well in forecasting the stock market. It has the lowest root mean squared error (RMSE), root mean squared percentage error (RMSPE) and Theil's inequality coefficient (U). The cointegration model therefore outperforms the other two models in terms of these three criteria. The null hypothesis that the random walk and cointegration model are equally accurate in forecasting the stock market is rejected against the alternative that they are not equally accurate. There are no statistically significant difference between the forecasting accuracy of the random walk and the VAR or between that of the VAR and the cointegration model using loss functions that are symmetric or nearly symmetric. However, the null hypothesis of equal accuracy of the cointegration and FM-VAR models is rejected with asymmetric loss functions in which the cost of overpredicting share prices is higher than that of underpredicting.

### **8.4.3 Profitability**

Investors are investing in the stock market to maximize their profits following a basic strategy of buying when share prices are low and selling when they are high. In order to evaluate the usefulness of the cointegration stock market model for investors, the profitability of the different stock market models have been compared following this strategy. It was assumed that investors receive the short-term interest rate on their money while they do not hold the all share index and that the returns are reinvested

according to the same strategy as the original investment. This was compared to the returns of a buy-and-hold the JSE all-share index strategy over the sample period as well as receiving the short-term interest rate on their money over the sample period. The modelling and forecasting accuracy of the models in the previous section, namely the cointegration, FM-VAR and random walk models, are compared in modelling the direction of the stock market. The simulated values of these models are used to calculate the implied predicted direction of the stock market. In addition, they are compared to one of the most popular models used by technical analysts, a 30-week moving average. It has been showed that the trading according to the cointegration model would have yielded a higher return than the return on the buy-and-hold strategy. In fact, the return yielded by the cointegration model is higher than that of all the other models except the moving average model. The cointegration model also outperforms all the models except the moving average in terms of the number or percentage of times that it correctly predicts the direction of the stock market.

## **8.5 Conclusion**

The cointegration model of the South African stock market developed in this study made a contribution to the literature by establishing the factors that determine the level of the stock market in both the long-run and the short run, while capturing stock market asymmetry. The model can also be used to forecast the stock market. This will enable investors and policy makers to simulate the impact of changes in macroeconomic indicators on the future course of the stock market and accurate forecasts of the stock market could be used by economists to forecast other macroeconomic indicators that lag the stock market such as consumption and investment. In addition, forecasts of the stock market will predict the future direction of share prices and can hence be used by investors to construct profitable trading rules.

A suggestion for further research is to employ different approaches and techniques to capture stock market asymmetry. In this study, a linear cointegration relationship was established and the asymmetry was captured in the ECM by allowing different speeds of adjustment to equilibrium. In addition, tests for threshold cointegration indicated that the speed of adjustment is symmetric with respect to the direction of the stock

market and whether the stock market is over- or undervalued. These results were obtained with quarterly data and one suggestion for further research is to determine whether the results differ with higher frequency data. As explained earlier (see section 6.1), the characteristics and behavior of stock prices have been found to differ substantially for high and low frequency data. Another suggestion for further research is to employ some of the newly developed non-linear cointegration techniques to test for nonlinearities in share prices. A final suggestion for extending this study is to model the error correction model with the Markov switching regime technique in order to allow the speed of adjustment to switch between two states. In this study the speed of adjustment was restricted to differ only based on the state of the business cycle, the under- or overvaluation of the stock market and the direction of the stock market. By employing a Markov switching regime model, the two (or more) states of the speed of adjustment term will be unrestricted and determined by the data instead of being imposed by the researcher.



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## APPENDIX 1

### PREDICTING TURNING POINTS IN THE SOUTH AFRICAN ECONOMY

#### A1.1 INTRODUCTION

Following the recent trend in the literature, the term structure was used as explanatory variable in the Markov switching regime model of the South African business cycle (see chapter five). Theoretically the term structure can be used as leading indicator of turning points in the economy, but it has to be established whether it is superior to other indicators in practice as well. The appendix is organized as follows: The next section gives a brief overview of the relevant literature. Section A1.3 describes the econometric technique, and section A1.4 describes the leading indicators used in the empirical analysis. Section A1.5 presents the results of the empirical analysis, while section A1.6 provides the conclusion.

#### A1.2 LITERATURE REVIEW

Estrella and Mishkin (1998) compared the performance of various financial variables, including four term structures of interest rates, stock prices, monetary aggregates, indices of leading indicators and other economic variables such as GDP, CPI and exchange rates, as predictors of US recessions. They estimated probit models with quarterly data for the period 1959 to 1995, and evaluated the performance of the leading indicators by using the pseudo- $R^2$  value developed for dichotomous models by Estrella (1998). Their results indicated that the interest rate spread outperforms the other indicators for forecasting beyond one quarter ahead. They also tested the performance of all the possible models that includes both the interest rate spread and one other indicator as explanatory variables.

