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ASSESSING THE ABILITY OF THE INTEREST RATES TERM STRUCTURE TO FORECAST RECESSIONS IN SOUTH AFRICA: A COMPARISON OF THREE BINARY-TYPE MODELS

By

Neo Motloung

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I simply could not have done it without the support and encouragement of you all.
The use of the yield curve spread in forecasting future recessions has become popular as it is a simple tool to use, due to the positive relationship between the yield curve spread and economic activity. The inversion or flattening of the yield curve spread usually signals a future recession. This has been the subject of several studies both internationally and in South Africa.

This research provides an analysis of the yield curve spread’s ability to accurately forecast future recessions in South Africa through the use of three probit models. Furthermore, the yield curve spread’s ability to estimate is compared to that of share prices, using the JSE All Share Index. This research extends on studies by Khomo and Aziakpono (2006) and Clay and Keeton (2011), who used the static and dynamic probit models to forecast recessions in South Africa. In addition to these models, this research also makes use of the business cycle conditionally independent probit model for estimation.

The findings suggest that share prices improve the yield curve spread’s ability to forecast recessions when estimating using the static probit model; however when comparing the results between the financial variables, the yield curve spread continues to produce the best forecast of recessions in South Africa. These results support those of Khomo and Aziakpono (2006) and Clay and Keeton (2011). Of the three probit models, the dynamic probit model estimate using the yield curve spread produced the most accurate forecast of recessions one quarter ahead. Therefore, the yield curve spread continues to provide the most accurate forecast of recessions in South Africa.

Keywords: South Africa; term structure of interest rates; yield curve; business cycle; recession
# Table of Contents

Acknowledgements ............................................................................................................................. ii

Abstract .............................................................................................................................................. iii

Table of Contents ................................................................................................................................ iv

Chapter One: Introduction to the Implication of the Yield Curve’s Ability to Forecast Recession ........ 1

1.1. The significance of the yield curve in the context of the South African economy ....................... 1

1.2. Problem Statement & Objectives of the Research ........................................................................ 2

1.3. Methodology to be Implemented in Forecasting Recessions ...................................................... 3

1.4. Structure of the Research .............................................................................................................. 3

Chapter Two: Theoretical Foundation of the Yield Curve .................................................................. 5

2.1. Introduction ....................................................................................................................................... 5

2.2. Background of the Yield Curve ........................................................................................................ 5

2.2.1. Theoretical Context of the Yield Curve ....................................................................................... 5

2.3. Term Structure Theories of Interest Rates ...................................................................................... 9

2.3.1. The Expectations Hypothesis ..................................................................................................... 9

2.3.2. The Liquidity Preference Hypothesis .......................................................................................... 11

2.3.3. The Market Segmentation Hypothesis ...................................................................................... 12

2.3.4. The Preferred Habitat Hypothesis ............................................................................................. 13

2.3.5. Bond Yields and Monetary Policy ............................................................................................. 14

2.3.6. Bond Yields and the Marginal Rate of Substitution ................................................................. 15

2.4. Conclusion ...................................................................................................................................... 16

Chapter Three: Empirical Literature Review on the Yield Curve as a Recession Forecasting Tool ...... 19

3.1. Introduction ...................................................................................................................................... 19

3.2. The Use of Financial Variables as Forecasting Tools ..................................................................... 19

3.3. Forecasting Models .......................................................................................................................... 23

3.3.1. Forecasting Economic Growth Using the Yield Curve.............................................................. 24
3.3.2. Forecasting Recessions: the Static Probit Model ................................................................. 27
3.3.3. Forecasting Recessions: Extensions of the Static Probit Model ........................................... 29
3.4. Conclusion ............................................................................................................................... 33

Chapter Four: Methodology of the Yield Curve as a Forecasting Tool of Recessions ................. 35
4.1. Introduction ............................................................................................................................... 35
4.2. Methodology ............................................................................................................................ 35
  4.2.1. Models that Use a Dummy Variable .................................................................................... 35
  4.2.2. The Static Probit Model ..................................................................................................... 36
  4.2.3. The Dynamic Probit Model ............................................................................................... 38
  4.2.4. The Business Cycle Specific Conditionally Independent Probit Model ......................... 41
4.3. The Akaike Information Criterion (AIC) ................................................................................ 41
4.4. The Schwarz Information Criterion (SIC) ............................................................................. 42
4.5. The Root Mean Squared Error (RMSE) .................................................................................. 43
4.6. Conclusion ............................................................................................................................... 43

Chapter Five: Empirical Results of the Yield Curve’s Ability to Forecast Recessions ................. 45
5.1. Introduction ............................................................................................................................... 45
5.2. Data ....................................................................................................................................... 45
5.3. The Static Probit Model .......................................................................................................... 48
  5.3.1. The Static Probit Model and Yield Curve Spread ............................................................ 48
  5.3.2. The Static Probit Model and JSE ALSI ............................................................................ 52
  5.3.3. The Static Probit Model and the Financial Variables ....................................................... 54
  5.3.4. Evaluating the Static Probit Model’s Accuracy Across the Explanatory Variables ........ 55
5.4. The Dynamic Probit Model .................................................................................................... 56
  5.4.1. The Dynamic Probit Model and Yield Curve Spread ....................................................... 56
  5.4.2. The Dynamic Probit Model and JSE ALSI ...................................................................... 59
  5.4.3. The Dynamic Probit Model and the Financial Variables ................................................ 61
Figure 5.6. Downswings and recession probabilities of the static vs. dynamic probit forecasts - spread .. 59
Figure 5.7. Downswings and recession probabilities of the static vs. dynamic probit forecasts –JSE ALSI 61
Figure 5.8. Downswings and recession probabilities of the yield curve spread and JSE ALSI returns ....... 63
Figure 5.9. Downswings and recession probabilities of the static, dynamic & business cycle probit forecasts – yield curve spread .................................................................................................................... 66
Figure 5.10. Downswings and recession probabilities of the static, dynamic and business cycle probit forecasts – JSE ALSI ..................................................................................................................................... 68
Figure 5.11. The business cycle probit’s downswings and recession probabilities of the yield curve spread and JSE ALSI returns ....................................................................................................................................... 70

LIST OF TABLES
Table 5.1. Business cycle phases of South Africa since 1978 ..................................................................... 46
Table 5.2. In-sample static probit results using the yield curve spread .......................................................... 49
Table 5.3. Granger causality test of the yield curve spread and recessions .................................................... 50
Table 5.4. In-sample static probit results using the JSE ALSI ....................................................................... 52
Table 5.5. In-sample static probit results using the yield curve spread and JSE ALSI ..................................... 54
Table 5.6. Accuracy of the static probit models ............................................................................................. 55
Table 5.7. In-sample dynamic probit forecast using the yield curve ................................................................. 57
Table 5.8. In-sample dynamic probit results using the JSE ALSI returns ....................................................... 60
Table 5.9. In-sample dynamic probit results using the yield curve spread and JSE ALSI ............................... 62
Table 5.10. Accuracy of the dynamic probit models .................................................................................... 63
Table 5.11. In-sample business cycle conditionally independent probit results using the yield spread ... 64
Table 5.12. In-sample business cycle conditionally independent probit results using the JSE ALSI returns .................................................................................................................................................. 67
Table 5.13. In-sample business cycle probit results using the yield curve spread and JSE ALSI ................. 69
Table 5.14. Accuracy of the business cycle probit models ............................................................................. 70
Table 5.15. Accuracy of the probit models .................................................................................................... 71

LIST OF ABBREVIATIONS
Gross Domestic Product (GDP); Johannesburg Stock Exchange (JSE); All Share Index (ALSI); United States (US); United Kingdom (UK); Dow Jones Industrial Index (DJIA); New York Stock Exchange (NYSE); Standard & Poor’s (S&P); Consumer Price Index (CPI); Gross National Product (GNP); European Union (EU); Bayesian Information Criterion (BIC); Akaike Information Criterion (AIC); Schwarz Information Criterion (SIC); Root-Mean Square Error (RMSE); Ordinary Least Squares (OLS); National Bureau of Economic Research (NBER); South African Reserve Bank (SARB)
CHAPTER ONE

INTRODUCTION TO THE IMPLICATION OF THE YIELD CURVE’S ABILITY TO FORECAST RECESSIONS

1.1. THE SIGNIFICANCE OF THE YIELD CURVE IN THE CONTEXT OF THE SOUTH AFRICAN ECONOMY

The South African economy is characterised by a society that is becoming urbanized at a rapid rate, by high levels of poverty, unemployment, and a significant income gap between the rich and the poor, resulting in increased disgruntlement by those in lower income brackets. Based on this current economic environment, the Gross Domestic Product (GDP) growth rate becomes a key economic indicator that should concern all members of society. Recent data shows that the South African GDP growth rate was 3% in the second quarter of 2013, and the current unemployment rate stands at 24.9% (Statistics South Africa, 2013). These figures describe a country that is characterised by a high level of unemployment and poverty within the context of a growing economy.

It is fundamental for the GDP growth rate to continue increasing in order for the economy to expand to accommodate the increasing level of development, and reduce the current level of unemployment and poverty. This requires commitment from government, as was expressed in the Budget Speech (Gordhan, 2013), in which government focused on continued investment in infrastructure, human capital, and job creation in order to grow the economy and to produce a more equitable society.

If the current level of economic growth is not maintained, or at least grows, an economic slowdown or recession could be experienced. This may lead to a further increase in the unemployment rate, poverty and an even wider income gap between the rich and poor. It is therefore necessary for policymakers to estimate the future economic outlook, so that in the event of a recession occurring, the government can act to reduce the adverse effects of a recession through various monetary and fiscal policies. Accuracy in forecasting recessions is important for government to implement the correct policy at the appropriate time. Investors and businesses would also benefit from being able to forecast the future economic outlook in order to mitigate their own potential losses (Filardo, 1999).

Rather than looking towards the future economic growth rate, it could be more productive to forecast possible recessions as from the advantages of knowing when a recession might occur could mitigate potential losses. A popular tool that is often used to assist is the yield curve, which is a graph that plots similar bonds of different maturities (Reilly & Brown, 2003).
The yield curve is used as a warning sign for recessions as it flattens or inverts prior to a recession. It has been proven to be accurate at forecasting future recessions, as it is a simple tool to use and has previously surpassed other financial and economic indicators (Estrella & Mishkin, 1996). In forecasting recessions, the yield curve is used as an explanatory variable in the probit model, which forecasts the probability of recessions. This model has become popular as it produces a result in the form of a probability, which is fairly simple to interpret and produces good forecasts that can be used to check econometric models and judgmental forecasts (Estrella & Mishkin, 1998). Moreover, the model makes the use of complex macroeconomic models redundant if the concern lies in forecasting the occurrence of recessions and not in estimating the economic growth rate (Moolman, 2003).

1.2. PROBLEM STATEMENT & OBJECTIVES OF THE RESEARCH

As the number of probit models is now growing with the introduction of variations by Chauvet and Potter (2005), it is not clear which model would produce the optimum and most accurate forecasts of recessions. Accuracy is crucial as it will allow government to implement the correct monetary and fiscal policy at the right time, in order to prevent any adverse effects on the economy that would result from a recession.

The goal of this study is to build on the knowledge obtained from the studies currently available on using the yield curve to forecast recessions in South Africa, but more specifically to identify the probit model that produces the most accurate forecast of recessions. This study will extend the research produced by Moolman (2003) who have used the static probit model to identify the explanatory variable that best forecasts recession; and Khomo and Aziakpono (2006) who identified the model that produces the best forecast when comparing the static and dynamic probit models with the use of different explanatory variables. In an effort to achieve this goal, three main objectives will be addressed in this study:

- the relationship between the term structure of interest rates and the business cycle will be evaluated against that of share prices and the business cycle to determine which of these explanatory variables best forecasts recessions;
the possibility of improving the model's forecasting ability by incorporating both the term structure of interest rate, or yield curve spread, and the share price as explanatory variables; and

lastly, a comparative analysis between the probit models will be used in order to determine the model that most accurately forecasts recessions in South Africa.

1.3. METHODOLOGY TO BE IMPLEMENTED IN FORECASTING RECESSIONS

This research is an extension of Khomo & Aziakpono's (2006) study as it not only conducts a comparative analysis of the static probit and dynamic probit model but includes a third probit model, the business cycle specific conditionally independent probit model with the use of the yield curve spread and Johannesburg Stock Exchange (JSE) All Share Index (ALSI) as explanatory variables. The study will seek to identify whether the yield curve spread continues to provide a good forecast of recessions, and to identify the probit model that produces the most accurate forecast.

