

THE SOUTH AFRICAN YIELD CURVE AS A PREDICTOR OF ECONOMIC DOWNTURNS: AN UPDATE

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Abstract

This study reexamines the yield curve's forecasting abilities in South Africa and investigates its ability to predict the economic downturn of 2008/09. The simple and modified probit models are used to examine the yield curve's ability to forecast economic downturns. This is compared to the forecasting abilities of the JSE All Share Index, the SA Reserve Bank's leading economic indicator and M3 money supply. The yield spread was successfully able to predict the 2008/09 downturn and is better than any of the other variables at predicting all the downturns since 1980. The best forecast is found to be 2 quarters ahead. This indicates that the yield spread is still a powerful forecasting tool for predicting economic downturns in South Africa.

1. INTRODUCTION

THE TERM STRUCTURE OF INTEREST RATES, also known as the yield curve, refers to the relationship between the yields on bonds with different terms to maturity (Bain and Howells, 2008:336). Extensive research has been conducted on the relationship between the yields on different financial instruments and their term to maturity. The yield curve makes use of the return or yield spread on long- and short-term securities differentiated solely by their term to maturity (Estrella and Truben, 2006:1). In South Africa the yield curve is generally constructed by comparing the yields offered on 91-day Treasury Bills (short-term) and 10 year government bonds (long-term) (Nel, 1996, Moolman, 2002 and Aziakpono and Khomo, 2007). The importance of the yield curve is its link with real economic activity and the use of this relationship as a potential forecasting tool for future economic activity (Aziakpono and Khomo, 2007:194-195).

According to Cohen (2006:60) interest in the yield curve was shown as early as 1913 by Mitchell (1913) who investigated the business cycle, but it was Kessel (1965) who first focused specifically on the behaviour of the term spread across the business cycle. The perceived relationship between the business cycle and the term structure of interest rates provides the basis for the latter's use as a forecasting tool for predicting future economic activity.

Aziakpono and Khomo (2007) examined the yield curve's predictive powers from 1980 to 2004 in South Africa and found that although the yield curve successfully predicted the four economic downswings that occurred over this period it falsely predicted a downswing in 2002/03. In this last period the yield curve signalled an 84% probability of a downswing which never occurred.

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Studies conducted by Dombrosky and Haubrich (1996) and Estrella and Mishkin (1997) had already begun to notice a deterioration in the yield curve's forecasting abilities in the US and in some European countries prior to 2000. The deterioration of the yield curve's forecasting abilities in some major economies and the false prediction of a downturn in South Africa in 2002/03 has led to a loss of confidence in its forecasting abilities. The 2008/09 downturn in the South African economy provides an opportunity to test whether the yield curve had forecast an occurrence of a downswing which, along with the global crisis that precipitated it, seemingly took most economic analysts by surprise.

The rest of this paper is structured as follows: section 2 provides an overview of literature on the yield curve and its ability to forecast economic downswings. Section 3 provides the data used in the study including other economic indicators and section 4 sets out the methodology used. Section 5 presents and discusses the empirical results and section 6 concludes by discussing the implications of the findings for investors and policymakers.

2. LITERATURE REVIEW

Definition

The yield curve reflects the rates of return offered on both long- and short-term securities. More specifically it reflects the yield spread between long- and short-term securities - generally government issued bonds of different maturities (Estrella and Truben, 2006:1). In South Africa the yield curve is generally constructed by comparing the yields offered on 91-day Treasury Bills and 10 year Government Bonds (Nel, 1996, Moolman, 2002 and Aziakpono and Khomo, 2007).

An economy is generally characterized by higher long-term rates relative to short-term interest rates which is considered "normal" and reflects the higher-risk premium which investors usually demand on long-term securities (Bonga-Bonga, 2009:4; Nel, 1996:162). An economy characterized by low short-term rates is considered to be a "growth economy" where the lower interest rates on loans and credit aim to stimulate demand for borrowing within the economy for investment and consumption purposes.

However, an economy in which demand is fuelled by debt can become overheated causing inflation to rise. In this situation low short-term rates are no longer desirable and the expectation that the monetary authorities will increase short-term rates in the near future is reflected in rising short-term bond yields. High short-term rates are generally associated with slow growth or even negative growth and an economy can fall into recession. When the yields on long-term financial instruments are lower than the yields on short-term financial instruments the yield curve is negative or inverted and this is generally seen as a precursor to an economic downswing. When short-term rates are very high relative to long-term rates an economy may be in recession. It is then likely that in an attempt to stimulate the economy the monetary authorities will lower short-term rates in the future, thereby boosting investment and consumer spending.

When the yields on short-term and long-term financial instruments are equal the yield curve will be flat. A flat yield curve can occur when an economy is coming out of a recession and short-term rates begin to rise relative to long-term rates in

anticipation that the monetary authorities will start to raise the policy rate. A flat yield curve can also occur when short-term rates fall in anticipation of the monetary authorities cutting rates.

The yield curve can also change as a result of changes on long-term yields as a result of changed expectations about future inflation and future short-term yields.

Theory

According to Mishkin (2007:135) a theory of the term structure of interest rates should explain three features of the yield curve. These are: how interest rates on bonds with different terms to maturity move together over time; how and why the yield curve is normally upward sloping; and how during periods of low short-term interest rates the yield curve is upward sloping, but when short-term interest rates are high the yield curve is likely to become downward sloping or inverted. There are three accepted theories which attempt to explain the term structure of interest rates.

The first is the expectations hypothesis, which is able to explain how interest rates on bonds with different maturities move over time and how the yield curve is likely to become inverted when short-term interest rates are high. According to Mishkin (2007:136) the expectations hypothesis states that “the interest rate on a long-term bond will equal an average of the short-term interest rates that people expect to occur over the life of the long-term bond”. The idea is that an investor can choose between holding a long-term bond with a set term-to-maturity and long-term interest rate or hold a succession of short-term bonds. However, interest rates on short-term bonds are known only for the first period. Interest rates for the subsequent years can only be speculated upon. Long-term rates therefore reflect investors’ expectations about what future rates will be.

The second theory is the segmented markets theory, which is only able to explain why the yield curve is usually upward sloping. The segmented market theory assumes that financial instruments with different maturities are not perfect substitutes (Bonga-Bonga, 2009:2) and that there are therefore separate markets for financial instruments with different maturities (Mishkin, 2007: 139). The interest rates for these securities are determined independently of each other and are driven primarily by supply and demand forces unique to the market for those particular securities and maturities, with the assumption that investors are unwilling to shift from one maturity sector to another (Cohen, 2006:60). The determination of interest rates for securities within particular market segments has no influence on interest rates in other market segments and there is no affect from investors’ expectations about the possible returns on other assets with different maturities (Mishkin, 1999:142). The existence of separate markets for financial assets with different maturities is due to investors and issuers having specific but fixed maturity preferences driven by the nature of their liabilities.

The inability of the expectations hypothesis and the segmented market theory to explain all three features set out by Mishkin (2007:135) has led to a combined theory known as the liquidity premium theory. The liquidity premium theory (and the closely related preferred habitat theory) states (like the expectations hypothesis) that the interest rate paid on long-term bonds is equal to the average interest rate paid on short-term bonds over the life-time of the long-term bond. However, in

addition to this interest rate, investors require a premium to encourage them to purchase long-term securities. This premium contains a risk premium which is dependent on the degree of capital risk aversion in the market and the residual maturity of the bond on which it is paid (Bain and Howells, 2008:342; Mishkin, 2007:140-141).