Several studies confirmed the result of Estrella and Mishkin (1998) that the interest rate spread is successful with predicting business cycle turning points. Estrella and Hardouvelis (1991) were the first to empirically analyze the term structure as a

predictor of real economic activity. Regressions of future GNP growth on the slope of the yield curve and other information variables showed that a steeper (flatter) slope implies faster (slower) future growth in real output. The forecasting accuracy in predicting cumulative changes is highest 5 to 7 quarters ahead. In addition, they also used a probit model to analyze the predictive power of the term structure on a binary variable that simply indicates the presence or absence of a recession.

Bernard and Gerlach (1996) tested the ability of both the domestic and foreign term structures to predict business cycle turning points in eight industrial countries for the period 1972 to 1993. Using probit models, they show that the domestic term spreads are statistically significant in explaining business cycle turning points in all eight countries. The period over which the domestic term spread successfully forecasts the turning points vary across countries, but the optimal forecast period ranges from two to five quarters. Nel (1996) studied the relationship between the term structure of interest rates and the South African business cycle. He found that they were cointegrated, in other words a contemporaneous relationship, despite a poor overall fit.

Cook and Smith (2001) assessed the effectiveness of transplanting a forecasting method based on a probabilistic approach in the South African context. They tested the ability of some of the components of the composite index of leading indicators to predict both the official Reserve Bank turning points as well as the mechanistic turning points of the composite index of coincident indicators. This is done by estimating a probit model with all the chosen leading indicators simultaneously as explanatory variables. Their results indicate an ability of the model to accurately forecast business cycle turning points in the 1980s. However, in the 1990s, the model displays a diminished capacity to forecast the turning points. The present analysis differs from their study in several ways. Instead of evaluating the joint performance of the leading indicators, we are evaluating the performance of the leading indicators individually to find the individual leading indicator that most accurately predicts business cycle turning points. Methodologically, we use the pseudo  $R^2$  developed by Estrella (1998) for models with dichotomous dependent variables to evaluate the models, unlike their qualitative evaluation.

### A1.3 THE TECHNIQUES

#### A1.3.1 The Probit Model

Several authors have used probit models to model business cycle turning points (see e.g. Estrella and Hardouvelis, 1991; Dueker, 1997; Dotsey, 1998; Estrella and Mishkin, 1998; Bernard and Gerlach, 1996). The probit form is dictated by the fact that the variable being predicted takes on only two possible values – whether the economy is in a recession or not. The model is defined in reference to a theoretical linear relationship of the form:

$$Y_{t+k}^* = \alpha + \beta * x_t + \varepsilon_t \quad (A1.1)$$

where  $Y_t^*$  is an unobserved variable that determines the occurrence of a recession at time  $t$ ,  $k$  is the length of the forecast horizon,  $\varepsilon_t$  is a normally distributed error term, and  $x_t$  the value of the explanatory variable at time  $t$ . The parameters  $\alpha$  and  $\beta$  are estimated with maximum likelihood. The observable recession indicator  $R_t$  is related to this model by

$$R_t = 1 \text{ if } Y_t^* > 0, \text{ and } 0 \text{ otherwise.} \quad (A1.2)$$

The form of the estimated equation is

$$P(R_{t+k} = 1) = F(\alpha + \beta * x_t) \quad (A1.3)$$

where  $F$  is the cumulative normal distribution function.

The model is estimated by maximum likelihood. The recession indicator is obtained from the South African Reserve Bank, that is,  $R_t = 1$  if they classify the economy to be in a downward phase at time  $t$ , and 0 otherwise (see table A1.1).

**Table A1.1 Business Cycle Phases According to SARB since 1978**

Upward phase		Downward phase	
January 1978	August 1981	September 1981	March 1983
April 1983	June 1984	July 1984	March 1986
April 1986	February 1989	March 1989	May 1993
June 1993	November 1996	December 1996	August 1999

### A1.3.2 Pseudo-R<sup>2</sup> for Models with Dichotomous Dependent Variables

Estrella (1998) developed a pseudo R<sup>2</sup> that is a simple measure of goodness of fit in the context of a dichotomous dependent variable, which corresponds intuitively to the widely used coefficient of determination (R<sup>2</sup>) in a standard linear regression<sup>1</sup>. Models for dichotomous dependent variables, such as probit and logit models, are usually estimated by maximizing the likelihood function, which is defined as:

$$L = \prod_{\{y_j=1\}} F(\beta'x_j) \prod_{\{y_j=0\}} F(1-\beta'x_j) . \quad (A1.4)$$