The data that will be used is that of the three-month Treasury bill, 10-year government bond, and the JSE All Share Index. The three-month Treasury bill and 10-year government bond are retrieved from the I-Net bridge database, and the JSE ALSI from the JSE.

Each of the probit models will be estimated using different lag lengths, of which the Akaike Information Criterion (AIC) and Schwarz Information Criterion (SIC) will be used to identify the model with the optimal lag length. Once selected across the yield curve spread, share prices and the optimal lag length with both explanatory variables included, the root-mean square error (RMSE) will be used to identify the explanatory variable that most accurately forecast recessions. The RMSE will furthermore be used to select the probit model that best forecasts recessions across all three probit models.

1.4. STRUCTURE OF THE RESEARCH

This study comprises six chapters. Chapter two provides a discussion on the theoretical background of the yield curve, beginning with a brief discussion on the pricing of bonds and the shape of the yield curve in order to provide context for the yield curve, and to identify the reasons behind the use of the
yield curve for forecasting. Furthermore, this chapter seeks to identify the theoretical relationship that may exist between the yield curve and the business cycle.

Chapter three presents a review of existing empirical research that has been conducted on the use of various financial variables in forecasting future economic growth and the results of these. This is an important analysis as it seeks to identify the financial variables that have shown evidence of a relationship with the business cycle. Furthermore, it is a dialogue on the results of methodologies that may be used; the use of linear regression models in forecasting future economic growth and probit models that look only at predicting future recessions; the differences between the models, and the advantages and shortcomings of these are discussed. In addition, the chapter provides a discussion on the possible reasons behind the use of a probit model rather than a linear regression model when forecasting recessions. Above all, this chapter is a review of some of the different types of probit models and whether or not evidence has shown that variations of the probit model may or may not have improved its forecasting ability.

Chapter four is a description of the various models that will be used; these include the static probit model, the dynamic probit model, and the business cycle specific conditionally independent probit models. The discussions in this chapter outline the methodology used to obtain the forecasts, as well as how these forecasts will be evaluated for accuracy.

Chapter five is a presentation and discussion of the estimation results.

Lastly, in chapter six, concluding remarks on the findings, limitations, possible policy implications, and further recommendations for further research will be discussed.
CHAPTER TWO
THEORETICAL FOUNDATION OF THE YIELD CURVE

2.1. INTRODUCTION

Although the yield curve provides a simple representation of bond rates, it has significant effects in terms of its inference of future economic activity. The yield curve tool is widely used for the forecasting of future economic activity. The ability to forecast economic activity is particularly beneficial to government as it allows government to implement the necessary fiscal, and/or monetary policy to curb the effects of a future recession, or to further benefit from a potential economic boom (Filardo, 1999).

This chapter will attempt to provide a theoretical background and context for the yield curve, in an effort to identify the reasons behind the use of the yield curve for forecasting, and to identify the theoretical relationship that may exist between the yield curve and economic growth.

This chapter is structured as follows. Section two places the yield curve in context and provides a theoretical background, which includes a theoretical discussion on the yield curve and the different shapes of the yield curve. This is followed by section three, which is a review of the theories and notions that determine the shape of the yield curve, in order to explain why the yield curve may rise, flatten, invert, or become humped (Reilly & Brown, 2003). The relationship between the yield curve and economic activity will also be explored. This relationship is crucial as it suggests that the yield curve may be used to forecast future economic activity (Estrella & Hardouvelis, 1991).

2.2. BACKGROUND OF THE YIELD CURVE

2.2.1. THEORETICAL CONTEXT OF THE YIELD CURVE

Financial assets and stocks and bonds provide individuals with a conduit to lay claim to real assets or to any income that may be generated from those assets or income from the government. A bond is a security that is the result of a borrowing agreement. It is one in which a borrower sells a bond to a lender in return for a specified amount of cash. The borrower is therefore required to make payments to the bond holder over a specified period of time, as stipulated by the agreement (Bodie, Kane & Marcus, 2003). The alternative to estimating the value of a bond in rand terms is to price it using yields. A yield is defined as the promised rate of return given specific conditions. The yield may be estimated using the
current market price of the bond, and the expected cash flows, or future payments on the bond. The yield may be estimated using the below formula (Reilly & Brown, 2003).

\[
P_m = \sum_{t=1}^{2n} \frac{C_t/2}{1+i/2} + \frac{P_p}{(1+i/2)^{2n}}
\]

(1)

where:

- \(P_m\) is the current market price of the bond,
- \(n\) is the number of years to maturity,
- \(C_t\) is the annual coupon payment for bond \(i\),
- \(P_p\) is the bond par value,
- \(i\) is the yield to maturity or the promised rate of return given the specified conditions.

Lastly, a factor of 2 is used as this bond makes semi-annual coupon payments (i.e. \(i/2\)).

The yield curve is defined as a graph that plots the yield to maturity and term to maturity (i.e. the amount of time prior to the maturity of the bond) of bonds (Bodie, Kane & Marcus, 2003). The yield curve plots the relationship between similar bonds of different maturities, in particular, the bonds should have common features, and the bonds should have the same coupon for instance (the coupon is defined as the interest rate the borrower will pay to the lender). Bonds that have common features will be more alike and therefore should produce a yield curve that is more precise. Different yield curves may be assembled for different types of bonds, for treasuries and corporate bonds, for instance (Reilly & Brown, 2003). The yield curve spread is defined as the difference between the long- and short-term government bond rates (Estrella & Hardouvelis, 1991). Although the yield curve is defined as a graphical representation, similar to it is the term structure of interest rates, which is defined as the relationship between the yield to maturity and term to maturity of bonds (Bodie, Kane & Marcus, 2003). However, the term structure has become widely known as the yield curve.

There are primarily four different types or shapes of the yield curve: the upward sloping, downward sloping, flat, and lastly the humped yield curve (Bodie, Kane & Marcus, 2003).
Figure 2.1. The relationship between the upward sloping yield curve & maturity

Source: Adapted from Reilly and Brown (2003: 753)

The upward sloping yield curve is the most common, it occurs when short-term yields are lower than long-term yields; it therefore has a positive slope (Reilly & Brown, 2003).

Figure 2.2. The relationship between a flat yield curve & maturity

Source: Adapted from Reilly and Brown (2003: 753)

A flat yield curve is one in which the yields across all maturities are the same (Reilly & Brown, 2003).
The downward sloping or inverted yield curve occurs when the long-term yields are lower than the short-term yields, the slope on the yield curve is therefore negative (Reilly & Brown, 2003).

Source: Adapted from Reilly and Brown (2003: 753)

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The humped yield curve occurs when there is a peak in the yield curve at some intermediate maturity, indicating a positive slope at shorter maturities and a negative slope at longer maturities.

Source: Adapted from Reilly and Brown (2003: 753)
Lastly, a humped yield curve occurs when the short-term yields are lower than the medium-term yields, which begin to decline such that the long-term rates fall below the short-term levels until they level out (Reilly & Brown, 2003).

The shape of the yield curve may be explained by various macroeconomic theories. These theories attempt to explain the term structure of interest rates, the relationship between the yield to maturity and term to maturity. These theories attempt to clarify why the yield curve may be upward sloping, flat, downward sloping, or even humped. Furthermore, some of these theories identify the relationship that exists between the term structure and economic activity. The theories are identified as the term structure theories of interest rates and include the expectations, liquidity preference, market segmentation, and preferred habitat theories. In addition to these theories are two views. The first states that the shape of the yield curve is determined by monetary policy (Moneta, 2005), and the second states that the yield curve is determined by the marginal rate of substitution (Harvey, 1989). These views attempt to explain the shape of the yield curve and suggest that a relationship exists between the term structure and economic activity.

2.3. TERM STRUCTURE THEORIES OF INTEREST RATES

2.3.1. THE EXPECTATIONS HYPOTHESIS

The expectations theory states that the slope of the yield curve is determined by market participants’ expectations of future interest rates. In particular, the long-term interest rate is the geometric average of the current rate and all the anticipated future one-year interest rates over the bond’s maturity. Consequently, the long-term rate is the rate an investor may look forward to receive if they were to roll over a series of short-term bonds over the same term to maturity as that of the long-term bond. The expectations theory may be expressed using the below formula (Reilly & Brown, 2003):

\[
(1 + tR_n) = [(1 + tR_1)(1 + t_{+1}r_1) \ldots (1 + t_{+n-1}r_1)]^{1/N}
\]

(2)

where:

\(R_n\) is the long-term rate, \(N\) is the term to maturity of the long-term bond in years, \(R\) is the current one-year interest rate, and \(t_{+i}r_1\) is the anticipated one-year rate at time \(t + i\), otherwise known as the forward rate at time \(t + i\) (Reilly & Brown, 2003).
The expectations theory states that the expectations of higher future short-term rates results in an upward sloping yield curve as the long-term rate is a geometric average of the future short term rates. An inverted yield curve is due to expectations of declining future short-term rates that result in the average of the long-term rate being less than the current short-term rate (Reilly & Brown, 2003).

Furthermore, the expectations theory advocates a relationship between economic activity and the yield curve. A contractionary monetary policy is often associated with economic growth, as a means of reducing inflationary pressure by government. Consequently, if market participants expect the economy to grow, future short-term interest rates and long-term rates may be expected to rise, relative to the current short-term rate, thereby resulting in an upward sloping yield curve (Moneta, 2005).

Conversely, an expansionary monetary policy is often associated with economic slowdowns, or recessions, in order to encourage economic spending. Therefore, if a recession is expected in the future, the expected future short-term interest rates and long-term interest rates are likely to be lower, due to market participants’ expectations of an expansionary monetary policy by government. Furthermore, because the spread is calculated using nominal interest rates, and the expected inflation rate is built into the nominal rate, a lower inflation rate may be likely in the event of a recession, resulting in the expectation of lower future short-term rates and long-term rates. Moreover, if a recession is expected in future, lower credit demand is anticipated, thus reducing the long-term interest rates. This may result in a declining or inverted yield curve (Moneta, 2005).

The business cycle is defined as recurring phases of growth and contraction experienced by the economy. The lengths and depths of these growth and recession cycles generally tend to be irregular. The peak of a business cycle begins from where an expansion ends to the beginning of a contraction. A trough begins from the bottom of a recession to the beginnings of an expansion (Bodie, Kane & Marcus, 2003). The yield curve spread is defined as the difference between the long-and short-term government bond rates (Estrella and Hardouvelis, 1991). The expectations hypothesis suggests that there is a relationship between the yield curve spread and business cycles. The yield curve spread appears to contain information about financial market participants’ expectations of the business cycle. This is echoed in the positive relationship that exists between the yield curve spread and economic growth. It is suggested that a positive spread occurs prior to future economic growth, and a negative spread signals a future economic slowdown, or recession (Moneta, 2005).
However, the expectations theory has been questioned as it assumes that market participants are both rational and risk neutral (Karunaratne, 2002). Rational expectations are defined as the ability by market participants to collect all the existing information and to use it to come to a certain conclusion or prediction. Any other prediction should be considered to be illogical. The assumption that market participants are rational may not be realistic, as it would likely take a considerable amount of time, be inconvenient and it would be costly to gather all of the necessary information and to use it correctly to produce the same prediction as the other market participants (Kohn, 1993). Additionally, the assumption that all market participants have the same risk profile may not be realistic; some investors are risk-averse. This concept is further explored in the liquidity (Karunaratne, 2002) and preferred habitat theories (Kohn, 1993).

2.3.2. THE LIQUIDITY PREFERENCE HYPOTHESIS

The risks associated with long-term interest rates and short-term interest rates are not the same, as there is usually a higher level of interest rate risk for long-term bonds. Interest rate risk is defined as the risk of possible losses on the investment value due to interest rate fluctuations. As there is an inverse relationship between yields and prices, an increase in the yield will result in a decrease in the bond price and a capital loss for the investor. Thus lenders prefer short-term bonds as they are more liquid as the short-term market experiences very high volumes of trading, and therefore viewed as less prone to interest rate risk (Kohn, 1993).