Forecasting abilities

According to Moneta (2003:10) there has historically been a positive relationship between the yield curve and economic growth. An upward sloping yield curve is associated with an increase in real economic activity while a downward sloping yield curve is associated with a decrease in real economic activity (Aziakpono and Khomo, 2007:198). There are theoretical explanations of this relationship between the slope of the yield curve and future changes in real economic activity (Estrella and Trubin, 2006:2).

The market expectations theory (based on the expectations theory above) assumes that long-term rates represent an average of future expected short-term rates (Moolman, 2002:44). The monetary authority's ability to change short-term rates influences market participant's expectations about future short-term rates and consequently also long-term rates (Aziakpono and Khomo, 2007:198). If investors anticipate a future economic downturn or recession, they expect future short-term rates to fall as the monetary authorities attempt to stimulate the economy. Depending on the expected magnitude and duration of the downturn, the yield curve would move downwards in response but would also be downward sloping. Conversely, a future economic expansion would be reflected in investors' beliefs that future short-term rates will increase and the yield curve will be upward sloping (Moneta, 2003:10).

Thus, while the central bank can only directly influence short-term rates through changes in the policy rate, such changes directly influence investors' expectations about future short-term rates and consequently also long-term rates. The way market participants form their expectations about the nature of future interest rates determines the slope of the yield curve (Aziakpono and Khomo, 2007:199). An increase in short-term rates is seen to be only temporary. Thus long term rates rise, but by lesser amount than the current change, leading to a downward sloping yield curve (Moneta, 2003:11).

The investor hedging theory assumes that individuals prefer steady levels of income over the business cycle to higher levels of income during periods of economic expansion and lower income during periods of contraction (Moneta, 2003:11). In anticipation of a period of rapid economic expansion, when short-term rates are expected to increase, investors will attempt to purchase short-term bonds, financing their purchases by selling long-term bonds. When investors anticipate a recession, short-term rates are expected to decrease, so they will invest in long-term bonds, financing their purchases by selling short-term bonds. This shift between short-term and long-term bonds during recessionary and expansionary stages changes the prices and yields of bonds, changing the slope of the yield curve. The yield curve steepens in periods of rapid expansion and may invert during economic downturns. (Moneta, 2003:11).

Both these theories suggest that the yield curve will be positive in times of economic expansion and negative in times of economic weakness or recession. A change in the yield curve from a “normal” positive slope to a negative slope is therefore seen to predict an economic downturn or recession.

Mishkin (2007: 142-143) concludes: “A steeply rising yield curve... indicates that short-term interest rates are expected to rise in the future. A moderately steep yield curve... indicates that short-term interest rates are not expected to rise or fall much in the future. A flat yield curve... indicates that short-term interest rates are expected to fall moderately in the future. Finally, an inverted yield curve... indicates that short-term interest rates are expected to fall sharply in the future.”

3. EMPIRICAL EVIDENCE

Estrella and Hardouvelis (1991) and Estrella and Mishkin (1996) tested the predictive powers of the yield curve for the US using data from 1955:Q1 to 1988:Q4 and 1960:Q1 to 1995:Q4 respectively. These authors were able to verify the forecasting ability of the yield curve, establishing a positive relationship between the term structure of interest rates and economic activity. Estrella and Mishkin (1996:4) also compared the predictive power of the yield curve with other leading economic indicators, including the New York Stock Exchange (NYSE) stock price index, and found that the NYSE stock price index and the yield curve successfully predicted the recession in 1990-91 four quarters ahead, significantly better than other leading economic indicators. The yield curve was also able to predict the recessions of 1973-75, 1980 and 1981-82, but to a lesser extent than other indicators such as the Stock-Watson index.

Estrella and Trubin (2006) used data from 1968:Q1 to 2006Q2 and found that for each of the six recessions in the US short-term rates rose above long-term rates producing an inverted yield curve. Dombrosky and Haubrich (1996) examined the predictive powers of the yield curve for the US from 1961:Q1 to 1995:Q3 and found that the yield curve provides one of the best forecasting tools of economic activity four quarters into the future. Dombrosky and Haubrich (1996) however found that in the last decade of the study (1985-1995) the yield curve was one of the worst forecasting tools - suggesting that the relationship between the yield curve and real economic activity was changing.

Research in Europe confirmed the predictive power of the yield curve demonstrated in the US. Estrella and Mishkin (1997) also analyzed the predictive power of the yield spread in France, Italy, Germany and the UK from 1973:Q1 to 1994:Q4 and found that the yield curve significantly predicted real economic activity four to eight quarters ahead. Moneta (2003) found that in France, Germany, and Italy over the period 1970:Q1 to 2002:Q2, the yield curve’s forecasting power was strong in the 1970’s and 1980’s, but less so in the 1990’s. These findings of the diminishing predictive powers of the yield curve correspond to the finding of Dombrosky and Haubrich (1996) for the United States.

Chinn and Kucko (2009) analyzed the predictive power of the yield curve across various countries, including France, Canada, Italy, Germany, Japan, Sweden, Netherlands, UK and the US, from 1970 to 2008. They found that yield spreads contain significant predictive power when forecasting industrial production growth

over a one-year time horizon (Chinn and Kucko, 2009:18). However, they also found evidence that the predictive power of the yield curve seemed to be declining over time, although there are some exceptions.

In South Africa, Nel (1996) using data from 1974:Q1 to 1993:Q4 concluded that the yield curve in South Africa was positively related to growth in real economic activity and that the term structure is also an indicator of current and expected monetary policy. Moolman (2002) using data from 1979:Q1 to 2001:Q3 also found that the yield curve contains information about future real economic activity and that the probability of a recession in a specific quarter is a negative function of the yield spread. According to Moolman (2002) the yield curve is able to successfully predict turning points in the business cycle two quarters ahead, which seems to be quite short when compared to the perceived four to eight quarters in the US.

Aziakpono and Khomo (2007) covered the period from 1980:Q1 to 2004:Q2. Their findings support those of Nel (1996) and Moolman (2002) that the yield curve can be used to forecast future recessions in South Africa. Aziakpono and Khomo (2007) found that the yield spread is able to forecasts recessions up to six quarters ahead but, like Moolman (2002), found that it works best two quarters ahead. However, they also found that the yield curve falsely predicted a recession in 2002/03 which suggested that the yield curve might also be losing its predictive powers in South Africa.

Positive evidence about the historical relationship between the yield curve and economic activity globally and in South Africa, as well as the more recent evidence of its declining predictive value suggest that an updated study of the yield curve in South Africa will be valuable. It will determine whether the yield curve retains its predictive value in the South African context and, therefore, whether it continues to be a beneficial tool to policy makers and investors.

4. DATA

The South African Reserve Bank (SARB) Quarterly Bulletins publish dates for the turning points between upward and downward phases of the business cycle in South Africa since 1946. The SARB uses various methods in order to determine the upper and lower turning points of the business cycle as well as the duration of each phase (Venter and Pretorius, 2001: 63).

The methods used by the SARB however, are used specifically to classify the beginning of “downswings” (or “upswings”) in the business cycle not actual “recessions”. An economic downswing is considered to be an overall reduction in economic activity whereas a recession is often defined as two consecutive quarters of negative real GDP growth. In SA four of the past five economic downswings have also been recessions in the sense of two consecutive quarters of negative growth. The exception is the 1998 downturn when real GDP fell in only one quarter. The most recent downturn saw 4 consecutive quarters of negative real GDP growth all of which were in 2009. In all the other downturns negative growth occurred only late into the actual downswing period.