Let the unconstrained maximum value of the likelihood function (L) be L<sub>U</sub>, and its maximum value under the constraint that all coefficients are zero except for the constant as L<sub>C</sub>. Denote the number of observations with n. Then

<sup>1</sup> Estrella (1998) suggest the following three requirements for an R<sup>2</sup> analog for models with dichotomous dependent variables: (i) It has to be contained by the interval [0,1], where zero represents no fit and one represents a perfect fit. (ii) It has to be based on a valid test statistic for the hypothesis that all the coefficients, except the constant, are zero. (iii) Its derivative with respect to the test statistic should be consistent with the corresponding derivative in the linear case. Estrella (1998) shows that most previous measures of fit, specifically McFadden (1974), Cragg and Uhler (1970), Aldrich and Nelson (1989), Veall and Zimmermann (1992), Morisson (1972), Goldberger (1973) and Davidson and McKinnon (1993) , lacks at least one of the three abovementioned properties that an R<sup>2</sup> should have.

$$\text{Pseudo } R^2 = 1 - \left( \frac{\log(L_U)}{\log(L_C)} \right)^{-(2/n)\text{Log}(L_C)} . \quad (\text{A1.5})$$

The form of this function ensures that the values 0 and 1 correspond to “no fit” and “perfect fit” respectively, and that intermediate values have roughly the same interpretations as their analogues in the linear case.

Estrella’s pseudo  $R^2$  is easy to apply. First, a probit model with only a constant as explanatory variable is estimated to calculate the maximum value of the restricted likelihood function ( $L_C$ ). Next, a probit model is estimated with the appropriate number of months ahead of the explanatory variable in order to calculate the unconstrained maximum likelihood ( $L_U$ ). These two values are simply substituted into the formula of the pseudo  $R^2$ . These  $R^2$ -values are comparable, and the model with the highest is the best model.

#### **A1.4 INDICATORS EXAMINED AND DATA USED**

The primary focus of this analysis is to compare the performance of different individual economic indicators in predicting business cycle turning points. Variables such as interest rates, international indicators, stock price indices and monetary aggregates are examined. The performance of these individual indicators will also be compared with the performance of the composite index of leading indicators compiled by the South African Reserve Bank. Most of the components of the composite index of leading indicators for example share prices, money supply and the number of residential building plans passed are also tested individually.

It should be kept in mind that the objective of the composite index of leading indicators is not solely to predict the turning points of the business cycle, but also to provide information regarding the levels of economic growth. It is therefore possible that an individual indicator, even a single component of the composite index, can outperform the index in terms of predicting turning points, even though the index itself is better at predicting the course of the business cycle or the business cycle

turning points. All the variables included in the analysis are well-established leading economic indicators, and the selection is based on that of Estrella and Mishkin (1998).

Financial variables such as different stock indices are commonly associated with the expectations of future economic events. According to the dividend model of Williams (1938), stock prices are the sum of expected future dividends discounted by future interest or discounting rates. This means that stock indices are forward-looking indicators of expected economic conditions and interest rates and should therefore be good leading economic indicators. Following Estrella and Mishkin (1998), the overall stock index as well as the financial, mining and commercial share indices and the price-earnings ratio were included in the analysis.

Two monetary policy variables, namely short-term interest rates and (different definitions of) money supply, were also included in the analysis. In addition, the long-term interest rate was included since it should reflect expected future short-term interest rates according to the expectations hypothesis.

Recently the yield spread, defined as the difference between the long-term interest rate and the short-term interest rate, as leading indicator has received considerable attention in the literature (see e.g. Estrella and Hardouvelis (1991), Bernard and Gerlach (1996), and Estrella and Mishkin (1998)). Assume that the country is currently enjoying high growth, so that there is a general agreement among investors that the country is heading for a slow-down or recession in the future. Consumers want to hedge against the recession, and therefore purchase financial instruments (e.g. long-term bonds) that will deliver pay-offs during the economic slowdown. The increased demand for long-term bonds causes an increase in the price of long-term bonds, in other words a decrease in the yield on long-term bonds. In order to finance these purchases, investors sell their shorter-term assets, which results in a decline in the price of short-term assets, and an increase in the yield on short-term assets. In other words, if a recession is expected, long-term interest rates will fall and short-term interest rates will rise. Consequently, prior to the recession, the slope of the term structure of interest rates will become flat (or even inverted), which means that the yield spread declines. Similarly, long-term interest rates rises while short-term interest