Therefore, in order to attract lenders into investing in long-term bonds, long-term bonds should offer a higher yield than short-term bonds, in the form of a liquidity premium. In other words, when viewing an upward sloping yield curve, the higher long-term interest rate on the yield curve may be seen as the additional rate investors expect to receive when taking on additional risk relative to the rates that could be received on short-term bonds. The liquidity premium should therefore result in an upward sloping yield curve, over and above the expected forward rate, as described by the expectations theory. (Kohn, 1993). The liquidity premium compensates risk-averse investors for the additional risk of investing in long-term bonds; consequently the liquidity preference theory is as an extension of the expectations theory, as it makes provision for risk-averse investors (Karunaratne, 2002). Moreover, if the yield curve is flat, humped, or downward sloping, this should only be short-term and the yield curve should return to its normal upward sloping shape (Reilly & Brown, 2003).
Equation (3) below mathematically expresses the notion that the liquidity theory builds on the expectations theory by adding a liquidity premium to the expected future interest rate when estimating the return on the long-term bond from equation (2) (Reilly & Brown, 2003).

\[
(1 + t R_N) = [(1 + t R_1)(1 + t+1 r_1 + L_2) \ldots (1 + t+N−1 r_1 + L_n)]^{1/N} \tag{3}
\]

As the bond price volatility tends to increase with maturity, the various liquidity premium values (defined as the \( L \) variables) in the equation should increase with maturity (Reilly & Brown, 2003).

Thus, the liquidity theory suggests that the yield curve should be upward sloping due to the liquidity premium that lenders expect to receive (Kohn, 1993), unlike the expectations theory, which suggests that a relationship exists between the yield curve and the business cycle (Moneta, 2005). It is not entirely clear if this relationship exists under the liquidity theory, as it suggests that the yield curve should always be upward sloping, therefore it is not clear how changes, if any, of the yield curve may be used to anticipate changes in the business cycle.

2.3.3. MARKET SEGMENTATION HYPOTHESIS

The market segmentation theory suggests that individuals select investments based on their preferences, thus the rates in the short-term, medium-term and long-term markets are determined by the level of supply and demand in each of these markets, which should be reflected in the slope of the yield curve. However, this theory suggests that the various markets operate independently from one another; therefore there may be no relationship between the short-term and long-term bond markets and their interest rates (Bonga-Bonga, 2009).

The market segmentation theory may not be realistic, as it has been observed that short-term and long-term yields have changed simultaneously when the yield curve has shifted parallel, either by moving up or down from its original position in reaction to a particular event. This shift suggests that there must be a common factor to the short-term, medium-term and long-term markets that influences all of the bond yields across the different markets. Therefore, the markets cannot operate independently from one another; there must be a relationship between the yields at different maturities, which may not be explained by the market segmentation theory (Kohn, 1993).
Furthermore, it may not be pragmatic to suggest that individuals will always stick to a particular market preference if it may be in their best interests to change. For instance an investor wanted to enter into a long-term project such as building a warehouse, and they were faced with the option of taking out a traditional loan, such as a bond, over a number of years equivalent to the period of time it would take to complete the project versus short-term debt that would have to rolled over annually at a significantly lower interest rate. The investor may choose to take on the short-term debt and roll it over annually and take on the additional risk that the interest rates may fluctuate in order to save on the additional interest they may have had to pay on the long-term debt (Kohn, 1993).

2.3.4. PREFERRED HABITAT HYPOTHESIS

The expectations theory states that individuals do not have a preference between short-term and long-term bonds, as they are perfect substitutes for one another (Kessel, 1971). Conversely, the market segmentations hypothesis states that individuals have a strong preference for short-term or long-term bonds, and will not deviate away from their preference. The preferred habitat hypothesis marries these two theories: it suggests that although investors have a preference in terms of long- or short-term bonds, investors who have a preference for short-term bonds may invest in long-term bonds if they receive an incentive in the form of a risk or term premium. The premium compensates investors for the additional risk of investing in longer-term bonds whereby interest rates may fluctuate and possibly reduce the value of their investment (Kohn, 1993: 760-762).

The value of the term premium may be interpreted as investors’ preference for bonds of varying maturities. Furthermore, as the preferred habitat theory builds on the expectations theory, it stands to reason that the shape of the yield curve is determined by both the market participants’ expectations of the forward rates and the term premium. Therefore, a yield curve may be upward sloping if the term premium will be positive and investors’ are due to receive compensation for the additional risk they are to take on. Furthermore, if investors expect forward rates to increase, this should result in a steeper positive yield curve. Conversely, the term spread may be negative if investors’ prefer long-term bonds such that the price increases and yields on long-term bonds decline, resulting in an inverse yield curve. Moreover, the decline in the yield curve may be steeper if investors expect forward rates or long-term rates to decline (Kohn, 1993).
The preferred habitat theory proposes that a relationship exists between the yield curve and economic activity. During an economic boom, there is a risk that inflation may increase due to the higher levels of spending within the economy (Hamilton & Kim, 1999). As nominal rates are used for the yield curve spread (Moneta, 2005), the term premium should therefore rise, as it incorporates both a real value and inflation value. Therefore, the yield curve will be upward sloping as a result of the higher long-term interest rates. The increasing long-term rates will be due to a higher term premium, which will increase in order to make provision for the anticipated growth in inflation, and not due to an expectation of higher forward rates by market participants. Consequently, a positively sloped yield curve may be used to forecast future economic growth. The preferred habitat theory thus asserts that a positive relationship exists between the yield curve and economic activity (Hamilton & Kim, 1999).

The expectations, liquidity preference, preferred habitat, and market segmentation theories attempt to explain the shape of the yield curve. However, in addition to this, the expectations and preferred habitat theories propose a positive relationship between economic activity and the yield curve (Karunaratne, 2002). The liquidity preference theory indicates that the yield curve should constantly be upward sloping (Kohn, 1993), thus it is not clear whether or not a relationship exists between the yield curve and future economic booms or recessions. The market segmentation theory argues that there is no relationship between the short-term and long-term interest rates, thus it is not clear how the yield curve may affect economic activity (Bonga-Bonga, 2009).

Apart from the term structure theories of interest rates, there are two other views that attempt to explain the shape of the yield curve. Furthermore, these ideas suggest that there is a relationship between the term structure and economic activity. The first concept states that the shape of the yield curve is determined by monetary policy (Moneta, 2005), and the second argues that the yield curve is determined by the marginal rate of substitution (Harvey, 1989).

2.3.5. BOND YIELDS AND MONETARY POLICY

The first concept claims that that the slope of the yield curve contains information about the government’s current monetary policy (Estrella & Hardouvelis, 1991). Hikes in short-term interest rates are usually interpreted as a means by which government attempts to curb high levels of inflation, and once the level of inflation is perceived by government to be under control, the short-term rates are reduced again (Estrella & Trubin, 2006). Therefore, if government implements a tight monetary policy by
increasing short-term rates, market participants will not consider this to be a permanent change, and will therefore increase their expectations of forward rates by a marginal amount relative to the current short-term rate. As a result, the rise in the current short-term rate will be high compared to the long-term interest rate; consequentially the yield curve will invert, or flatten (Ahrens, 2002).

Additionally, the higher current short-term interest rate will discourage investment and the level of production and output, and will thereby result in a decrease in the level of economic growth (Estrella & Hardouvelis, 1991). Furthermore, the higher current short-term interest rate will reduce the level of consumer demand for credit, resulting in a decline in the level of expenditure and consumption, resulting in a decline in economic growth and an increase in the likelihood of a future recession. As a flat or an inverted yield curve often precedes periods of economic slowdowns, or recessions, it appears that there is a relationship between the yield curve and economic activity (Moneta, 2005).

Alternatively, government may implement an expansionary monetary policy by decreasing the current short-term interest rate; the forward short-term rate and long-term rates will also decline, but by less than the current short-term rate, resulting in a steeper yield curve. This will similarly result in an increase in the level of economic growth through increases in the investment and consumption levels. Consequently, an upward sloping yield curve occurs prior to periods of economic growth (Haubrich & Dombrosky, 1996).

From the above view, it may be concluded that a relationship exists between the current monetary policy and the slope of the yield curve. Furthermore, as an upward sloping yield curve precedes periods of economic growth; and the yield curve becomes flat, or inverts prior to an economic slowdown or recession, it appears that there is a positive relationship between the yield curve and economic activity (Estrella & Hardouvelis, 1991).

The second concept seeks to explain the shape of the yield curve spread. Furthermore, it affirms that a positive relationship exists between the yield curve and business cycles; it provides a link between the yield curve spread and the marginal rate of substitution (Harvey, 1989). The idea is described below.

### 2.3.6. BOND YIELDS AND THE MARGINAL RATE OF SUBSTITUTION

A compelling argument states that there is a relationship between the return on bonds and economic activity reflected through the marginal rate of substitution due to investors’ need to smooth
consumption as a means of hedging against a future economic decline. Investors derive more utility from one unit of consumption during a recession than during periods of economic growth, this is due to the fact that consumption is expected to be low in periods of recession and high during periods of economic growth. Thus, investors attempt to smooth their consumption by forfeiting some consumption today for tomorrow, in an effort to ensure future consumption will be likely in the event of a possible economic slowdown, or recession, which could result in lower consumption due to possible job losses.

The rate at which investors’ substitute consumption today for tomorrow is the marginal rate of substitution, represented by the asset prices. Therefore, if there are fears of an economic slowdown, investors will buy long-term bonds and sell short-term bonds, thus increasing the price of long-term bonds and reducing the price of short-term bonds. This will result in a decline in the interest rates on the long-term bonds and an increase in the short-term bonds, resulting in a flat or inverted yield curve (Harvey, 1989).

2.4. CONCLUSION

The focus of this chapter has been on the introduction of the yield curve and the relevant theories. Four theories have been discussed in an attempt to explain the shapes of the yield curve. There are four shapes of the yield curve, namely the upward sloping, flat, inverted, and humped yield curve. The foremost theories used to describe the shapes of the yield curve are the term structure theories of interest rates, namely the expectations, liquidity preference, market segmentation and preferred habitat theories that have been discussed. In addition to these theories are two views that describe the relationship between the yield curve and monetary policy; and the relationship between the yield curve and the marginal rate of substitution.

The expectations theory states that market participants’ expectations of future interest rates are what influence the shape of the yield curve. Thus, an upward sloping yield curve is due to expectations of higher future short-term rates, and an inverted yield curve is due to expectations of lower future short-term rates. Conversely, the market segmentation theory alludes that the yield curve is determined by the separate demand and supply factors present in the short-term, medium term and long-term bond markets. Thirdly, the liquidity preference theory suggests that the positive slope of the yield curve is not only due to market participants’ expectations of the long-term rate, but that they additionally require a
liquidity premium in order to invest in long-term bonds. This theory suggests that the yield curve should be upward sloping and that any other shape will only be temporary. Lastly, the preferred habitat theory indicates that the shape of the yield curve is due to market participants’ expectations of forward rates, and a term premium that they expect to receive in exchange for investing in longer-term bonds. A steep upward sloping yield curve is due to expectations of higher forward rates and a positive term premium, whereas an inverted yield curve is due to investors’ preference for long-term bonds that results in lower long-term rates and a declining yield curve.

Furthermore, from the expectations and preferred habitat theories of the term structure theories of interest rates, it has been suggested that a positive relationship exists between the yield curve and the business cycle, as an upward sloping yield curve occurs prior to periods of economic growth, and the yield curve inverts prior to a recession. The expectations hypothesis surmises that the yield curve contains information about market participants’ expectations of the business cycle, because expectations of high future short-term and long-term rates are associated with economic growth, a positively sloped yield curve may therefore be associated with economic growth. The preferred habitat theory argues that a higher term premium may be due to expectations of a higher inflation rate often associated with periods of economic growth, thus an upward sloping yield curve may be linked to economic growth.