For the purpose of this study the SARB’s classification of the economic downswings and upswings in SA will suffice. *Table 1* presents data on the phases of

the business cycle for SA from the early 1980's to 2010 and the duration of each phase. Since 1980 the South African economy has been through five downswings.

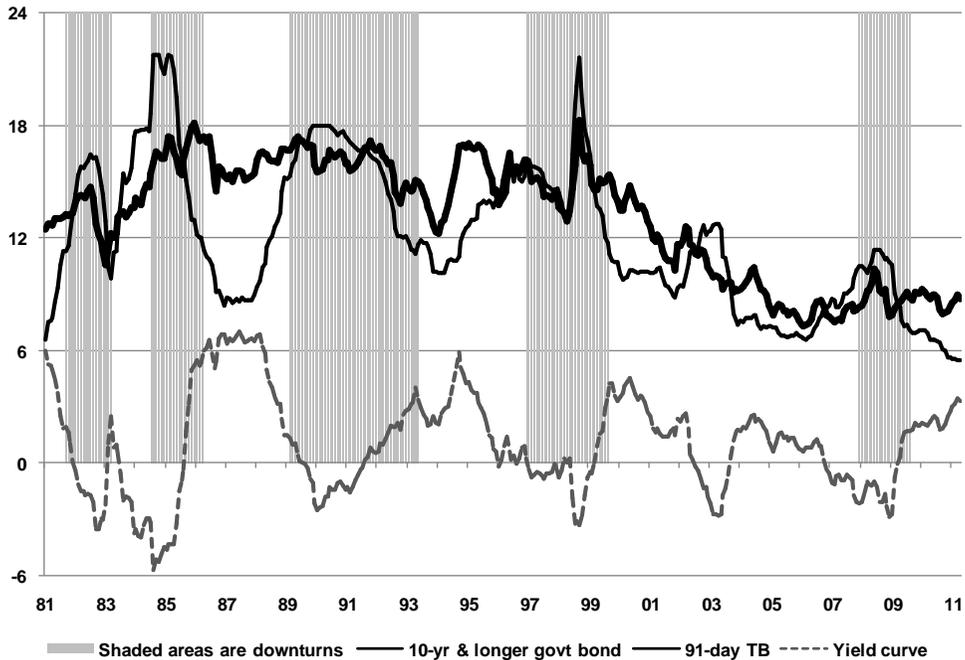
Table 1. Business Cycle Phases of South Africa 1981-2011

Cycle	Downward Phase	Length (Months)	Upward Phase	Length (Months)
1	Sept 81 - March 83	19	April 83 - June 1984	15
2	July 84 - March 86	21	April 86 - February 89	35
3	March 89 - May 93	51	June 93 - November 96	42
4	December 96 - August 99	33	September 99 - November 07	99
5	December 07 - August 09	21	September 09 -	

Source: SA Reserve Bank Quarterly Bulletin, June 2011

In order to determine the power of the yield curve to predict economic downturns, monthly data on 91-day Treasury Bill yields and the yields on long-term government bonds (10 years and over) were taken from the SARB's online database for the period January 1981 to April 2010 (SARB, 2010). 91-day Treasury Bill yields are weekly data and were converted to monthly data by taking the average of the weekly data for the month. By subtracting 91-day treasury bills from 10 year and over government bond yields, the SA yield curve was constructed from 1981 to 2010. The relationship between the South African yield curve and the business cycle is illustrated in *Figure 1*. It shows that since 1980 the yield curve has become inverted prior to or during all five downswings including the latest downswing. In addition the yield curve was negative in 2002/03, falsely predicting that an economic downswing would occur. This led many to believe the yield curve had lost its forecasting abilities (Aziakpono and Khomo, 2007:208).

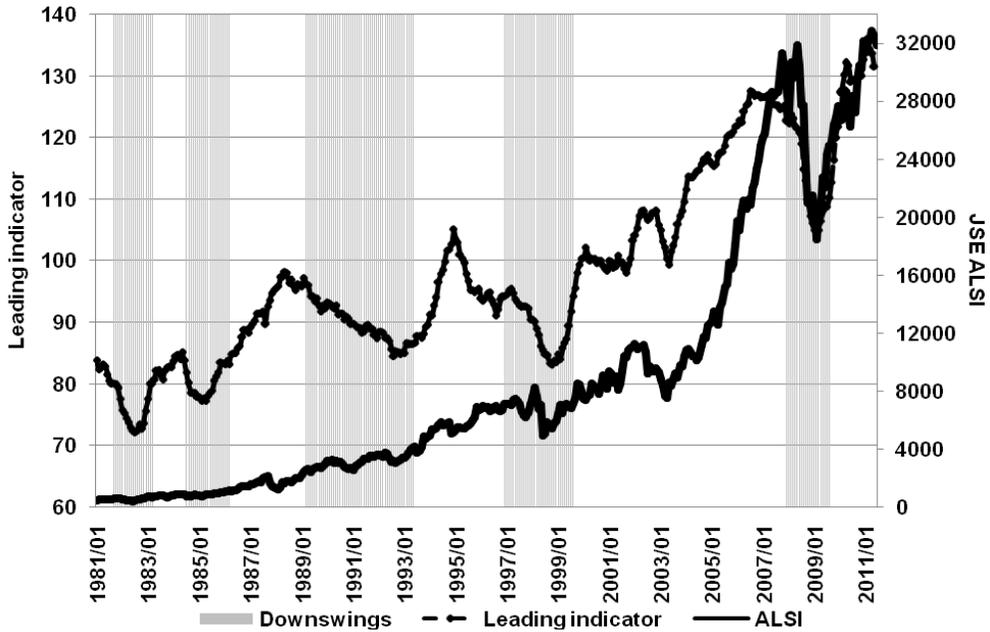
Figure 1: 91-day TB & 10-year & longer government bonds & yield curve
(Yield Curve is 10 year & longer government bond yield minus 91-day TB)



In addition to the yield curve, other variables have also been included to determine whether any of these variables were better able than the yield curve to predict downswings including the latest downswing. The variables chosen are money supply (M3), the leading economic indicator provided by the SARB (LEI) and the JSE All Share Index (ALSI). Data on M3 and LEI were also taken from the SARB's online database, while data on the JSE ALSI was taken from the JSE database. *Figure 2* shows the relationships between the leading economic indicator and the JSE All share Index and the South African business cycle.

By definition the leading economic indicator (LEI) is expected to predict economic downswings. During the five downswing phases since 1980 the LEI always declined. *Figure 2* shows that in four of the five downswing phases the LEI had declined slightly prior to the actual downswing and in all five began increasing mid-way through the downswing phases in anticipation of the subsequent upswing. In 1995 the LEI declined significantly and then increased slightly towards the end of 1997 just before the 1998/99 downswing actually began. The LEI, like the yield curve, also falsely predicted a downswing in 2002/03. It is also evident that the LEI may not offer much advance warning of a downswing, as it did not decline significantly prior to the start each downswing.

Figure 2: JSE All Share Index & Reserve Bank Leading Indicator



The JSE ALSI and M3 show very little relationship with the SA business cycle suggesting that these variables are not very useful as forecasting tools.