**Table A1.2 List of Variables**

<b>Series</b>	<b>Description</b>	<b>Transformation Used</b>
<i>Interest Rates</i>		
RS	Short-term nominal interest rate (3 month BA rate)	
RL	Long-term nominal interest rate (10-year government bond yield)	
SPR	Yield spread, defined as the long-term minus the short-term interest rate (RL-RS)	
<i>Monetary Aggregates</i>		
M3 (RM3)	Nominal (real) M3 money supply	Year on year growth
M2 (RM2)	Nominal (real) M2 money supply	Year on year growth
M1 (RM1)	Nominal (real) M1 money supply	Year on year growth
<i>Stock Prices</i>		
JSE	All-share index	Year on year growth
FS	Financial shares	Year on year growth
MS	Mining shares	Year on year growth
CS	Commercial shares	Year on year growth
PE	Price-earnings ratio	
<i>International Indicators</i>		
NEE	Nominal effective exchange rate	Year on year growth
REE	Real effective exchange rate	Year on year growth
R\$	Rand-US\$ exchange rate	Year on year growth
US	US composite index of leading indicators	Year on year growth
TR	Composite index of leading indicators of trading partners	Year on year growth
<i>Macroeconomic Indicators</i>		
BP	Building plans passed	
INF	CPI inflation rate	
UO	Manufacturing, unfilled orders	Year on year growth
NO	Manufacturing, new orders	Year on year growth
CIL	Composite index of leading indicators	Year on year growth

rates falls when an expansion is expected, so that an upward-sloping yield curve predicts an expansion.

South Africa is a small, open economy and is therefore extremely vulnerable to changes in economies in the rest of the world, especially those of our trading partners and the dominant economies such as the US and Europe. This is increasingly the case since the early 1990s when South Africa re-entered the international economy after



economic sanctions were lifted and globalization generally increased interdependence amongst countries. This motivated the inclusion of the composite index of leading indicators of South Africa's trading partners as well as that of the US. Since South Africa is such an open economy, exchange rates have a significant influence on the performance of the economy, and since it takes time for changes in the exchange rate to affect domestic prices and hence economic growth, the exchange rate could be a leading indicator of the economy, especially when using high frequency data.

Lastly some macroeconomic indicators such as building plans passed, and unfilled and new manufacturing orders are included on the basis that they reflect the expectations of economic agents.

## **A1.5 EMPIRICAL ANALYSIS**

Monthly data for the period March 1978 to March 2001 was used in the empirical analysis. Forecasts for 1 to 18 months ahead, in other words up to a year and a half, were considered.

### **A1.5.1 Performance of Individual Leading Indicators**

The pseudo  $R^2$  developed by Estrella (1998) (see section A1.3.2) is used to compare the forecast performance of each individual leading indicator in forecasting business cycle turning points for 1 to 18 months ahead. The pseudo  $R^2$  values of the models are given in table A1.3. Three different transformations of each variable were tested, namely the series in levels, in first differenced form, and the year on year growth in the series. Only the transformation of each series that performed best is reported, the rest of the results are omitted for brevity and available from the author upon request. The transformation of each series that was used is reported in table A1.1. The highest  $R^2$  value of each series is indicated in bold print.

**Table A1.3 Pseudo R<sup>2</sup>-values of Leading Indicators**

<b>Months ahead</b>	<b>SPR</b>	<b>RL</b>	<b>R\$</b>	<b>M3</b>	<b>RM3</b>	<b>TR</b>	<b>INF</b>	<b>US</b>
1	0.409	0.158	0.231	0.008	0.083	0.017	0.016	<b>0.141</b>
2	0.478	0.160	0.266	0.010	0.077	0.023	0.016	0.131
3	0.540	<b>0.163</b>	<b>0.287</b>	0.018	0.074	0.028	0.016	0.119
4	0.587	<b>0.163</b>	0.283	0.033	0.079	0.031	0.017	0.108
5	0.618	0.162	0.268	0.059	0.091	0.033	<b>0.018</b>	0.099
6	0.635	0.160	0.253	0.087	0.108	0.037	<b>0.018</b>	0.093
7	<b>0.643</b>	0.160	0.234	0.122	0.131	0.040	0.017	0.089
8	0.627	0.160	0.214	0.155	0.158	0.043	0.016	0.082
9	0.578	0.152	0.196	0.194	0.190	0.047	0.016	0.076
10	0.536	0.144	0.173	0.238	0.230	0.052	0.015	0.071
11	0.483	0.132	0.152	0.283	0.270	0.058	0.015	0.068
12	0.424	0.118	0.134	0.340	0.324	0.065	0.014	0.066
13	0.358	0.106	0.120	0.383	0.368	0.073	0.014	0.068
14	0.297	0.096	0.116	0.421	0.406	0.079	0.013	0.071
15	0.245	0.090	0.120	0.452	0.439	0.084	0.012	0.074
16	0.203	0.088	0.131	<b>0.466</b>	0.398	0.088	0.010	0.078
17	0.172	0.087	0.148	0.452	0.446	0.091	0.009	0.082
18	0.150	0.087	0.170	0.455	<b>0.450</b>	<b>0.096</b>	0.008	0.088