In addition to the term structure theories of interest rates, two other views have been discussed, these seek to explain the shape of the yield curve and its link to the business cycle. The first view argues that the shape of the yield curve is due to government’s current monetary policy; therefore an increase of short-term rates by government will result in the current short-term rates being higher than long-term rates, and consequently an inverted yield curve. Moreover, the higher short-term rate will slow economic growth through a reduction in business investment, and lower credit demand by consumers. The second view suggests there is a relationship between the yield curve and investors’ marginal rate of substitution, in an effort to smooth consumption. An inverted yield curve may be due to a high demand for long-term bonds thus increasing their price and reducing the long-term rate in anticipation of an economic slowdown or recession. Investors would demand more long-term bonds in an effort to smooth consumption during periods of economic decline. These concepts also imply the existence of a positive relationship between the yield curve and the business cycle, i.e. an upward sloping yield curve occurs prior to periods of economic growth, and the yield curve inverts prior to a recession.
The positive relationship between the yield curve and the business cycle is important as it suggests that the yield curve may be used to forecast business cycles.
CHAPTER THREE

EMPIRICAL LITERATURE REVIEW ON THE YIELD CURVE AS A RECESSION FORECASTING TOOL

3.1 INTRODUCTION

The previous chapter provided a theoretical background on the term structure of interest rates, the shape of the yield curve, and the relationship between the yield curve and the business cycle. This theoretical relationship is important, as it suggests that the yield curve may be used to forecast business cycles. This chapter will include an empirical analysis of the relationship between the term structure and the business cycle. A number of empirical studies have demonstrated that the yield curve may be used to forecast future economic activity, amongst a number of other financial variables. Financial variables are used as the prices of financial variables are said to contain information about future economic activity (Estrella & Mishkin, 1998). The relationship between financial variables, including the yield curve and economic activity will be discussed, followed by the models that are used to forecast future economic activity.

This chapter is structured as follows. Section two provides a discussion on the relationship between the use of financial variables in forecasting future economic activity, and identifies the variables that have been found to provide good forecasts on economic activity based on various empirical findings. Section three is a review of the models that are used for the forecasting of economic activity, this section is divided into three parts, the first sub-section is an analysis of the ability of linear regression models to forecast future economic activity; this is followed by a discussion on the static probit model, which may only be used to forecast future recessions, and how this model’s predictive ability fares against that of the linear regression model. The number of variations of the probit model has since grown since the introduction of the static probit model; a brief review of some of these is discussed in the last sub-section, and considers how these may or may not have improved the probit model’s forecasting ability.

3.2 THE USE OF FINANCIAL VARIABLES AS FORECASTING TOOLS

The use of financial variables, rather than macroeconomic variables, is favoured when forecasting future economic activity. This is due to the fact that the data is immediately available which may, for instance, assist in identifying the possible effects of any discrete economic changes on the economy, such as fiscal policy changes on future economic activity. Furthermore, because financial data is not revised, there is
no risk of forecasting future economic activity using preliminary data; this applies when forecasting recessions using the yield curve, for instance. The revision, and in some cases redefinition, often associated with macroeconomic variables, may lead to significant bias that may result in a good real-time forecast of previous recessions, but poor forecasts of possible future recessions (Chen, Iqbal & Lai, 2011). Lastly, in the case of interest rates, the data is available for long maturities, therefore forecasts can be run in the long-run, unlike some macroeconomic forecasts that may only be run for a maximum period of two years. Thus, variables such as the yield curve spread and share prices may be considered to be good explanatory variables when forecasting future economic growth or recessions (Bernard & Gerlach, 1998).

The yield curve spread has proven to be a superior forecast of recessions, as demonstrated by Estrella (2005) who documented that the yield curve has become inverted before every recession from 1960 in the United States (US), and that the probability of recession, estimated by running a probit model using the yield curve, has been higher than 30% before each recession since 1960, with the exception of a single false signal in 1966. Other financial variables contain information about economic activity, thus they too should provide good forecasts of recessions, e.g. variables such as share prices (Estrella & Mishkin, 1998: 45). A share price is defined as the present value of future dividends, thus share prices contain information not only about the future value of the company, but that of future interest rates as well, and information on the expected future economic outlook as a result (Estrella and Mishkin, 1998: 45).

Levine (1996) is in agreement, and suggests that share prices may be used to forecast future economic activity as increased liquidity in stock markets results in, or occurs prior to, economic growth. Countries that had very liquid stock markets had higher levels of economic growth in the long run when compared to countries with illiquid markets. The article argues that the liquidity of the stock market, not the size of the stock market is what drives economic growth, as investors want the security of investing their money and withdrawing it at any given moment without any risk attached to it. Some financial variables that have been used in various studies include commercial paper, stock indices, money supply, various GDP growth rates, CPI, and indices of leading indicators (Dueker, 1997; Estrella & Mishkin, 1998; Moolman, 2003; Chionis, Gogas & Pragidis, 2010).

Financial variables are used by Estrella and Mishkin (1998) and Moolman (2003) in a static probit model in order to examine how various explanatory variables compared in forecasting the probability of recessions in the US and South Africa, respectively. Moolman (2003) makes use of amongst others, the
yield curve spread, the short-term interest rate, the Rand-Dollar exchange rate, money supply, the JSE ALSI, Consumer Price Index (CPI), and the composite index of leading indicators. The pseudo $R^2$ is used as a measure of fit, or as the standard of comparison between the explanatory variables. The higher the pseudo $R^2$ is, the more accurately the explanatory variable forecasts recessions. The author reports that the short-term rate and yield curve provide the best forecasts, and their results improved over the sample period.

The yield curve and share prices are believed to produce the best in-sample-forecasts across a number of explanatory variables, which include the yield curve, CPI, the Dow Jones Industrial Index (DJIA), New York Stock Exchange (NYSE), Standard & Poor’s (S&P) 500, money supply, various indices of leading indicators, and GDP in a study conducted by Estrella and Mishkin (1998). Although the yield curve and share prices are found to produce the best results, when forecasting from the second quarter going forward the yield curve surpassed all the variables including the share price in the long-run. Moreover, Estrella and Mishkin (1998) believe that although the yield curve produces a superior forecast in comparison to the other variables, the yield curve’s forecasting ability can be enhanced by including both the share prices and yield curve in a single model, as the share price would enhance forecasting in the short-run and the yield curve in the long-run.

From the above studies, it has been suggested that the yield curve has repeatedly been found to produce an accurate forecast of recessions when compared to other financial variables. Similarly, the yield curve amongst other explanatory variables is used to forecast economic growth and the probability of recessions in the US (Dotsey, 1998) and Australia (Karunaratne, 2002). Both studies declare that the yield curve produces the best forecast across all the other variables. As confirmed by Estrella and Mishkin (1996), and Estrella (2005); Estrella and Mishkin (1996) argue the yield curve has surpassed financial and macroeconomic indicators in forecasting recessions two to six quarters ahead. Estrella (2005) argues that the yield curve produces a superior forecast over other financial variables due to its accuracy and consistency over time, unlike share prices and credit-quality interest rate spreads that have produced some false signals or have unsuccessfully forecast certain recessions.

A recession may lead to lower share prices as a result of lower earnings and dividends, and this suggests that a relationship may exist between economic activity and share prices; however, the use of share prices may not produce accurate and consistent results when forecasting future economic activity. In agreement is Harvey (1989), who warns that although lower share prices could reflect investors’
expectations of future recessions, share prices may not always provide a good measure of future economic activity due to the fact that the share price could be a reflection of investors’ views on how risky the future cash flows of the specific company may be, rather than future economic growth. Thus, share prices may not always be a reliable explanatory variable.

In addition to the yield curve’s ability to accurately forecast recessions in its domestic country, it has also been argued that a foreign country’s yield curve spread may have forecasting ability in the domestic country. In a study conducted by Bernard and Gerlach (1998), the static probit model was used to forecast recessions in eight countries, namely Belgium, Canada, France, Germany, Japan, the Netherlands, the United Kingdom (UK) and the US. The yield curve was demonstrated to produce a good forecast in each of the domestic countries, Japan being the exception, with the weakest results. It is reported that the term spread forecast recessions as far ahead as seven quarters in some of these countries, which may be informative from a monetary policy viewpoint. Furthermore, the authors suggest that although the German and the US yield curve spreads were found to be significant in some of the foreign countries forecast results, the foreign yield curve was predictive for Japan and the UK, where the German yield curve spread was predictive for Japan, and the US spread was predictive for the UK. Moreover, leading indicators were added to the domestic models, and the authors concede that the addition of an index of leading indicators increased the model’s forecasting ability only in the short-run. Therefore, the yield curve continues to provide a better forecast of recessions, although adding the leading indicators would increase the model’s forecasting ability in the short-run.

In the study conducted by Bernard and Gerlach (1998), it is argued that the yield curve provides a good forecast of recessions in each of the domestic countries, with the spreads of Canada, Germany and the US providing the highest level of information about future economic activity, unlike Japan who produces the weakest results. The authors suggest that this could be due to differences in the regulations of the financial markets within the countries, and this may prevent the interest rates from correctly reflecting the financial market participants’ expectations of future economic activity. The authors highlight that it is imperative to define recessions in the same way when testing across various countries.

The ability of the yield curve spread to not only provide a good forecast of recessions for the domestic country, but also for another country was further explored by Harvey (1997). The author found that the yield curve produces a good forecast of the Canadian economic growth rate using an asset-pricing model. In addition, due to the correlation between the American and the Canadian yield curves and business cycles, a proportion of the Canadian yield curve’s ability to predict economic growth was due to
its correlation with that of the American yield curve. Moreover, the author suggests that it is possible to estimate the portion of the change in the Canadian growth rate that is due to the correlation between the American and Canadian business cycles.

Although it appears that the yield curve provides the most accurate forecast of economic activity when compared with other financial variables, the addition of other financial variables to a model that contains the yield curve may improve its forecasting ability, as demonstrated by Dotsey (1998). The results of the model were enhanced when two lags of GDP, the spread and four lags of the T-bill were included in the probit model. In Karunaratne’s (2002) study, the results from the probit model were improved by including a lagged dummy recession variable.

Dotsey (1998) and Estrella and Mishkin (1998) agree that not only does the yield curve produce good forecasts of recessions, but that it is a valuable, fairly simple tool to use, due to the perspective that a flat or inverted yield curve signals recessions. Furthermore, Estrella (2005) suggests that in forecasting recessions, special attention needs to be placed on the level of the yield curve spread, as it is the level and not the change in the spread that influences the probability of recession. A change in the spread could have different implications on the forecast based on the original level of the spread. Estrella and Mishkin (1998) go on to add that it should not replace macroeconomic and judgmental forecasts, but that the yield curve spread could be used as a swift way to verify the results obtained from the more complex models.

From the review of empirical studies, it is evident that the yield curve is used when forecasting economic activity. It would therefore appear to provide an accurate forecast of recessions and economic growth amongst a number of financial variables. Although the yield curve produces a better forecast, the addition of one or more of the other financial variables may improve the model’s forecasting ability, even if it is only in the short-run. The yield curve’s simplicity and ease of use makes it a popular tool in forecasting. The results that would be obtained from these forecasts would provide government with crucial information on which to base their future monetary policies (Moolman, 2003).

### 3.3 Forecasting Models

In forecasting economic activity, the yield curve has been widely used in linear regressions in order to forecast future economic growth, and in probit models to forecast the probability of recessions. Some of

### 3.3.1 Forecasting Economic Growth Using the Yield Curve

It has been proposed that the yield curve can be used to forecast economic growth by running a linear regression model. Hamilton and Kim (2002) used the yield curve spread to forecast real GDP growth. The authors suggest the yield curve's ability to forecast may be divided into future movements in short-term interest rates (expectations effect), the term premium of interest rates, and the effect both of these may have on the future economic growth rate.

The yield curve was again successfully used to forecast economic growth in studies conducted by Estrella and Hardouvelis (1991) and Karunaratne (2002) who made use of the yield curve to forecast economic growth when running a linear regression of economic growth on the yield curve spread, in the US and Australia, respectively. Estrella and Hardouvelis (1991) ran a linear regression of real Gross National Product (GNP) on the yield curve spread, and again on a number of other explanatory variables. The authors maintain that the yield curve spread forecast the real economic growth rate better than the other explanatory variables, four years ahead when forecasting cumulative changes, and a year and a half ahead when forecasting successive marginal changes in real growth. Similarly, Karunaratne’s (2002) study also made use of a linear regression model to forecast the future economic growth rate in Australia, where real GDP was instead used as the measure of economic activity. Karunaratne (2002) reaffirms that the yield curve produces a superior forecast of economic growth over the other financial variables used when forecasting more than four quarters ahead. The other financial variables used in the study are the all ordinaries, i.e. stock market index, monetary base, and leading indicator.

Kanagasabapathy and Goyal (2002: 3673,3676) look at using the yield curve spread to forecast industrial activity in India, by successfully running a linear regression of industrial output on the yield curve spread to measure growth. The authors suggest the slope of the yield curve spread influences industrial activity through working capital; the steeper the yield curve spread, the higher the demand for working capital, and thus the higher the level of industrial growth.
The yield spread of the term structure of interest rates is used by Alles (1995) to forecast economic growth in Australia by using a linear regression model. The author argues that the term spread produces a good forecast of real GDP growth, but not nominal GDP growth. Furthermore, the spread provides a more accurate forecast of cumulative rather than marginal growth.