5. METHODOLOGY

In order to predict future turning points in the business cycle there are two methods which can be used. The first method involves estimating future levels of GDP by running a multi-variable regression using past GDP growth rates, past growth rates of leading economic indices, the yield spread and past yields on 91-day treasury bills and 10 year and over government bonds (Filardo, 1999:39). This method would indicate a high likelihood of a recession occurring by forecasting two consecutive quarterly declines in GDP. However, this type of forecasting method can have large forecasting errors due to the large sampling size and can therefore be unreliable as a forecasting tool (Khomo and Aziakpono, 2007:202-203).

Estrella and Hardouvelis (1991) developed a second method of forecasting turning points in the business cycle. This method involves estimating a non-linear probit model to predict the probability of a downswing occurring using the yield spread. This is the method used by Estrella and Mishkin (1996), Dueker (1997), Estrella and Mishkin (1997), Moolman (2002), Estrella and Trubin (2006), Aziakpono and Khomo (2007) and Chinn and Kucko (2009). The dependent variable in the probit model is a binary dummy variable which can take on only two possible values for upswings and downswings.

Estrella and Hardouvelis (1991:562) suggest that the yield curve may be a predictor of a binary variable R_t which indicates that there is a good chance of a

recession/downswing occurring if $R_t = 1$ and if $R_t = 0$ there is a good chance that a recession/downswing will not occur. The standard linear regression model can be stated as:

$$R_t = \alpha + \beta X_{t-k} + \varepsilon_t \quad (1)$$

where R_t represents the unobserved dependent variable which determines the likelihood of a recession/downswing occurring at time t . The explanatory variable (X_{t-k}) represents the slope of the yield curve lagged at $t-k$, k representing the lag length required for the yield spread to become a predictor of downswings that will occur several months ahead. The parameters α and β are estimated with maximum likelihood, β denotes the standard cumulative distribution function and ε_t is a normally distributed error term. This model is used to relate the probability of a downswing in SA to the slope of the yield curve (Aziakpono and Khomo, 2007:203).

The SARB's classification of the SA business cycle is used to assign each downswing to $R_t = 1$ and each upswing to $R_t = 0$. The probit model is then used to relate the probabilities of a downswing occurring at time t , forecast k periods ahead, to the slope of the yield curve. This is given by the following probit model:

$$\Pr(R_t = 1) = F(\alpha + \beta X_{t-k}) \quad (2)$$

where $\Pr(R_t = 1)$ represents the probability that a downswing will occur conditional upon the observed value of the explanatory variable X lagged k periods ahead. F is the cumulative normal distribution and the parameters α and β are estimated by maximizing the log-likelihood function (Atta-Mensah and Thacz, 1998:5 in Aziakpono and Khomo, 2007:204).

In the simple probit model the error terms are assumed to be independent and evenly distributed around the mean of zero. Dueker (1997:45) has pointed out that this assumption is not plausible since for time series data the error terms may be highly correlated. This has led to the development of the modified probit model which involves adding a lag of the dependent variable to the simple probit model in order to remove the serial correlation that may exist between the error terms. By adding a lagged dependent variable it increases the validity of the assumption that the error term has a mean of zero. The modified probit model can be written as:

$$\Pr(R_t = 1) = F(\alpha + \beta X_{t-k} + \beta_2 R_{t-k}) \quad (3)$$

where R_{t-k} is the lagged dependent variable and β_2 is the lag coefficient. When comparing the goodness of fit for non-linear models the usual R^2 and adjusted R^2 is no longer a suitable measure. Estrella (1996) has suggested an alternative method for measuring the goodness of fit for non-linear estimated equations which corresponds to the coefficient of determination in a standard linear regression model. This measure is called the *pseudo* R^2 and can be stated as:

$$Pseudo R^2 = 1 - (L_n/L_c)^{-\left(\frac{2}{N}\right)L_c} \quad (4)$$

where L_n represents the value of the log-likelihood of the estimated model and L_c is the value of a constrained model containing only the constant term. The number of observations in the model is given by N . Estrella and Mishkin (1996:47) state that, “the form of the above function ensures that the values 0 and 1 correspond to no fit and perfect fit respectively, and their intermediate values have roughly the same interpretations as their analogues in the linear case”. The *pseudo* R^2 is used in conjunction with the estimated coefficients probabilities and z-statistic in order to determine the appropriate lag which produces the best fit model for all the variables studied (Aziakpono and Khomo, 2007:205).

The simple and modified probit models were estimated using the yield spread as the explanatory variable with forecast horizons ranging from 1 to 24 months ahead. The statistical significance of the estimated coefficients is measured by the z-statistic and probability statistic in both the simple and modified probit models in order to determine the explanatory power of the yield spread. The optimal forecast horizon is determined at the lag length which produces the highest *pseudo* R^2 .

At each lag the estimated equation is used to forecast estimated probabilities about the likelihood of a future downswing occurring. The lowest root mean squared error (RMSE) and variance proportion (VP) are used to determine at which lag the yield curve has the strongest forecasting abilities. In simple and modified probit models the lag length which provides the strongest forecasting abilities is used to compare the predicted probabilities with actual downswing periods in order to determine the accuracy of each model. The lag length which produces the best fit in both the simple and modified probit models is then used for comparison purposes.

Simple and modified probit models were then estimated using other economic indicators which may also predict future economic downswings as the explanatory variable with forecast horizons ranging from 1 to 24 months ahead. These variables include the JSE all share index (ALSI), the leading economic indicator (LEI) and the money supply (M3). The highest *pseudo* R^2 and statistical significance of the estimated coefficients is used to determine the optimal forecast horizon for each explanatory variable. In both the simple and modified probit models the *pseudo* R^2 s from the yield spread, the JSE all share index (ALSI), the leading economic indicator (LEI) and the money supply (M3) are compared in order to determine which variable has the best forecasting abilities at each lag length. The *pseudo* R^2 s in the modified probit model are compared to those obtained in the simple probit model in order to determine whether the explanatory power of these variables has increase by adding a lagged dependent variable to the model.

Finally, a multiple-regression model was run using the modified probit model. The yield spread, JSE ALSI, LEI and M3 were all included in the model to determine whether the predictive power of the yield spread remains statistically significant when controlling for the other variables. The probability statistic and z-

statistic are used to determine whether including these variables has decreased the yields curve's predictive powers.

6. EMPIRICAL RESULTS

The yield spread, from January 1981 to April 2010 was tested using the Kwiatkowski-Phillips-Schmidt-Skin test and it was found that this time series is stationary at level terms¹. The *a priori* expectation about the yield spreads relationship with the business cycle is that there will be an inverse relationship between the yield spread and the probability of a downswing. An increase in the yield spread reduces the likelihood of a downswing occurring while an inversion of the yield spread increases the probability of a downswing occurring (Aziakpono and Khomo, 2007:206).

Simple Probit Model using the Yield Spread

The results from the simple probit model using the yield spread as the explanatory variable are provided in *Table 2*. The β (beta) represents the coefficient associated with the explanatory variable at each lag length. The statistical significance of each β is given by the z-statistic and p-value. The results show that at each lag length the β coefficients are negative, indicating that there is an inverse relationship between the yield spread and the business cycle, which conforms to *a priori* expectation. The z-statistic and p-values associated with each estimated β coefficient indicate that the yield spread is statistically significant and is a useful predictor of downswings in South Africa up to 18 months ahead at the 1% level of significance. The lag length which provides the best fitting simple probit model, as measured by the highest *pseudo R*², is at 5 months with 0.2421. These results confirm the findings by Aziakpono and Khomo (2007) who found that the term structure is a useful predictor of downswings in SA up to 18 months ahead with the best fit model at 5 months.