Months ahead	BP	CIL	PE	UO	NEE	CS	NO	MS	FS
1	0.037	0.644	0.435	<b>0.173</b>	0.132	0.118	<b>0.340</b>	0.228	0.153
2	0.052	0.691	0.450	0.139	0.137	0.146	0.274	0.258	0.168
3	0.064	<b>0.713</b>	0.462	0.114	0.139	<b>0.159</b>	0.229	<b>0.285</b>	<b>0.180</b>
4	0.084	0.705	0.469	0.099	0.134	0.160	0.228	0.272	0.159
5	0.113	0.665	<b>0.470</b>	0.083	0.127	0.162	0.187	0.271	0.156
6	0.120	0.618	0.463	0.074	0.118	0.164	0.152	0.283	0.158
7	0.143	0.553	0.448	0.070	0.108	0.153	0.140	0.268	0.145
8	0.174	0.478	0.428	0.064	0.100	0.129	0.116	0.254	0.131
9	0.192	0.393	0.410	0.064	0.096	0.104	0.102	0.218	0.110
10	0.227	0.310	0.391	0.065	0.096	0.076	0.084	0.182	0.084
11	0.258	0.234	0.373	0.068	0.101	0.048	0.069	0.144	0.058
12	0.269	0.167	0.359	0.074	0.111	0.028	0.067	0.106	0.036
13	0.287	0.114	0.348	0.078	0.125	0.014	0.067	0.076	0.019
14	0.298	0.072	0.341	0.082	0.145	0.009	0.069	0.056	0.012
15	0.301	0.041	0.337	0.086	0.168	0.002	0.031	0.036	0.009
16	<b>0.302</b>	0.022	0.341	0.088	0.191	0.009	0.080	0.029	0.008
17	0.294	0.012	0.341	0.091	0.216	0.010	0.085	0.021	0.009
18	0.295	0.008	0.337	0.093	<b>0.241</b>	0.012	0.089	0.012	0.011

From the results in table A1.3 it is clear that the year on year change in the Reserve Bank's composite index of leading indicators leading 3 months has the highest  $R^2$  value, followed by the yield spread leading 7 months. These three models explain 71.2595 percent and 64.3182 percent respectively of the variation in the dependent variable. However, the composite index of leading indicators is only available with a four to five month lag, and is subject to revision. In other words, the optimal number of months ahead is not available in time for forecasting. The months that are available yield lower  $R^2$  values than the yield spread, which is immediately available and not subject to revision.

**A1.5.2 Probit Models**

Table A1.4 presents the results of the probit models with the composite index of leading indicators and the yield spread. Each of the models was estimated with only one explanatory variable and a constant, with the leading time chosen on the basis of the pseudo R<sup>2</sup> values in table A1.3. The parameters were estimated with maximum likelihood.

**Table A1.4 Probit Models**

<b>Explanatory variable</b>	<b>Lead (months)</b>	<b>Constant</b>	<b>Standard error</b>	<b>Coefficient</b>	<b>Standard error</b>	<b>Pseudo R<sup>2</sup></b>
SPR	7	0.246	0.107	-0.493	0.050	64%
CIL	3	0.361	0.119	-0.273	0.030	71%

The results in table A1.4 are interpreted as follows:

$$P(R_{t+7} = 1) = F(0.246 - 0.493*SPR_t) \tag{A1.6}$$

$$P(R_{t+3} = 1) = F(0.361 - 0.273*CLI_t) \tag{A1.7}$$

where F is the cumulative normal distribution, R<sub>t</sub> is a dummy variable that takes on the values one if the economy is in a recession in period t, and P(R<sub>t+i</sub> = 1) is the probability that the economy is in a recession in period t+i.

These results are consistent with *a priori* expectations. According to the results in equation A1.7 there is a negative relationship between the composite index of leading indicators and the probability of a recession, which means that an increase in the composite index of leading indicators predicts a decline in the probability of a future recession. In other words, an increase in the composite index of leading indicators

indicates a higher probability of an economic upswing, which is consistent with the construction of the composite index of leading indicators. According to equation A6 there is a negative relationship between the interest rate spread and the probability of a recession in future, which means that increases in the interest rate spread lowers the probability of a future recession. This is consistent with the theoretical relationship between the interest rate spread and economic activity, according to which the interest rate spread will decline prior to a recession (see section A1.4).