Nel (1996) used the yield curve to forecast GDP growth in South Africa by running a regression, whereby the first differences were used. Quarterly data ranging from the first quarter of 1974 to the fourth quarter of 1993 is used. The author concurs that a positive relationship exists between the yield curve and real GDP growth in South Africa, consequently the yield curve contains useful information about the South African business cycle. Moreover, the slope of the yield curve is essentially a product of monetary policy as the short-term rate is widely used by government as a monetary policy tool, whereas the long-term interest rate is primarily determined by the market. Therefore the yield curve reflects government’s current and expected monetary policy, and expectations of economic activity. Nonetheless, Nel (1996) believes that the yield curve’s ability to forecast economic growth in South Africa has waned from the mid 1980s.

In agreement are Dotsey (1998) and Haubrich and Dombrosky (1996) who concede that although the yield curve continues to produce the best forecast of economic growth, its forecasting ability has declined over the years. Dotsey (1998) used data ranging from the first quarter of 1955 to the fourth quarter of 1997 to run a simple regression of GDP on the yield curve spread to estimate cumulative and marginal growth. A regression was also run, which included a dummy variable that represents three categories of the term spread, a spread which has unusually high, normal, and low values, to determine whether this would result in different regression results, indicating a differing relationship between economic growth and the yield curve spread. The author reports that the yield curve’s forecasting ability has waned over the latter period of his study, possibly due to an economic shift, or choice of sample period that included very little volatility in activity. Haubrich and Dombrosky (1996) ran a regression of real GDP on the spread, over a sample period that ranged from the first quarter of 1961 to the third quarter of 1995, and later ran a regression of real GDP on a lag of the index of leading economic indicators. This was followed by a regression of the real GDP rate on a lag of GDP growth and the spread. The authors report that although the yield curve has provided a forecast of economic activity, this forecasting ability has waned over the latter 10 years of the sample period. This may be the result of a change in the relationship between economic growth and the spread, which has resulted in a break in the continuous model such that running an in-sample regression would not produce the best results.
This would be due to the fact that the data used would model the relationship that existed prior to the change in relationship.

Following the studies of Haubrich and Dombrosky (1996), Dotsey (1998), and Giacomini and Rossi (2006) have examined the stability of the yield curve spread in forecasting future economic growth, specifically in forecasting future GDP growth in the US. The authors used various forecast breakdown tests, structural break tests and out-of-sample predictive ability tests to examine the yield curve’s ability to forecast future economic growth. The tests for structural breaks determine whether the model’s variables are stable over time. Conversely, forecast breakdown tests determine the model’s general ability to forecast, whether the model will continue to provide a good forecast given changes in the economy, i.e. that the results obtained when running future models will be consistent with the results obtained in the past. This is endorsed by Silvia, Bullard and Lai (2008: 17), who state “The success of a model’s forecast ability depends on the existence of common factors that drive both the future recessions and the historical recessions and on the extent to which the model can capture those common factors”. Although Silvia, Bullard and Lai (2008) refer to the forecasting of recessions, rather than economic growth, their statement supports that of Giacomini and Rossi (2006), in that a model’s ability to produce good forecasts is determined by its ability to be consistent over time, regardless of any changes that may occur in the economy.

Thus the empirical results obtained by Giacomini and Rossi (2006) suggest forecast breaks during 1974-1976 and 1979-1987, are most likely due to changes in monetary policy. Most of the 1990s was a period during which the authors found the yield curve produced a good forecast of recessions, which they suggest is due to economic stability that resulted in a stable relationship between the spread and economic growth, thus ensuring the yield curve to be a more reliable predictor. Therefore, it is suggested that poor forecasts of economic growth by the spread may be due to an unstable relationship between the yield curve spread and economic activity, possibly due to monetary policy changes.

Research by Estrella, Rodrigues and Schich (2003) confirms that forecasting economic growth using the yield curve spread may display some instability. The study was conducted using German and American data in continuous models and binary models, to determine the yield curve’s ability to forecast economic activity or inflation using break testing econometric methodology. The continuous models involved running a regression of inflation or growth in industrial production on the yield curve spread, and the binary models to forecast future recessions or inflation. The authors demonstrate that the continuous model, or the model used to forecast economic growth, is less stable than the binary model,
which is used to forecast recessions. It is suggested that the stability of the model may be influenced by changes in monetary policy. Despite these findings, the authors generally recommend the use of stability tests whenever forecasting.

From the studies presented, the yield curve provides a good forecast across a number of explanatory variables when forecasting economic growth by running a regression. However, in certain studies it has been suggested that the yield curve’s forecasting ability was less stable in later years (Dotsey, 1998; and Haubrich & Dombrosky, 1996). The instability between the yield curve and economic growth could be subject to real shocks within the economy, which would result in a change in the relationship between the yield curve and economic growth, resulting in a structural break in a continuous model, or it may be due to monetary policy changes. This could be the reason why some regression models have found the yield curve to be less stable from the mid 1980s. Furthermore, business cycles display cyclical asymmetry, thus the economy behaves differently during phases of economic growth and recessions, and linear models, e.g. linear regressions, may not be equipped to model business cycle asymmetries (Moolman, 2004). Therefore it might be wise to look at alternative models of economic activity.

Models that generate a forecast of a dummy variable representative of either a recession or economic expansion, such as the probit model, have been found to be more stable over time (Chauvet & Potter, 2005: 78). Khomo and Aziakpono (2006) concede that due to forecasting errors that may arise from predicting future GDP from running a regression, a probit model could be run as an alternative model when forecasting business cycle turning points. Moreover, using the yield curve in a probit model makes the use of complex macroeconomic models redundant if concern lies in forecasting the occurrence of recessions, and not in estimating the economic growth rate (Moolman, 2003).

### 3.3.2 Forecasting recessions: the static probit model

The probit model is a popular tool used to forecast the probability of recessions. This model is used when the focus of the research is centered on forecasting the occurrence of recessions, rather than the future economic growth rate. It could be more productive to forecast possible recessions rather than the future economic growth rate as you would gain more from knowing when a recession might occur in order to mitigate the potential losses. Moreover it provides results in the form of a probability which is simple to use and to interpret. Many variations of the static probit model have been introduced in an effort to improve the model’s forecasting ability.
The static probit model has been shown to produce good forecasts of recessions. Business cycle data was successfully used in a probit model by Moolman (2002) and Chionis, Gogas and Pragidis (2010) in forecasting the probability of recessions in South Africa and the European Union (EU), respectively. The use of business cycle data proved to be successful as the business cycle was being forecast in these models, but more specifically, the recession phases of the business cycle was forecast. The definition of a business cycle is as follows, “Business cycles are a type of fluctuation found in the aggregate economic activity of nations that organize their work mainly in business enterprises: a cycle consists of expansions occurring at about the same time in many economic activities, followed by similarly general recessions, contractions, and revivals which merge into the expansion phase of the next cycle; this sequence of changes is recurrent but not periodic; in duration, business cycles vary from more than one year to ten or twelve years” (Burns and Mitchell, 1946: 3). From this definition, Diebold and Rudebusch (1996: 67) emphasise two critical elements. The first being the existence of co-movements of economic variables over business cycles, which take potential leads and lags in timing into consideration. Thus, the observed turning points of various economic time series, including interest rates, were used by Burns and Mitchell (1946) to forecast the business cycle turning points. Secondly, the idea that business cycle expansions should be treated independently from contractions, or recessions is encouraged.

Consequently, using business cycle data in a probit model in order to forecast future recessions should provide good forecasts as the two crucial elements identified by Diebold and Rudebusch (1996: 67) form the basis of this methodology. In using the yield curve as an explanatory variable, the application of the two elements may be explained as follows. Firstly, this method explores the link between the business cycle phases and the yield curve spread. And secondly, it is this relationship that will be made use of in order to forecast only the recession phases of the business cycle (Moolman, 2002: 43).

Therefore the successful use of the probit model in forecasting business cycle turning points is demonstrated by Moolman (2002) who used the recession dates stipulated by the South African Reserve Bank website (SARB, 2011). The author reports that the yield curve forecasts turning points in the business cycle two quarters ahead. Chionis, Gogas and Pragidis (2010) successfully made use of business cycle data as the dependent variable when running the probit model; thus in forecasting the probability of recessions, the model explores recessions as the deviation of the business cycle below the long-term trend. The probit model used is of an inverse cumulative distribution function of the standard distribution. The data range was from the first quarter of 1994 to the third quarter of 2008. The authors
declare that the yield curve along with the composite stock index produced a good forecast of recessions in the EU.

A static probit model was again successfully used by Estrella and Mishkin (1998) and Shoesmith (2003). Estrella and Mishkin (1998) used the model to forecast the probability of recessions in the US using recession dates from the National Bureau of Economic Research (NBER) website (http://www.nber.org). The model was run using the yield curve and a number of other financial variables including the Dow Jones Industrial Index, the NYSE composite, S&P500, monetary aggregates, CPI, GDP, and a few indices of leading indicators using data ranging from the first quarter of 1959 to the first quarter of 1995 for both in- and out-of-sample forecasting. The authors highlight the importance of determining the optimal forecast horizon for each variable, and warn of overfitting when too many variables are added to the model, as this could weaken the model’s forecasting ability. Moreover, they find that the yield curve spread and stock prices produced good forecasts and they believe that including both the yield curve and stock price in one model should result in an improved forecast. Shoesmith (2003) ran a static probit model in order to forecast recessions both nationally and within the 50 states in US. The author’s national results were similar to those of Estrella and Mishkin (1996, 1998), in that a probit model can be run using the yield curve in order to forecast future recessions nationally; however, only 34 out of the 50 states produced a good forecast of recessions using the yield curve spread.

When forecasting future recessions, the probit model is favoured over a linear regression model, as it has been found to be more stable over time. However, it has been argued that the static probit model has prematurely forecast recessions. This has been the case where economic slowdowns have occurred, but have been forecast as future recessions when running the static probit model. It is therefore important that the model distinguish between the two occurrences so as not to produce a false signal. Consequently, various extensions of the static probit model have been introduced as a means of producing more accurate forecasts (Chauvet & Potter, 2005: 101).

3.3.3 FORECASTING RECESSIONS: EXTENSIONS OF THE STATIC PROBIT MODEL

Although the static probit model has been demonstrated to produce good forecasts of recessions, in an effort to improve its forecasting ability, one or more of its assumptions have been adjusted, thus producing extensions or variations of the static probit model.
Similarly, a non-normal cumulative distribution function is used by Katayama (2009) in an effort to improve the static probit model's ability to forecast recessions in the US by incorporating positive skewness and excess kurtosis. Moreover, the generalised Edgeworth expansion is also used. The author proposes that the results obtained are more accurate and result in fewer false signals as it incorporates a more flexible, or realistic functional form.

Furthermore, as the static probit model does not take the autocorrelation of the dependent variable into account, the dynamic probit model was introduced as a means of including the historical information contained in the binary or dependent variable, and removing serial correlation in the errors. Dueker (1997) proposes that adding a lag of the dependent variable makes the assumption that the error has a mean of zero, conditional on the availability of information over time, more credible. Thus, the inclusion of a lag of the dependent variable to the static probit model yields a dynamic probit model (Dueker, 1997; Nyberg, 2010). Dueker (1997) demonstrates that the addition of a lag of the dependent variable has improved the yield curve’s forecasting ability in the US when compared to a static probit model. In agreement are Karunaratne (2002), Moneta (2005), Khomo and Aziakpono (2006), and Nyberg (2010).

Karunaratne (2002) looked at forecasting recessions in Australia, using data ranging from the third quarter of 1972 to the third quarter of 1997. The author observes that adding a lag of the binary variable resulted in a superior forecast of the probability of recessions, evident in a better fit from a higher pseudo $R^2$. Using data ranging from January 1980 to June 2004 to forecast recessions in South Africa using the static and dynamic probit model, Khomo and Aziakpono (2006) argue that the results were similar; however, the dynamic probit model produced superior results over the short-run, specifically within three months. The addition of a lagged dependent variable to a static probit model appears to have improved the model’s forecasting ability, even if it was only in the short-run.