The estimated equations for the simple probit model were then used to forecast the probabilities of a downswing at each lag. The root mean squared error (RMSE) and the variance proportion (VP) were obtained at each lag length and are also shown in *Table 2*. The lowest RMSE and VP help determine which lag length produces the best forecast horizon. The VP is lowest at 5 lags confirming the finding made by the highest *pseudo R*² and the findings of Aziakpono and Khomo (2007:206). The lowest RMSE however, suggests that the best forecasting horizon is at 6 lags which would confirm the findings made by Moolman (2002). The statistical criteria of the *pseudo R*², RMSE and VP at 5 and 6 lags are however very similar and it is therefore possible that the best forecast horizon could be at either lag length. The estimated equations of the simple probit model using the yield spread at 5 and 6 lags are given by:

$$Pr(R_{t+5} = 1) = F(0.090797 - 0.326796X_t) \quad (5)$$

$$Pr(R_{t+6} = 1) = F(0.094404 - 0.324444X_t) \quad (6)$$

¹ The simple and modified probit models were estimated and tested using Eviews 6

The forecasted probabilities from the simple probit model at 5 and 6 lags can be compared with actual downswings for South Africa in order to determine the accuracy of the model and possibly which lag length provides the best forecast horizon. These comparisons are illustrated in *Figures 3* and *4*. It is evident that the simple probit model using the yield spread can successfully predict changes in the business cycle 5 to 6 months ahead. It is also evident that there is relatively little difference between the probability forecasts at 5 or 6 lags indicating that either lag model can be used.

The yield spread using the simple probit model falsely signaled a downswing in 2002/03 reaching a probability of around 80%, although the economy never officially went into a downturn.

After the spike in 2002/03 the probability of a downswing declined to around 25% in 2005 and fluctuated between 25% and 45% between 2005 and 2007. Mid-2007, 6 months prior to the global economic collapse, the probability of a downturn in SA increased sharply to around 70% indicating that there was a high probability of a downturn occurring 5 to 6 months ahead. The accuracy of this prediction suggests that the yield spread could still be used as a forecasting tool amongst other economic indicators.

Modified Probit Model using the Yield Spread

The modified probit model attempts to remove the possible serial correlation that may exist between the error terms by adding a lagged dependent variable as an independent variable. The yield spread is still used as the explanatory variable with the addition of a lagged dependent variable which forecasts the likelihood of a downswing occurring. The results are provided in *Table 3* and at each lag the explanatory variable and the lagged dependent variable have corresponding estimated β coefficients and corresponding z-statistics and p-values indicating the statistical significance of the β 's.

The β coefficients for the yield spread at each lag are negative, conforming to *a priori* expectation as in the simple probit model. The z-statistic and p-values indicate that the estimated β coefficients for the yield curve have increased in significance from 18 months ahead in the simple probit model, to 21 months ahead at the 1% level of significance. The β coefficients for the lagged dependent variable are positive and statistically significant up to and including 12 months, thereafter they become negative and statistically insignificant. This confirms the findings made by Aziakpono and Khomo (2007:210).

The results indicate that the lag which produces the highest *pseudo* R^2 and therefore the best fit modified probit model is at 1 lag or a forecast horizon of only 1 month ahead. When compared to the findings by Aziakpono and Khomo (2007:210) who found that the highest *pseudo* R^2 was at 6 lags these results seem unusual.

Using the estimated equation at each lag to forecast the probability of a downswing the RMSE and VP were obtained and are also shown in *Table 3*. The lowest VP is at 1 lag confirming the finding made by the *pseudo* R^2 that the best fit model is at 1 lag and coincides with the findings by Aziakpono and Khomo (2007:210) who also found that the VP was lowest at 1 lag. The lowest RMSE

suggests that the best forecast horizon is at 4 lags which is lower when compared to the results of Aziakpono and Khomo (2007:210) who found that the RMSE was lowest at 6 months.

A graphical plot of the forecasted probabilities at 1 and 2 lags however provides little information about the likelihood of a downturn occurring. The probabilities indicate that there is either a 100% or 0% chance of a downturn occurring and most of the time it is telling us that SA should be in a downturn which is clearly false. At 1 or 2 lags the modified probit model provides little forecasting information and it is therefore not an appropriate forecast horizon. Aziakpono and Khomo (2007:210) found that the lag that produces the best fit modified probit model was at 6 lags and given that the best fit simple probit model was at 5 lags in order to find the best fit model, graphical plots of the forecast downturn probabilities at 5 and 6 lags are illustrated in *Figures 5 and 6*.

At these lag lengths the modified probit model provides more information about the likelihood of a downturn occurring. It also shows that there is relatively little difference between the forecasted probabilities at 5 months and 6 months ahead. The probability of a downturn occurring at each lag now varies between 100% and zero.

The modified probit model also shows the same anomaly in 2002/03 with the probability of a downturn occurring being around 80% which declined to around 40% at both lags. For the 2008/09 downturn the model showed a sharp increase prior to the actual downturn. This indicates that this model was successfully able to predict the latest downturn. The estimated equations for the modified probit model at 5 and 6 lags are given by:

$$Pr (R_t + 5 = 1) = F (-0.849890 - 0.246220X_t + 2.033421X_t) \quad (7)$$

$$Pr (R_t + 6 = 1) = F (-0.722081 - 0.236596X_t + 1.747555X_t) \quad (8)$$

Simple Probit versus the Modified Probit Model using the Yield Spread

In the simple and modified probit models the yield spread provides the most optimal forecasts at 5 and 6 months ahead. The forecast probabilities at these lag lengths are used to determine whether both models successfully predicted the most recent downswing and whether the modified probit model contains more explanatory power. These comparisons are provided in *Figures 7 and 8* at 5 and 6 lags respectively.

There is relatively little difference between the two models at each lag. Both models were able to successfully predict the latest downswing indicating that both models have good forecasting abilities up to 5 and 6 months ahead. The modified probit model produces slightly higher probabilities at the peak of each downswing compared to the simple probit model. Given these findings it is possible to conclude that the yield curve is still a good predictor of downswings 5 to 6 months ahead and that it would be better to use the modified probit model because it has been able to correct for possible autocorrelation.

Evaluating the Yield Curve's predictive powers versus other economic indicators

The aim of this section is to evaluate the predictive powers of the yield spread relative to the in-sample predictive powers of other economic indicators using both the simple and modified probit models. These other variables include the JSE all share index (ALSI), the leading economic indicator (LEI) and the money supply (M3).

The first part involves using these variables individually to estimate the simple probit model at different lag lengths in order to estimate the goodness of fit as measured by the highest *pseudo* R². The results obtained from these variables are compared with the *pseudo* R²s obtained for the yield spread in the simple probit model. This is done in order to determine which variable contains the highest forecasting abilities at each lag and to determine how the yield spread's performance as a forecasting tool compares relative to the other economic indicators.

The JSE ALSI, LEI and M3 are then used to estimate the modified probit model in order to correct for possible autocorrelation and to determine whether the explanatory power of these variables has increased by adding a lagged dependent variable. The results obtained from these variables are compared with the *pseudo* R²s obtained for the yield spread to determine which variable contains the highest explanatory power at each lag.