Table A1.5 Probability of a Recession Two Quarters Ahead as a Function of the Short-Term Interest Rate, the Interest Rate Spread and the Composite Index of Leading Indicators

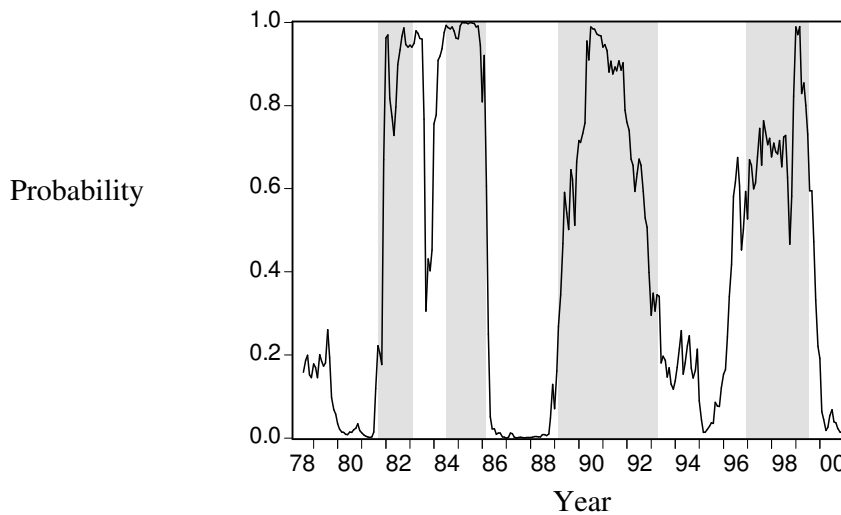
$SPR_t$	$P(R_{t+7} = 1)$	$CLI_t$	$P(R_{t+3} = 1)$
-6	1.00	-13.00	1.00
-5	1.00	-10.00	1.00
-4	0.99	-7.00	0.99
-3	0.96	-4.00	0.93
-2	0.89	-1.00	0.74
-1	0.77	2.00	0.43
0	0.60	5.00	0.16
1	0.40	8.00	0.03
2	0.23	11.00	0.00
3	0.11	14.00	0.00
4	0.04	17.00	0.00
5	0.01	20.00	0.00
6	0.00	26.00	0.00
0.499	0.5	13.322	0.5

Given these formulas, the probability of a recession associated with certain values of the explanatory variables can be calculated easily. For example, a yield spread of 0.6 percent in a certain period indicates that the probability that the economy will be in a

recession seven periods ahead is 25 percent. The recession probabilities of some of the possible values of the explanatory variables are given in table A1.5. The last row in table A1.5 presents the values of the three economic indicators associated with the probability of a recession of exactly 50 percent. In other words, values of the interest rate spread and composite index of leading indicators below that value predicts that the economy is more likely to be in a recession than an expansion seven or three months ahead respectively, while a short-term interest rate above the value predicts that the economy is more likely to be in an expansion than a recession seven months ahead.

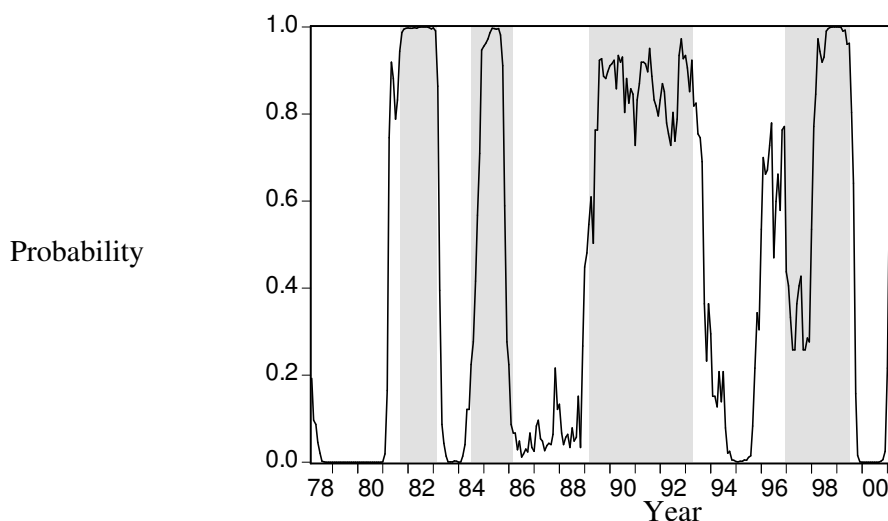
Figures A1.1 and A1.2 plot the estimated probability of a recession derived from each model. The shaded areas denote periods of actual recessions as classified by the South African Reserve Bank, and the lines indicate the probability that the economy is in a recession in that period.