Another study was conducted by Moneta (2005), who found the yield curve spread of the ten-year government bond and three-month interbank rates to provide the best forecast of recessions in the Euro area by running both the static and dynamic probit model, as proposed by Dueker (1997). The author finds that the dynamic probit model resulted in improved results for only one quarter ahead forecast.

Furthermore, Nyberg (2010) ran the static and dynamic probit model in addition to the dynamic autoregressive and autoregressive model when forecasting recessions in the US and Germany. The
author observes that the dynamic models produced superior forecasts of recessions when compared to the static model. Moreover the autoregressive models provided better results than even the dynamic models. From the studies that explore dynamic probit models, it appears that the dynamic models appear to improve the accuracy of the forecast, even if only in the short-run in some cases. However, as there are a number of variations of the probit model, it is not clear which one of the dynamic models best forecasts recessions.

Kauppi and Saikkonen (2008) use in and out-of-sample forecasting to predict the probability of recessions in the US using various dynamic probit models. Moreover, instead of using a model whereby the lag of the binary variable is the same as the forecast horizon, the authors explore using a model where the lag of the recession variable varies to that of the forecast horizon. In addition, Kauppi and Saikkonen (2008) use a one period ahead model to create iterated multi-period ahead forecasts. The authors conclude that in comparing a model that makes use of the lagged recession variable with one that uses the lagged probability variable, the results from the lagged recession variable produce superior results.

Other variations of the probit model include the probit stepwise regression models used by Silvia, Bullard and Lai (2008) and the real time dynamic probit model examined by Proaño (2010). Silvia, Bullard & Lai (2008) begin by running a probit model with auto-correlated errors in order to forecast the probability of recession, which is followed by running a stepwise regression of the dependent variable on 570 variables, including the yield curve spread in order to identify the significant variables. Using the significant variables, additional regressions are then run beginning with a regression with one variable then two, and three and so on, up to six variables. The authors used the Pseudo $R^2$ for in-sample regressions; and the RMSE and Bayesian Information Criterion (BIC) for out-of-sample regressions, to determine the best model. The authors find that the probit stepwise regression models produce better results than the static probit model.

Proaño (2010) forecast recessions in Germany using a real-time dynamic probit model using monthly financial and economic data. Significant variables are determined using an automated general-to-specific variable lag selection method. The author reports both good in-sample and out-of-sample forecasts.

Further extensions of the probit model include the use of a time-varying autoregressive probit model in a study conducted by Chauvet and Morais (2010), whereby the static probit and time-varying
Autoregressive probit models were run to forecast recessions in Brazil. The Brazilian economy is influenced by various policy regimes and instability, which may have resulted in structural breaks in the economy and short business cycles. The time-varying autoregressive probit model accounts for such breaks as it allows for structural or parameter changes across each business cycle. Furthermore, the model allows for serial correlation in the latent variable, thus including the impact the duration each business cycle phase has on the probability of recession. Moreover, the authors make use of hitting probabilities. Chauvet and Morais (2010) find that the time-varying autoregressive probit model provides a better forecast of recessions when compared to the static probit model, as its assumptions are better suited to the Brazilian economy.

Continuing the evolution of the static probit model, Chauvet and Potter’s (2005) study compares a few variations of the probit model in forecasting recessions in the US using the yield curve spread. The models used in the study include the static probit; the business cycle specific probit, which allows for shifting variances in the innovations; the time invariant probit model with autocorrelated errors; and the business cycle probit model with autocorrelated errors. The two business cycle models will take multiple breakpoints across the business cycles into consideration. These models are run using the standard probabilities and “hitting probabilities,” which consider the length of a business cycle phase. Chauvet and Potter (2005) reaffirm that the business cycle model with the autocorrelated errors provides a superior in-sample forecast than the static probit model, as it permits breaking points within the business cycle and autocorrelation within the errors.

Chen, Iqbal and Lai (2011) produced an empirical analysis for forecasting recessions in the US using a probit-dynamic factor model. The study involved using the principal component analysis method to identify common factors from a number of economic variables, in order to determine the critical factors that influence the economy that are common to the economic variables. The common factors are then used to run the probit model. This probit-dynamic factor model is reported by the authors as producing better in-sample and out-of-sample forecasts when compared to a few other chosen forecasting models. Furthermore, a simulated real-time analysis successfully forecast all of the five recessions from 1980. The authors attribute the results to the model’s ability to identify the common factors that influence changes in the economy, and it is suggested that these common factors may incorporate the lag effects of the fundamental macroeconomic factors. Moreover, if instability from a possible structural change is experienced within a number of the economic factors, these instabilities should negate each other. Chen, Iqbal and Lai (2011) emphasise that the model may be more suited to the dynamic nature
of business cycle changes, and that it is not susceptible to issues of not having sufficient explanatory variables or stringent model conditions.

These variations of the probit model have been introduced as a means of improving the static probit model’s recession forecasting ability, by adjusting one or more of its assumptions. Although there are a number of variations of the probit model, some of which are reviewed here, it is not clear which of these produces the best recession forecast. This research will focus on the forecast accuracy of these models, since there is no clear indication which model best forecasts recessions. In this study, two variations of the probit model will be compared against the static probit in an effort to determine which of these best forecasts recessions in South Africa. The probit models that will be used are the static, dynamic, and business cycle specific conditionally independent probit model, as described by Chauvet and Potter (2005).

### 3.4 CONCLUSION

The empirical analysis of forecasts of economic activity using financial variables including the yield curve has been the focus of this chapter. To begin with, the relevant explanatory variables were identified, and it was found that in comparison to macroeconomic variables, financial variables provide a better forecast of economic activity. This may be attributed to the fact that financial data is immediately available, it is not revised, and some of it is available for long maturities. Therefore, financial variables, such as the yield curve or share prices should provide good forecasts of recessions. Furthermore, the studies examined observe that the yield curve has produced the best forecasts of economic growth, or the probability of recessions, in comparison to various other financial variables. The results from the models that use the yield curve tend to be more accurate and consistent over time, there are fewer false signals and missed forecasts. However, it has been reported that the addition of other financial variables to a model that contains the yield curve may improve its forecasting ability, even if it is only in the short-run.

Following this, a discussion was conducted on primarily two methodologies that forecast business cycles. The first is regressions that predict the future economic growth rate, and the second the probit model, which predicts the probability of future recessions. The reviewed literature argues that the yield curve provides a good forecast across a number of explanatory variables when forecasting economic growth by running a regression. Although in certain studies it has been suggested that the yield curve’s
forecasting ability has been less stable in later years. This instability may be the result of real economic
shocks that cause a structural break in the continuous model, resulting from the shift in the relationship
between the yield curve and economic growth, or it may be the result of a change in the monetary
policy. Furthermore, because business cycles display cyclical asymmetry and the economy behaves
differently during phases of economic growth and recessions, linear models such as linear regressions
may not be equipped to model business cycle asymmetries, and thus may not produce the best
forecasts.

A better forecast may be attained when running a model that predicts a dummy variable of either a
recession or economic expansion, such as the probit model. These models have been found to be more
stable over time. When forecasting future recessions, the probit model is a popular tool as it produces
the results of future recessions in the form of a probability value that is simple to use and interpret. The
static probit model is the original probit model, although extensions of it have been introduced in an
effort to improve its forecasting ability. These extensions have been introduced as it has been found
that the static probit model has produced false signals of recessions in cases where economic
slowdowns, rather than recessions, have taken place. The extensions of the probit model reviewed
include a probit model that has a non-normal cumulative distribution function, the dynamic probit
model, dynamic autoregressive and autoregressive models, probit stepwise regression models, real-time
dynamic probit, a time-varying autoregressive probit, the business cycle specific probit, time invariant
probit model with autocorrelated errors, the business cycle probit model with autocorrelated errors,
and the probit dynamic factor model.
CHAPTER FOUR

METHODOLOGY OF THE YIELD CURVE AS A FORECASTING TOOL OF RECESSIONS

4.1. INTRODUCTION

Variations of the probit model have been established subsequent to the introduction of the static probit model in an effort to improve the model’s forecasting ability of recessions. This is often achieved by adjusting one or more of the probit model’s assumptions in order to improve its accuracy in forecasting. As there are so many extensions of the probit model, it is not clear which of these provides the better forecast of recessions. This research will provide a comparative study in forecasting recessions in South Africa with the use of three probit models. This chapter will review the methodology of the static probit model, and two variations, or extensions of the static probit model.

To begin with, an overview of the methodology of models that use dummy variables is presented; first to be reviewed is the linear probability model, followed by a brief review of the probit model. A detailed analysis of the methodology of the three probit models is discussed. The models are the static, dynamic, and the business cycle specific conditionally independent probit model, as described by Chauvet and Potter (2005), all of the above are found in the sub-sections of section two. Section three describes the Akaike Information Criterion (AIC), section four reviews the Schwarz Information Criterion (SIC), and section five presents a discussion on the RMSE.

4.2. METHODOLOGY

4.2.1. MODELS THAT USE A DUMMY VARIABLE

Models which have a binary or dummy variable are used when the outcome is either defined as the absence or occurrence of a particular event; or if the outcome may be modelled around a decision between two competing choices. These models look at the factors that influence the outcome, and the degree to which these explanatory variables influence the outcome. These models make use of a dummy dependent variable that takes on only one of two figures, either zero or one. One is the occurrence of a particular event, or the decision to take on a particular option, and zero is the absence of the event, or the decision to take on the alternative option (Hill, Griffiths & Lim, 2008: 418).
The linear probability model is one such model; it makes use of a linear regression model to estimate the results as a probability (Hill, Griffiths and Lim, 2008: 419-420).

The equation is as follows:

\[ P(Y = 1) = \beta_0 + \beta_1 x_1 + \cdots + \beta_k x_k + \epsilon \]  

Where: \( P \) is the probability, \( Y \) is the dummy variable, the \( \beta \) values are coefficients, \( x \) is the explanatory variables, and \( \epsilon \) is the error term. \( \beta \) is the change in the probability that the event occurs when \( x \) changes (Wooldridge, 2003:241).

When applying the linear probability model, certain problems have been identified. Firstly, when using the ordinary least squares method (OLS), it has been said that there is heteroskedasticity in the error term, i.e. the variance of the error term changes when \( x \) changes. In an effort to overcome this, the use of the generalised least squares method instead of the OLS has been recommended. Secondly, due to the linear relationship between the probability value and the explanatory variable, the model assumes that an increase in the explanatory variable results in an increase in the probability variable at a constant rate, which may produce probability values that are not in the accepted probability range of zero and one, it may produce values that are either negative or larger than one, therefore a resulting increase in the probability value at a constant rate is unfeasible. These two problems are related, as the use of the generalised least squares method may lead to the second problem. Therefore, in order to avoid the abovementioned problems, a non-linear model, the probit model is often used (Hill, Griffiths & Lim, 2008: 420-421).

4.2.2. THE STATIC PROBIT MODEL

In an effort to overcome the problems that are associated with the linear probability model, namely heteroskedasticity in the error term, and probability values that lie outside the range of zero and one, the use of the probit model has been advocated (Hill, Griffiths & Lim, 2008: 420-421). It is the non-linear nature of the probit model that seeks to address and rectify these issues, through the S-shaped relationship between the explanatory variable and probability. As the value of the independent variable increases, the probability value increases at an increasing rate initially, after which it continues to increase, but at a decreasing rate, there is therefore an S-shaped relationship between the independent variable and probability (Hill, Griffiths & Lim, 2008: 421).
Figure 4.1. The relationship between the explanatory variable and probability of recessions

Source: Adapted from Hill, Griffiths and Lim (2008: 421)

The probit model has been widely used to forecast recessions or business cycle turning points (Estrella & Hardouvelis, 1991; Dueker, 1997; Estrella & Mishkin, 1998; Karunaratne, 2002; and Moolman, 2003).

Three variations of the probit model will be run to conduct a comparative study in order to identify the model that best forecasts recessions in South Africa, with the least number of false signals and missed recessions. The probit models that will be run include the static probit, the dynamic probit model, and the business cycle specific conditionally independent probit model, as described by Chauvet and Potter (2005). The individual models are described below.

The probit model is one in which the variable being forecast takes on only one of two values, either the economy is in a recession, or it is not in a recession.