Using the Dickey-Fuller unit root test and the Kwiatkowski-Phillips-Schmidt-Skin test the JSE ALSI, LEI and M3 were tested for stationarity. It was found that the JSE ALSI and the LEI were stationary at 1st difference at the 1% level of significance. M3 was found to be stationary at 1st difference but only at the 5% level using the Dickey-Fuller unit root test.

Comparison of pseudo R² for all variables using the Simple Probit Model

After differencing the JSE ALSI, LEI and M3 time series data, these variables were used individually to estimate the simple probit model. The *pseudo* R²s were obtained for each variable at different lags ranging from 1 month to 24 months and the results as well as the *pseudo* R² results from the simple probit model using the yield spread are shown in *Table 4*.

The results indicate that the yield spread is the best variable at providing information about the probability of a downswing occurring at all the lag lengths studied up to the 10% level of significance, providing the best probability forecasts 5 to 6 months ahead. The only other variable which is able to provide information about the probability of a downswing occurring in the future is the LEI. The LEI is statistically significant up to 24 months ahead up to the 10% level of significance and provides the best forecast 9 months ahead. This is 3 months earlier than the yield spread, but the *pseudo* R² is substantially lower than that provided by the yield spread at each lag length. Although the results indicate that the LEI should contain some ability to forecast future downswings in SA, a graphical plot of the estimated probabilities provides very little information, and is very high frequency, reducing the effectiveness of the LEI as a forecasting tool.

The results provided by the JSE ALSI and M3 are only statistically significant 12 to 6 months ahead respectively; thereafter they become statistically insignificant even at the 10% level of significance. For each of these variables the *pseudo* R²s are very low providing very little information about the probability of a downswing

occurring in the future. These results indicate that as a forecasting tool the JSE ALSI and M3 provide very little information and should not be used to predict future downswings.

Comparison of pseudo R² for all variables using the Modified Probit Model

The JSE ALSI, LEI and M3 were used individually to estimate the modified probit model in order to determine whether the explanatory power of these variables increased by adding a lagged dependent variable. The model was estimated for each variable at lag lengths ranging from 1 to 24 months ahead and the *pseudo* R²s for each variable were obtained. The results are illustrated in *Table 5* along with the *pseudo* R² results from the modified probit model using the yield spread in order to determine how the explanatory power of the yield spread compares to these other variables.

The results indicate that the yield spread is the best variable at providing information about the likelihood of a downswing up to 24 months at the 10% level of significance and provides the best probability forecasts 5 to 6 months ahead. The only other variable which is able to provide information about the likelihood of a downswing in the future is the LEI. The LEI however is statistically insignificant at 1 lag, but thereafter becomes significant up to 24 months ahead at the 10% level of significance. The *pseudo* R²s obtained indicate that the explanatory power of the LEI has increased. However it still does not exceed that of the yield spread and the highest *pseudo* R² indicates that the optimal forecast horizon is 3 months ahead.

The JSE ALSI is now only statistically significant at 1 lag and thereafter becomes statistically insignificant even at the 10% level of significance. This indicates that the JSE ALSI is not a useful variable for predicting future downswings. The predictive power of the money supply has increased to 24 lags however at much lower lags it has lost its statistical significance and the measure of fit is still very low.

The forecast probabilities of the likelihood of a downswing for the JSE ALSI and M3 were plotted against actual downswings, but provide very little information about future downswings and therefore should not be used as a forecasting tool in either probit model.

The LEI does provide some information about future downswings however its forecasting ability is still lower than that of the yield spread.

Multi-Variable Modified Probit Model using all variables

This section uses each variable (the yield spread, LEI, JSE ALSI and M3) to estimate a multi-variable modified probit model in order to determine the statistical significance of the yield curve after controlling for the other variables. In order to determine the statistical significance of the β coefficient associated with the yield curve the p-values and z-statistics were obtained and the results are illustrated in *Table 6*.

The results indicate that the yield spread remains statistically significant at the 1% level of significance 18 months ahead, which increases to 24 months at the 10% level of significance. This indicates that the yield spread has not lost any of its statistical significance after controlling for the other variables.

7. CONCLUSION

The empirical evidence presented in this paper suggests that although the yield curve falsely predicted a downswing in South Africa in 2002/03 it was successfully able to predict the downswing in 2008/09 in both the simple and modified probit models. The yield curve's success in predicting the most recent downswing suggests that it remains a powerful tool for predicting downswings in South Africa.

The yield curve is able to forecast downswings up to 18 months ahead but provides the best predictive power two quarters ahead. When the predictive powers of the yield curve are compared to other economic indicators such as the JSE All Share Index, the leading economic indicator and the money supply it was found that the yield curve provides the best forecasts of future downturns.

The leading economic indicator provides some forecasting powers as indicated by the *pseudo* R^2 s in both the simple and modified probit models. However, when the forecast probabilities are graphed they are not as clear as those of the yield curve. It was also found that the JSE All Share Index and the money supply do not provide any information about future downturns in South Africa which confirms the findings made by Aziakpono and Khomo (2007:210).

From these results and given the simplicity of the yield curve it can be concluded that the yield curve is still a powerful tool for predicting economic downswings in South Africa.

TABLES

Table 2: Results from Single Probit Model $\Pr(R_t = 1) = F(a + \beta X_{t-k})$

Months Ahead	K = 1	K = 3	K = 4	K = 5	K = 6	K = 9	K = 12	K = 15	K = 18	K = 21	K = 24
Beta's	-0.2585	-0.3043	-0.3192	-0.3268	-0.3244	-0.2891	-0.2407	-0.1698	-0.1162	-0.0774	-0.0483
Z-Stat	-8.2620	-9.0087	-9.2529	-9.3409	-9.0651	-8.3536	-7.3609	-5.7508	-4.1744	-2.8636	-1.8279
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0042	0.0676
Pseudo R ²	0.1724	0.2190	0.2340	0.2421	0.2417	0.2095	0.1623	0.0917	0.0455	0.0208	0.0083
RMSE	0.4396	0.4253	0.4207	0.4181	0.4170	0.4256	0.4394	0.4632	0.4788	0.4867	0.4903
VP	0.3866	0.3210	0.3072	0.3006	0.3045	0.3381	0.3939	0.4992	0.6130	0.7180	0.8113

Table 3: Results from modified Probit Model $\Pr(R_t = 1) = F(a + \beta_1 X_{t-k} + \beta_2 R_{t-k})$

Months Ahead	K = 1	K = 2	K = 3	K = 4	K = 5	K = 6	K = 9	K = 12	K = 15	K = 18	K = 21	K = 24
Spread												
Beta's	-0.2551	-0.2784	-0.2640	-0.2549	-0.2462	-0.2366	-0.2127	-0.1929	-0.1520	-0.1180	-0.0961	-0.0722
Z-Stat	-3.7178	-4.9045	-4.9542	-5.0393	-5.2140	-5.3328	-5.7391	-4.5810	-4.8635	-3.9769	-3.3036	-2.5166
Probability	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0010	0.0118
R_{t-k}												
Beta's	4.0164	3.3131	2.7736	2.3675	2.0334	1.7476	1.0875	0.5930	0.2162	-0.0299	-0.0961	-0.0722
Z-Stat	12.2271	12.9482	12.4181	11.8016	11.0607	10.1367	6.9255	3.9076	1.4296	-0.1969	-1.5348	-1.9982
Probability	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.1528	0.8439	0.1248	0.0457
Pseudo R ²	0.8561	0.7611	0.6733	0.5966	0.5268	0.4619	0.3022	0.1907	0.0956	0.0456	0.0256	0.0165
RMSE	0.5526	0.4219	0.4145	0.4140	0.4160	0.4200	0.4378	0.4466	0.4668	0.4781	0.4799	0.4856
VP	0.0044	0.0353	0.0750	0.1231	0.1765	0.2317	0.3554	0.4414	0.5282	0.6083	0.6772	0.7382