**Figure A1.1 Recession Probability Predicted by Interest Rate Spread**



Source: Own calculations

**Figure A1.2 Recession Probability Predicted by Composite Index of Leading Indicators**



Source: Own calculations

The lines in figures A1.1 and A1.2 represent the probability that the economy will be in a recession in a particular period as calculated by the three different probit models using the interest rate spread and the composite index of leading indicators respectively as explanatory variables. If the probability of a recession is greater (lower) than 50 percent, it will be regarded as a predicted recession (expansion). These predicted recessions can be compared with the official dates of the South African Reserve Bank presented by the shaded areas. For example, the composite index of leading indicators predicted a recession early in 1981 (when the probability of a recession exceeded 50 percent) compared with the actual recession that occurred at the end of 1981.

None of the two models missed any cycle. However, the model with the composite index of leading indicators gave a false signal of a downswing in January 1996 and an upswing in January 1997. In addition, the model with the composite index of leading indicators gave a false signal of a downswing in January 2001. In general, all three models performed fairly well. The model with the yield spread seems to have performed somewhat worse at the beginning of the sample with the 1983-1984 upswing, while they performed quite well for the rest of the period. On the other hand,

the performance of the model with the composite index of leading indicators seemed to have deteriorated over the sample period.

The deteriorating performance of the composite index and the improving performance of the interest rate model might be the result of important structural change in the economy. And, unlike the composite index, neither of the interest rate models gave any false signals. In addition, the optimal forecast period of the yield spread model is seven months compared to three months in the case of the composite index, and the interest rate variables are available in time and are not revised. Therefore, the yield spread model is preferred to the model with the composite index of leading indicators.

#### **A1.6 CONCLUSION**

The objective of this analysis was to compare the performances of difference leading indicators in terms of predicting turning points of the South African business cycle. The pseudo  $R^2$  indicated that two best individual indicators are the yield spread and the composite index of leading indicators compiled by the South African Reserve Bank. They led the turning points with seven and three months respectively. A close inspection of the probit models of these two individual indicators as explanatory variables indicated that the yield spread model is preferred to the model with the composite index. Data availability is better in the case of the yield spread, and unlike the composite index, it did not give any false signals. In general, the yield spread model's performance seemed to have improved over the course of the sample period, while the performance of the composite index seemed to have deteriorated over the course of the sample period. Performance at the end of the sample is obviously more important for forecasting purposes, but these trends might also be reflecting an underlying structural change in the economy, which makes the interest rate models even more desirable since it seems as if they are better at predicting the new structure than the composite index.



APPENDIX 2

MODEL EVALUATION FOR DIFFERENT LOSS FUNCTIONS

A2.1 INTRODUCTION

In chapter seven the forecasting and modeling accuracy of different stock market models were compared using the RMSE, RMSPE and Theil's inequality coefficient U. In addition, the sign and signed rank tests of Diebold and Mariano (1995) for testing whether the forecasting accuracy of two models are statistically different, were used. These tests require that a loss function be specified. In chapter seven the results of these tests are presented for loss functions that minimize the error terms and the squared error terms. In addition, asymmetric linex loss functions were used since the theory presented in chapter three suggested that investors may behave asymmetrically. The linex loss function is specified as follows:

$$g(e_t) = \frac{\beta}{\alpha^2} \{ \exp(\alpha e_t) + \alpha e_t - 1 \} \quad (A2.1)$$

where  $e$  is the error term of the estimated model. The parameter  $\alpha$  determines the degree of asymmetry. If  $\alpha > 0$ , then the losses are approximately linear for negative error terms and approximately exponential for positive error terms. By defining the error ( $e$ ) as the actual value less the simulated value, positive values of  $\alpha$  corresponds to the case in which underpredictions are more costly than overpredictions. Negative values, on the other hand, corresponds to the case where the function is exponential to the left of the origin and linear to the right. Furthermore, the closer  $\alpha$  is to zero, the closer the function approximates the standard quadratic case.

As explained in chapter six, overpredictions are more dangerous to investors than underpredictions, and therefore negative values of  $\alpha$  are used in this study so that overpredictions are more costly than underpredictions. In chapter seven the results of

the sign test<sup>2</sup> was already given for different negative values of  $\alpha$ , which are consistent with the case where overpredictions are more costly than underpredictions. In this appendix, the results will be presented for different positive values of  $\alpha$ , in other words where overpredictions are less costly than underpredictions. In addition, the influence of different values of  $\beta$  on the results will also be illustrated.

## A2.2 ESTIMATION RESULTS

In tables A2.1 and A2.2 the models are compared for the sample and forecast periods respectively using the sign test with linex loss functions with different positive values of  $\alpha$ . In other words, overpredictions are assumed to be less costly than underpredictions<sup>3</sup>. The null hypothesis of equal modeling accuracy of the random walk and cointegration models during the sample period is rejected for all the loss functions except the first two, which are the closest to being symmetric loss functions. In none of the cases is the null hypothesis of equal forecast accuracy rejected for any pair of models. In other words, using loss functions for which overpredictions are assumed to be less costly than underpredictions, the only statistically significant difference in accuracy is between the random walk and the cointegration model during the sample period.