The static probit model may be characterised using the following theoretical linear regression model:

$$Y_{t+k}^* = \beta_0 + \beta_1 x_t + \epsilon_t$$

$$Y_t^*$$ is defined as an unobservable variable (as it is estimated through the use of various explanatory variables: Gujarati, 2003: 608) that verifies the existence of a recession at time $$t$$, $$k$$ is defined as the
forecast horizon length, and \( \epsilon_t \) is an error term that has a normal distribution, \( \beta_0 \) is the constant, \( \beta_1 \) is defined as a vector of coefficients, and \( x_t \) is a vector of the explanatory variables at time \( t \). \( \beta_0 \) and \( \beta_1 \) are estimated using the maximum likelihood method. The observable recession indicator \( R_t \) is associated with the regression model by:

\[
R_t = \begin{cases} 
1, & \text{if } Y_t^* > 0 \\
0, & \text{otherwise} 
\end{cases}
\]  

(3)

The form of the estimated equation is:

\[
P(R_{t+k} = 1) = F(\beta_0 + \beta_1 x_t)
\]

(4)

\( F \) is the cumulative normal distribution function, which represents the non-linear relationship between the \( \beta \) values and the probability of recession.

The maximum likelihood method is used to approximate the model.

The recession indicator, \( R_t \) is obtained from the South African Reserve Bank to determine the recession dates such that:

\[
R_t = \begin{cases} 
1, & \text{if the economy is in a downward phase at time } t \\
0, & \text{otherwise} 
\end{cases}
\]  

(5)

Once the model is run and the values for \( \beta_0 \) and \( \beta_1 \) are estimated at the optimal forecast horizon, the probabilities of recessions can then be calculated using Excel with the following formula = NORMSDIST(-“beta0 value” –“beta1 value”*S_t). \( S_t \) is the cell that holds the value of the yield curve spread, as a percentage (Estrella & Trubin, 2006).

The probit model has evolved through various extensions of the static probit model. One of the more popular models is the dynamic probit model, as it takes into account the information found in the previous states of the economy. Another is a probit model that permits the variance of the innovation term to change along with the business cycle.

4.2.3. THE DYNAMIC PROBIT MODEL

The static probit model is a time-series model that does not include the dynamic element of the dependent variable (Karunaratne, 2002). It excludes the information found in the autocorrelation
structure of the dependent or binary variable in forecasting recessions. Thus, all previous business cycle phases are not considered in the new model; this could be a hindrance as a variable’s history has been found to be significant in forecasting univariate time-series models (Dueker, 1997: 44).

Furthermore, from the static probit model equation, the dummy variable is estimated using the explanatory variable, $x$ and the random shock, or error term, $\varepsilon$. The model makes the assumption that the random shocks, $\varepsilon$ are independent, identically distributed, normal random variables with a mean of zero. However, it may not be sound to assume that the error term from a time-series model has a conditional mean of zero when only the $x$ variable is considered in the equation, without taking into consideration the previous states of economic expansion and contraction. Therefore it is suggested that the error terms from the static probit model may be correlated. This may be improved by adding a lag of the dependent or binary variable which yields the dynamic probit model (Dueker, 1997: 45).

The addition of a lagged dummy variable to the static probit model removes serial correlation in $\varepsilon_t$, and it gives more credibility to the assumption that $\varepsilon_t$ has a mean of zero, conditional on information across the time period $t - k$ (Dueker, 1997), as it is similar to adding the lag of the dependent variable to a linear regression model (K homo and Aziakpono, 2006: 12).

This can be illustrated with the use of an autoregressive model, i.e. AR(1) model that is a linear regression model that includes a lag of the dependent variable as an explanatory variable, expressed below (Wooldridge, 2003: 367-369, 381, 719).

$$Y_t = \beta_0 + \beta_1 Y_{t-1} + \varepsilon_t$$  \hspace{1cm} (6)

Where $\varepsilon_t$ has an expected value of zero, given all previous values of $Y$, i.e.

$$E(\varepsilon_t|Y_{t-1}, Y_{t-2}) = 0$$  \hspace{1cm} (7)

Given that $\varepsilon_t$ is an unobservable, random shock, when equation (6) and (7) are put together, the expected value of $Y$ given its previous lags is determined by the constant term and a lag of $Y$, as follows.

$$E(Y_t|Y_{t-1}, Y_{t-2}, \ldots) = E(Y_t|Y_{t-1}) = \beta_0 + \beta_1 Y_{t-1}$$  \hspace{1cm} (8)

Equation (8) suggests that once a single lag of $Y$ is included in the model, no other lags of $Y$ will influence the expected value of $Y_t$. 

39
The assumption of no serial correlation holds in the AR(1) model described in equations (6) and (7), for as long as the number of lags of the dependent variable does not exceed one. As the explanatory variable at time \( t \) is \( Y_{t-1} \), this will hold if it can be proven that \( E(\varepsilon_t \varepsilon_s | Y_{t-1}, Y_{s-1}) = 0 \), assuming \( s < t \). As \( \varepsilon_s = Y_s - \beta_0 - \beta_1 Y_{s-1} \), and although both \( \varepsilon_s \) and \( \varepsilon_t \) are functions of \( Y \), \( \varepsilon_s \) the dating of \( \varepsilon_s \) occurs prior to that of time \( t \). According to equation (7), which states that the error term at time \( t \) has an expected value of zero, given each and every previous value of \( Y \), therefore \( E(\varepsilon_t | \varepsilon_s, Y_{t-1}, Y_{s-1}) = 0 \), and as a result \( E(\varepsilon_t \varepsilon_s | \varepsilon_s, Y_{t-1}, Y_{s-1}) = E(\varepsilon_t, Y_{t-1} , Y_{s-1}) = 0 \). Applying the law of iterated expectations, which states that \( E[E(Y|X)] = E(Y) \), consequently the result is \( E(\varepsilon_t \varepsilon_s | Y_{t-1}, Y_{s-1}) = 0 \). Therefore, there will be no serial correlation between the error terms, provided that equation (6) only includes one lag of the dependent variable.

Although only one lag of the dependent variable is permitted for the error terms to be serially uncorrelated, if another explanatory variable is included in the model, its lag may be included in the model as well.

\[
y_t = \beta_0 + \beta_1 x_t + \beta_2 y_{t-1} + \beta_3 x_{t-1} + \varepsilon_t \tag{9}
\]

These equations illustrate the idea that the addition of more lags of \( Y \) and the explanatory variables will not influence the expected value of \( Y_t \). When this is true, the equation yields a dynamically complete model (Wooldridge, 2003: 381), similar to the dynamic probit model.

The dynamic probit model is expressed as follows:

\[
P(R_t = 1) = F(\beta_0 + \beta_1 x_{t-k} + \beta_2 R_{t-k}) \tag{10}
\]

\( \beta_0 \), \( \beta_1 \) and \( \beta_2 \) are estimated using the maximum likelihood method.

The dynamic probit model has extended the static probit model by including the previous business cycle phases of the economy into the equation in an effort to improve the model’s forecasting ability. Another model also attempts to improve recession forecasting by allowing the variance of the error term to change along with the changing business cycle. This model will be discussed next.
When forecasting, the historic pattern of a time series variable is used to predict the future performance of another variable. Consequently, when forecasting recessions, a structural break in the economy may result in a shift in the relationship between the explanatory variable and the probability of recessions, resulting in a false signal or missed recession (Silvia, Bullard & Lai, 2008: 16). Therefore, it may be wise to use a model that accounts for possible structural breaks when forecasting.

The static probit model makes the assumption that the error term, $\varepsilon$, is independent, identically distributed, normal random variables with a mean of zero, and it has a variance of one (Chauvet & Potter, 2005). It is again extended, by permitting the variance of the error term to change with the business cycle, this may account for possible structural breaks which may exist in the link between the yield curve and the economy (Chauvet & Potter, 2005). The model across $N$ business cycles is as follows:

$$Y_t^* = \beta_0 + \beta_1 S_{t-K} + \sigma(t) \varepsilon_t$$  \hspace{1cm} (11)

$S_{t-K}$ is the yield curve spread over time period $t - k$

Where:

$$\sigma_n = \sigma(t) \text{ if } t_{n-1} < t < t_n, n = 1, \ldots, N$$  \hspace{1cm} (12)

The initial business cycle is partially observed beginning at $t = K + 1$ ($t_1 = K$).

Once the models are run, in order to determine the model that best forecast’s future recessions, the AIC and SIC will be used as measures of comparison for the in-sample forecasting in selecting the optimal lag length. These measures will determine how well the model fits the selected data by minimising the residual sum of squares (RSS) (Gujarati, 2003).

### 4.3. AKAIKE INFORMATION CRITERION (AIC)

The AIC will be applied to a model with different lags in order to determine the model with the lag length that produces the best forecast horizon, along with the $t$ statistics of the models. The AIC is defined as follows:

$$AIC = e^{2k/n} \frac{\sum \hat{u}_i^2}{n} = e^{2k/n} \frac{RSS}{n}$$  \hspace{1cm} (13)
Or, it may be expressed as follows:

\[
\ln AIC = \left(\frac{2k}{n}\right) + \ln\left(\frac{RSS}{n}\right)
\]  

(14)

Where:

\(RSS = \sum \hat{u}^2\). The RSS is the unexplained deviation from the actual values.

\(\ln AIC\) is the natural log of AIC; \(k\) is the number of regressors, which include the constant term; \(n\) is the number of observations and \(\hat{u}\) the residual terms.

The AIC applies a fine for adding too many regression terms in a model, as although increasing the right amount of explanatory variables increases the model’s accuracy, having too many explanatory variables may increase the variance of the forecast error. This fine is expressed algebraically as \(2k/n\) from equation (14). This will become crucial when a single probit model is run using both the yield curve spread and share prices as explanatory variables to determine whether including both variables will increase the model’s forecasting ability.

Once the results of estimating the models with different lag lengths are obtained, the model with the lowest AIC is chosen (Gujarati, 2003).

4.4. SCHWARZ INFORMATION CRITERION (SIC)

Similarly to the AIC, the Schwarz Information Criterion is as follows:

\[
SIC = n^{k/n} \sum \frac{\hat{u}^2}{n} = n^{k/n} \frac{RSS}{n}
\]

(15)

Or it may be expressed as:

\[
\ln SIC = \frac{k}{n} \ln n + \ln \left(\frac{RSS}{n}\right)
\]

(16)

Where \(\ln SIC\) is the natural log of SIC. \(\left[\left(\frac{k}{n}\right) \ln n\right]\) is the fine for including too many explanatory variables in the model, this fine is larger than that of the AIC. Similarl to the AIC, when comparing the results from different models, the model with the lowest SIC is the best model. Both the AIC and SIC may be used for in-sample and out-of-sample forecasting (Gujarati, 2003).
4.5. **ROOT MEAN SQUARED ERROR (RMSE)**

In order to determine the accuracy of the forecasting model, the RMSE will be used. It is used to establish how a model’s ability to predict may change across the time horizons (Khomo & Aziakpono, 2006: 13). The equation for the RMSE is as follows:

\[
RMSE = \sqrt{\frac{1}{n^0} \sum_i (y_i - \hat{y}_i)^2} \tag{17}
\]

Where: \( n^0 \) is defined as the number of periods that will be forecast, \( y_i \) is the observed value, \( \hat{y}_i \) is the forecast value, and the difference between these two values is the forecast error.

The RMSE is applied as follows, if for instance, there are \( k + l \) observations, and the observations up to, and including \( k \) are used in the model in order to forecast the model’s parameters. The \( l \) observations will be used to estimate the forecasting errors, which are then substituted into the equation to determine the RMSE. In order to compare forecasts across the models, the RMSE will be used. It will therefore be applied to each of the three models, and the model with the smallest RMSE is the model that produces the most accurate forecast of recessions (Wooldridge, 2003: 629).

4.6. **CONCLUSION**

This chapter provides a discussion on the analytical framework that will be used to forecast recessions in South Africa in an effort to determine the model that provides the most accurate forecast. The chapter began with a discussion on models that use binary or dummy variables, specifically the linear probability model and the probit model.

Following this, was an analysis of the methodology of the three probit models that will be used to predict recessions, the static probit, and the dynamic, which extends the static probit by taking the autocorrelation of the binary variable into account, by including a lag of the binary variable into the equation. Thirdly, the business cycle specific conditionally independent probit also extends the static probit model by permitting the variance of the innovation term to change with the business cycle, which should account for possible structural breaks which may exist in the model.