Table 4: Measure of Fit (*psuedo* R^2) using the Yield Spread and other Economic Variables
Results from Single Probit Model $\Pr(R_t = 1) = F(\alpha + \beta X_{t-k})$

Months Ahead	K = 1	K = 3	K = 4	K = 5	K = 6	K = 9	K = 12	K = 15	K = 18	K = 21	K = 24
Spread	0.1759	0.2190	0.2340	0.2421	0.2417	0.2095	0.1623	0.0917	0.0455	0.0208	0.0083
ALSI	0.0098	0.0022	0.0079	0.0087	0.0087	0.0091	0.0086	-	-	-	-
LEI	0.0159	0.0326	0.0481	0.0576	0.0749	0.1147	0.1026	0.0782	0.0376	0.0148	0.0070
M3	0.0187	0.0175	0.0112	0.0086	0.0063	-	-	-	-	-	-

Note: - indicates that the *psuedo* R^2 's are not statistically significant even at the 10% level

Table 5: R^2 Results from modified Probit Model $\Pr(R_t = 1) = F(a + \beta_1 X_{t-k} + \beta_2 R_{t-k})$

Months Ahead	K = 1	K = 3	K = 4	K = 5	K = 6	K = 9	K = 12	K = 15	K = 18	K = 21	K = 24
Spread	0.8564	0.6733	0.5966	0.5268	0.4619	0.3022	0.1907	0.0956	0.0456	0.0256	0.0165
ALSI	0.8280	-	-	-	-	-	-	-	-	-	-
LEI	-	0.6188	0.5436	0.4742	0.4187	0.2928	0.1786	0.0974	0.0401	0.0152	0.0101
M3	-	-	-	-	-	-	0.1121	0.0446	0.0163	0.0123	0.0151

Note: - indicates that the *psuedo* R^2 's are not statistically significant even at the 10% level

Table 6: Multi-Variable Modified Probit Model, Probability and Z-stat for β associated with Yield Spread

$$\Pr(R_t = 1) = F(a + \beta_1 YC_{t-k} + \beta_2 LEI_{t-k} + \beta_3 ALSI_{t-k} + \beta_4 M3_{t-k} + \beta_5 R_{t-k})$$

Months Ahead	K = 1	K = 3	K = 4	K = 5	K = 6	K = 9	K = 12	K = 15	K = 18	K = 21	K = 24
Pobability	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0001	0.0017	0.0118	0.0871
Z-stat	3.8804	4.8393	4.8470	4.9047	4.8248	5.2299	4.9115	3.9394	3.1408	2.5169	-1.7111

Not Sign at 5%

FIGURES

Figure 3: Simple Probit Model: Forecasted Probabilities of a Recession Occurring at 5 Lags Compared to Actual Recessions

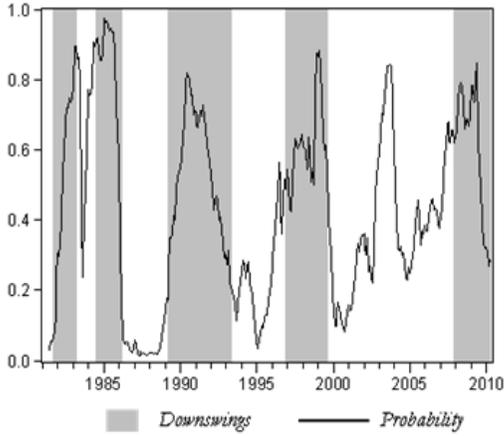


Figure 4: Simple Probit Model: Forecasted Probabilities of a Recession Occurring at 6 Lags Compared to Actual Recessions

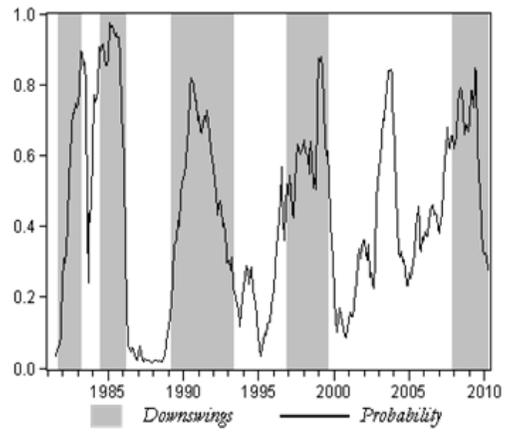


Figure 5: Modified Probit Model: Forecasted Probabilities of a Recession Occurring at 5 Lags Compared to Actual Recessions

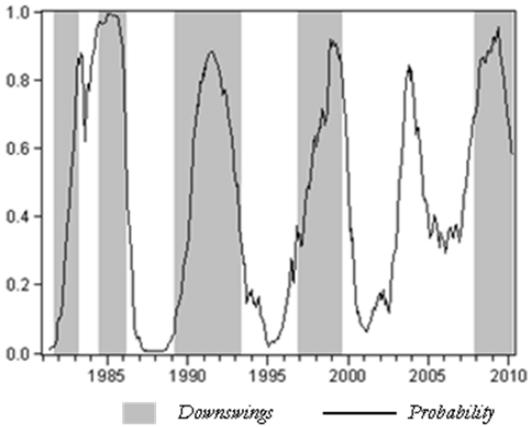


Figure 6: Modified Probit Model: Forecasted Probabilities of a Recession Occurring at 6 Lags Compared to actual Recessions