According to the results in table A2.2, the null hypothesis of equal forecasting accuracy is not rejected for any pair of models. The results in table A2.3 illustrate the impact of the parameter  $\beta$  in the linex loss function (see equation A2.1). According to these results  $\beta$  does not influence the conclusion of the sign test since the outcome remains constant for a given value of  $\alpha$ .

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<sup>2</sup> The signed rank test requires a symmetric loss function and is hence not relevant in this case.

<sup>3</sup> Theoretically overpredictions will be more costly to investors than underpredictions (see chapter seven). The comparisons of the models have been presented in chapter seven. However, the counter-intuitive counterpart, where overpredictions are less costly than underpredictions, are presented in this appendix for completeness.

**Table A2.1 Equal Accuracy Tests for Modelling Performance with Different  $\alpha$**

$\alpha$	0.1	0.5	1	1.5	2	3	4	10
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	1.48	1.69	2.9*	2.7*	3.2*	2.9*	2.7*	2.7*
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$								
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	1.05	1.26	1.26	1.26	1.26	1.26	1.26	1.48
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt}))\neq 0$								
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	-0.6	-1.5	-1.9	-1.7	-1.5	-1.9	-2.1	-2.1
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt}))\neq 0$								

\* Significant on a 10% level of significance.

**Table A2.2 Equal Forecast Accuracy Tests with Different  $\alpha$**

$\alpha$	0.1	0.5	1	1.5	2	3	4	10	15
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	4	3	3	3	3	3	3	3	3
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$									
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	4	4	4	4	4	4	5	5	5
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt}))\neq 0$									
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	3	4	4	4	4	4	4	4	4
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt}))\neq 0$									

\* Significant on a 10% level of significance.

**Table A2.3 Equal Modelling Accuracy Tests with Different  $\beta$**

$\beta$	0.1	0.5	1	2	4	10	100
	$\alpha=1$						
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	2.6*	2.6*	2.6*	2.6*	2.6*	2.6*	2.6*
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$							
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	1.26	1.26	1.26	1.26	1.26	1.26	1.26
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt})) \neq 0$							
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	-1.9	-1.9	-1.9	-1.9	-1.9	-1.9	-1.9
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt})) \neq 0$							
	$\alpha=-1$						
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	-1.48	-1.48	-1.48	-1.48	-1.48	-1.48	-1.48
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$							
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	1.05	1.05	1.05	1.05	1.05	1.05	1.05
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt})) \neq 0$							
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	1.26	1.26	1.26	1.26	1.26	1.26	1.26
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt})) \neq 0$							
	$\alpha=2$						
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	3.2*	3.2*	3.2*	3.2*	3.2*	3.2*	3.2*
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$							
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	1.26	1.26	1.26	1.26	1.26	1.26	1.26
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt})) \neq 0$							
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt})) \neq 0$							
	$\alpha=-2$						
$H_0: \text{med}(g(e_{Rt})-g(e_{Ct}))=0$	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5	-1.5
$H_A: \text{med}(g(e_{Rt})-g(e_{Ct}))\neq 0$							
$H_0: \text{med}(g(e_{Rt})-g(e_{Vt}))=0$	0.84	0.84	0.84	0.84	0.84	0.84	0.84
$H_A: \text{med}(g(e_{Rt})-g(e_{Vt})) \neq 0$							
$H_0: \text{med}(g(e_{Ct})-g(e_{Vt}))=0$	1.90	1.90	1.90	1.90	1.90	1.90	1.90
$H_A: \text{med}(g(e_{Ct})-g(e_{Vt})) \neq 0$							

### A2.3 CONCLUSION

In this appendix the null hypothesis of equal forecasting accuracy was tested using the sign test suggested by Diebold and Mariano (1995). An asymmetric linex loss function was used. The influence of the parameter  $\beta$  in the linex function was shown to be insignificant. In addition, the case in which underpredictions of the stock market is more costly than overpredictions was illustrated. The results showed that the null hypothesis of equal modeling accuracy of the random walk and cointegration models during the sample period is rejected for all the loss functions except the first two, which are the closest to being symmetric loss functions. In all the other cases the models are equally accurate. In other words, using loss functions for which overpredictions are assumed to be less costly than underpredictions, the only statistically significant difference in accuracy is between the random walk and the cointegration model during the sample period. All the models are equally accurate in forecasting the stock market when overpredictions are less costly than underpredictions.