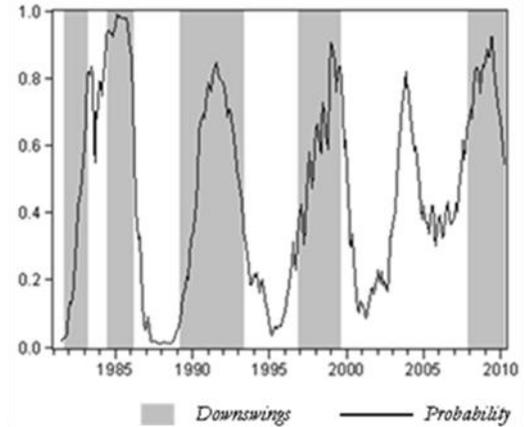


Figure 7: Modified Probit Model Compared to Simple Probit Model at 5 Lags

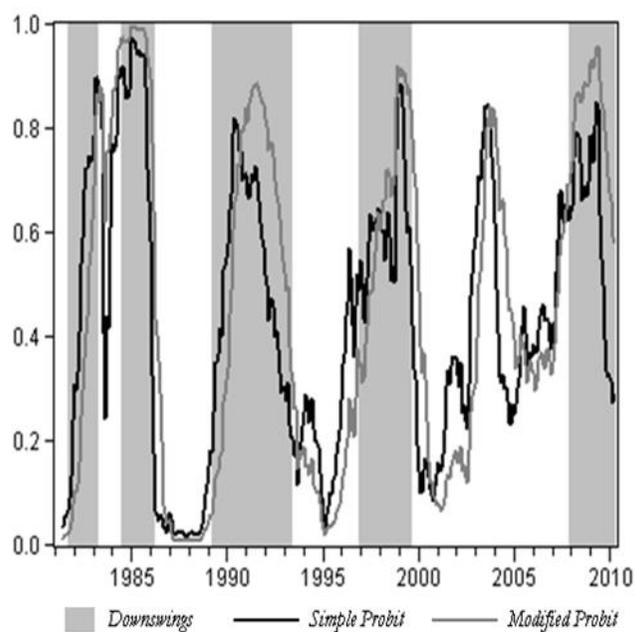
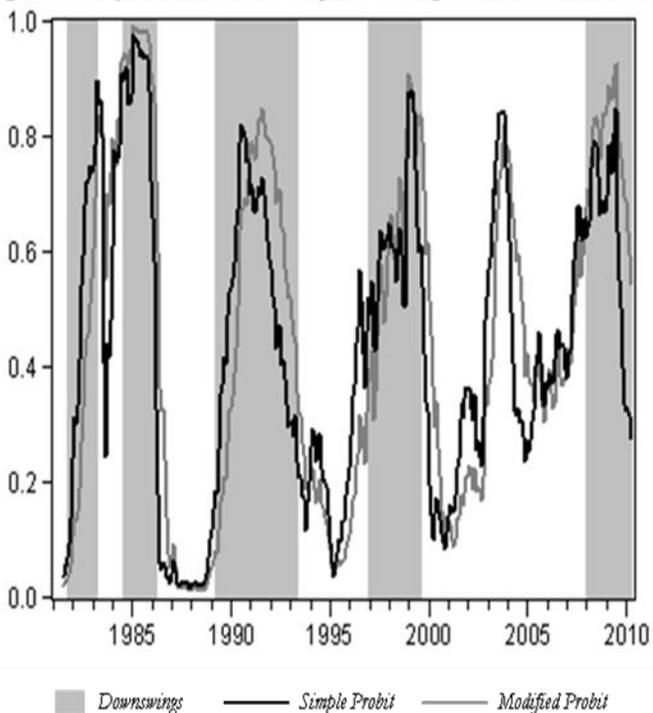


Figure 8: Modified Probit Model Compared to Simple Probit Model at 6 Lags



REFERENCES

- AZIAKPONO, M. J and KHOMO, M. M., 2007. Forecasting Recession in South Africa: A Comparison of the Yield Curve and other Economic Indicators. *South African Journal of Economics*. 75, 2:194-212.
- BAIN. K and HOWELLS. P., 2008. *The Economics of Money, Banking and Finance* (4th Edition). Pearson Education Limited.
- BONGA-BONGA, L., 2009. *Monetary Policy and Long-Term Interest Rates in South Africa*. Paper 125: University of Johannesburg.
- BURNS, A. F. and MITCHELL, W. C., 1946. *Measuring Business Cycles*. New York: National Bureau of Economic Research.
- CHINN, M, D and KUCKO, K., 2009. *The Predictive Power of the Yield Curve Across Countries and Time*. Federal Reserve Board, University of Wisconsin, Madison and NBER.
- COHEN, R, D., 2006. *A VaR-Based Model for the Yield Curve*. Published in Willmott Magazine. May 2006.
- DOMBROSKY, A. M and HAUBRICH, J. G., 1996. Predicting Real Growth Using the Yield Curve. The Federal Reserve Bank of Cleveland: *The Economic Review Journal*. Quarter 1, 32:26-35.
- DUEKER, M. J., 1997. Strengthening the case for the Yield Curve as Predictor of U.S. Recessions. *Federal Reserve Bank St. Louis Review*. 79, 2:41-51.
- ESTELLA, A and HARDOUVELIS, G. A., 1991. The Term Structure as a Predictor of Real Economic Activity. *The Journal of Finance*. 46, 2:555-576.
- ESTELLA, A and MISHKIN, F, S., 1996. The Yield Curve as a Predictor of U.S. Recessions. Federal Reserve Bank of New York: *Current Issues in Economics and Finance*. 2, 7:1-6.
- ESTRELLA, A. and MISHKIN, F.S., 1997. The predictive power of the term structure of interest rates in Europe and the United States: Implications for the European Central Bank. *European Economic Review*. 41, 7:1375-1401.
- ESTRELLA, A. and TRUBIN, M. R., 2006. The Yield Curve as a Leading Indicator: Some Practical Issues. Federal Reserve Bank of New York: *Current Issues in Economics and Finance*. 12, 5:1-8.
- FILARDO, J. C., 1999. How Reliable are Recession Prediction Models? *Federal Reserve Bank of Kansas City Economic Review*, 2nd Quarter: 35-57.

- GUJARATI, D. N., 2009. *Basic Econometrics*. (4th Edition). Boston: McGraw-Hill Irwin.
- HARVEY, C. R., 1998. The Real Term Structure and Consumption Growth. *Journal of Financial Economics*, 22:305-333.
- HU, Z., 1993. The Yield Curve and Real Activity. IMF Staff Paper, no. 40:781-806, December.
- KESSEL, R. A., 1965. The Cyclical Behavior of the Term Structure of Interest Rates. *National Bureau of Economic Research*. Occasional Paper No. 91.
- MISHKIN, F. S., 1999. Predicting U.S. Recessions: Financial Variables as Leading Indicators. *The Review of Economics and Statistics*. 80, 1:45-61.
- MISHKIN, F.S., 2007. *The Economics of Money, Banking and Financial Markets* (8e). Boston, MA: Addison-Wesley.
- MITCHELL, W. C., 1913. *Business Cycles*, Berkeley, University of California Press.
- MONETA, F., 2003. Does the Yield Curve Spread Predict Recessions in the Euro Area. *European Central Bank Working Paper No 294*.
- MOOLMAN, E., 2002. The Term Structure as a Predictor of Recessions. *Journal for Studies in Economics and Econometrics*. 26, 3:43-51.
- NATIONAL BUREAU OF ECONOMIC RESEARCH (NBER), 2003. Business Cycle Dating Committee. Available: [Online] <http://www.nber.org/cycles/recessions.pdf>. Accessed: 27 September 2010.
- NEL, H., 1996. The Term Structure of Interest Rates and Economic Activity in South Africa. *The South African Journal of Economics*. 26, 2:161-174.
- SHELILE, T., 2007. *The Term Structure of Interest Rates and Economic Activity in South Africa*. Master's Thesis, Rhodes University.
- SOUTH AFRICAN RESERVE BANK (SARB), 2010. Online Download Facility. Available: [Online] <http://www.resbank.co.za/qbquery/timeseriesquery.aspx>. Accessed: 18 September 2010.
- SOUTH AFRICAN RESERVE BANK (SARB), 2011. *Quarterly Bulletin No. 260, June 2011*. Available: [Online] <http://www.reservebank.co.za/>. Accessed: 4 August 2011.
- VENTER, J. C. and PRETORIUS, W. S., 2001. A Note on the Business Cycle in South Africa during the period 1997 to 1999. *South African Reserve Bank Quarterly Bulletin*, Article, September. SARB, Pretoria.

WALSH, C., 2003. *Monetary Theory and Policy*. 2nd Edition. The MIT Press.