Subsequently, there was a discussion on the AIC and SIC, which will be used as the measure of goodness of fit in order to determine the optimal lag length. Lastly, there was a review of the RMSE forecast.
evaluation measure, which will be used to evaluate the forecast accuracy of the three models used to predict recessions in South Africa.
CHAPTER FIVE

EMPIRICAL RESULTS OF THE YIELD CURVE’S ABILITY TO FORECAST RECESSIONS

5.1. INTRODUCTION

The ability to accurately forecast recessions is critical as it allows government to implement the correct monetary and fiscal policy at the right time, in order to prevent any adverse effects on the economy that would result from a recession. Furthermore, investors and businesses would also benefit from the ability to foretell the future economic outlook in order to mitigate their own potential financial losses (Filardo, 1999).

This chapter will provide a discussion based on the application of the methodology presented in Chapter Four. To begin with, the data that was used to run the models will be examined, namely the yield curve spread, the JSE All Share Index, and the relationships between these explanatory variables and the business cycle. Following this is a review of the results from running the static, dynamic, and business cycle conditionally independent probit models using the individual explanatory variables at various lag lengths. Both explanatory variables were also included in each of the three models to determine whether including both variables in a single model would increase its forecasting ability. Finally, a comparative analysis between the static, dynamic and business cycle conditionally independent probit models to identify the model that produces the most accurate forecast of recessions, is presented.

5.2. DATA

Quarterly data ranging from 1st January 1980 to 31st December 2010 will be used. Quarterly data is used as Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Dotsey (1998), Karunaratne (2002) and Moolman (2002) have used quarterly data in their models. Moreover, monthly data may be too noisy and therefore generate weaker results (Estrella & Mishkin, 1998). The data used will be that of the JSE ALSI as the financial variable, and the yield curve spread will represent the difference between the 10-year government bond and the three-month Treasury bill (Estrella & Hardouvelis, 1991). The chosen spread of the 10-year government bond and the three-month Treasury bill is recommended as it has proven to be accurate and robust when forecasting recessions (Estrella & Trubin, 2006). Moreover, it has been used in studies by Dotsey (1998), Moolman (2002), and Shoesmith (2003).
The yield curve spread data is retrieved from the I-Net bridge database and the JSE ALSI from the JSE. The JSE ALSI data was received monthly, and for every three months, the average was calculated in order to convert it into quarterly data. US recessions may be derived from the NBER dates, whereby a dummy recession’s monthly variable is determined by the number of months between the peak and the trough (Estrella & Trubin, 2006). This was similarly applied to the official business cycle dates provided by the South African Reserve Bank (SARB), whereby the number of months between the upward and downward phases may be considered to be the dummy recession variable’s recession dates, converted into quarterly data, where the dummy would take on a value of one; and zero otherwise. Therefore, the dependent variable is defined as the official growth and recession dates as classified by the SARB, seen below as the upward and downward phases, respectively. Over the chosen data period, five downswings have occurred, according to the business cycle downward phases (SARB, 2012).

Table 5.1. Business cycle phases of South Africa since 1978

<table>
<thead>
<tr>
<th>Upward Phase</th>
<th>Duration (months)</th>
<th>Downward Phase</th>
<th>Duration (months)</th>
</tr>
</thead>
<tbody>
<tr>
<td>September 1999 – November 2007</td>
<td>99</td>
<td>December 2007 – August 2009</td>
<td>21</td>
</tr>
<tr>
<td>September 2009 - date</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Source: South African Reserve Bank Quarterly Bulletin, September 2012

Unit root tests, similar to those by Moolman (2002), were run on all of the variables to determine stationarity. The results of these are found in Appendix A. The Augmented Dickey-Fuller and Kwiatkowski-Phillips-Schmidt-Shin test state that the JSE ALSI and yield curve spread are stationary at all levels of significance, i.e. the 1%, 5%, and 10% levels of significance. Thus all variables are I(0).

The relationship between the yield curve spread and the business cycle is represented in Figure 5.1, which plots the yield curve spread and the official downswings, as confirmed by the SARB. The blue
shaded areas represent downswings, and the line is the yield curve spread, which is the difference between the 10-year bond and three-month Treasury bill.

Figure 5.1 depicts an increasing spread that occurs prior to periods of economic upswings, verified by economic theory that states that an upward sloping yield curve precedes periods of economic growth (Estrella & Hardouvelis, 1991). Furthermore, the graph plots the inversion of the yield curve spread prior to each of the five economic downswings over the sample period, confirming that an inverse relationship exists between the yield curve spread and the business cycle in South Africa, which may be used to forecast future economic activity. However, there is a false signal that occurs, where the yield curve inverts, signaling negative growth around 2002/2003, as the yield curve inverted from the fourth quarter of 2002 to the second quarter of 2003, but no downswings occurred at the time.

The relationship between the JSE ALSI and the business cycle is also examined in Figure 5.2, where the line represents the Index; and the shades areas represent the downswings.
It is not clear from Figure 5.2 as to whether a relationship exists between the returns of the JSE ALSI and the business cycle, although the ALSI returns have dropped significantly during the 1982, 1998 and the 2008 recessions. The ALSI returns also dropped significantly during 1987, although no recession occurred. Therefore, a probit model would have to be run in order to determine whether the JSE ALSI predicts recessions, and whether a relationship exists between share prices and economic activity in South Africa.

The three models will be run using the individual explanatory variables, following which the variables that are found to be statistically significant will be used together in a model to determine whether this may increase the model’s forecasting ability.

**5.3. THE STATIC PROBIT MODEL**

**5.3.1. THE STATIC PROBIT MODEL AND YIELD CURVE SPREAD**

The static probit model was estimated using the business cycle dates as confirmed by the SARB as the dummy variable. The explanatory variable used was the yield curve spread. Probit models ranging from
a forecast horizon of one to eight lags were run in order to determine the optimal lag structure of the model when predicting recessions using the static probit model in South Africa. This would be determined by the model with the lowest Akaike and Schwarz criterion values and statistical significance. A summary of the models run can be seen in Table 5.2 below (estimations are in Appendix B). These results demonstrate that the probit model with a lag length of two quarters produced the best results. Consequently, the yield curve spread provides an optimal forecast of recessions two quarters ahead.

Table 5.2. In-sample static probit results using the yield curve spread

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_t )</td>
<td>-0.319</td>
<td>-0.391</td>
<td>-0.366</td>
<td>-0.291</td>
<td>-0.198</td>
<td>-0.114</td>
<td>-0.061</td>
<td>-0.024</td>
</tr>
<tr>
<td>Prob of ( x_t )</td>
<td>(0.000***)</td>
<td>(0.000***)</td>
<td>(0.000***)</td>
<td>(0.000***)</td>
<td>(0.000***)</td>
<td>(0.012**)</td>
<td>0.160</td>
<td>0.578</td>
</tr>
<tr>
<td>Akaike</td>
<td>1.066</td>
<td>0.980</td>
<td>1.008</td>
<td>1.104</td>
<td>1.230</td>
<td>1.330</td>
<td>1.371</td>
<td>1.382</td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.112</td>
<td>1.026</td>
<td>1.054</td>
<td>1.151</td>
<td>1.277</td>
<td>1.377</td>
<td>1.418</td>
<td>1.429</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The yield curve spread is found to be statistically significant up to a lag of six quarters, thus the relationship between the spread and business cycle is found to be statistically significant. Furthermore, the model with the lowest Akaike and Schwarz criterion together with the statistical significance of the yield curve spread demonstrate that the optimal lag structure of the model is one that forecasts the probability of downswings two quarters ahead. These results agree with those of Moolman(2002) and Khomo and Aziakpono (2006), who report that the yield curve best forecasts recessions two quarters and five months ahead, respectively. The finding of an optimal forecast horizon of two quarters is expressed algebraically in the equation below.

\[
P(R_{t+2} = 1) = F(0.009156 - 0.391151x_t)
\]  

(1)

Where: \( P \) is the probability of a recession, \( F \) is the cumulative normal distribution, \( x_t \) is the spread at time period \( t \), and \( R \) is the dummy recession variable that takes on the value of 1 when there is a recession, and 0 otherwise.
From equation (1), the negative sign demonstrates an inverse relationship between the yield curve spread lagged two quarters and the probability of recessions at any given quarter, verifying the economic theory. Thus, an increasing yield curve spread results in a decreasing probability of recessions; and a decreasing, or inverted yield curve spread results in an increasing probability of a recession.

The use of the spread in predicting recessions is explored through a causal relationship between the spread and recessions in Table 5.3 below (also found in Appendix B). The results confirm that the direction of causality is from the yield curve spread to recession.

**Table 5.3. Granger causality test of the yield curve spread and recessions**

<table>
<thead>
<tr>
<th>Null Hypothesis</th>
<th>No. of observations</th>
<th>Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>Recession does not Granger cause spread</td>
<td>122</td>
<td>0.146</td>
</tr>
<tr>
<td>Spread does not Granger cause recession</td>
<td></td>
<td>0.001***</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance

Figure 5.3 plots the optimal forecast of the probability of recessions from running a probit model using historical data on the yield curve spread lagged two quarters, as represented by the line. The shaded areas are the downward phases as confirmed by the SARB. The graph plots a graphical representation of equation (1).
An ideal model would produce a result of one during a recession, and zero otherwise. It can be seen that the model produced a good forecast, as the probability of downswings has risen to high values during each of the downswings experienced, reaching a probability of 0.99 during the July 1984/March 1984 downswing, and values above 0.7 during the remaining downward phases. Furthermore, the forecast probabilities have continued to stay below 0.25 during the upswings. There was however a false signal that occurred in 2002/2003, where the forecast probability rose to 0.84, but no downswing followed, similar to the findings of Khomo and Aziakpono (2006). This may have brought into question the yield curve spread’s forecasting ability when using the static probit model, although the yield curve spread seems to have recovered as it correctly predicted the following downswing in 2007/2009, reaching a peak with a probability of 0.82.

Moreover, from Figure 5.3, in each case the probability of recessions has decreased during the downswings, prior to economic upswings as an indication of future economic recovery and growth, with the exception of the September 1981/March 1983 downswings. This could be due to the fact that the forecast probability of an economic downswing was at a low of 0.13 at the beginning of the recession, unlike the other forecasts which were at a minimum of 0.34 at the beginning of each of the other
recessions. Although it began at a low of 0.13, the probability rose to a high of 0.86 during the recession to accurately forecast the downswing.

Share prices are said to contain information about future economic activity because they are defined as the present value of future dividends, and therefore contain information not only about the future value of the company, but that of future interest rates as well, and consequently information on the expected future economic outlook as a result (Estrella & Mishkin, 1998: 45). It is for that reason that the perception that South African share prices may influence the business cycle is explored in the next sub-section, where the JSE ALSI is used as a proxy for the share price.

### 5.3.2. THE STATIC PROBIT MODEL AND THE JSE ALSI

The static probit model was again run using the business cycle dates as confirmed by the SARB as the dummy variable. The returns of the JSE ALSI were used as the explanatory variable, and models ranging from a forecast horizon of one to eight lags were estimated in order to determine the optimal forecast period when predicting recessions. The results of all of the models estimated can be found in Appendix B. The results are summarised in Table 5.4 below.

**Table 5.4. In-sample static probit results using the JSE ALSI**

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>-1.709</td>
<td>-2.741</td>
<td>-3.551</td>
<td>-1.960</td>
<td>0.056</td>
<td>-0.554</td>
<td>0.524</td>
<td>1.178</td>
</tr>
<tr>
<td>Prob of $x_t$</td>
<td>0.136</td>
<td>(0.019***)</td>
<td>(0.003***)</td>
<td>(0.092*)</td>
<td>0.962</td>
<td>0.633</td>
<td>0.652</td>
<td>0.315</td>
</tr>
<tr>
<td>Akaike</td>
<td>1.355</td>
<td>1.330</td>
<td>1.304</td>
<td>1.358</td>
<td>1.385</td>
<td>1.386</td>
<td>1.383</td>
<td>1.372</td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.401</td>
<td>1.377</td>
<td>1.351</td>
<td>1.405</td>
<td>1.432</td>
<td>1.433</td>
<td>1.430</td>
<td>1.420</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The return of the JSE ALSI is found to be statistically significant from the second to the fourth quarter, during which time a negative relationship between the return of the JSE ALSI and the business cycle is suggested, thus the JSE ALSI may only supply information about the possibility of economic downswings from a lag of two to four quarters. Khomo and Aziakpono (2006) similarly argue that share prices in
South Africa forecast recessions up to 12 months. In terms of determining the optimal lag structure of the model, the model with the lowest Akaike and Schwarz criterion is the one that is lagged three quarters. Therefore, the JSE ALSI best forecasts downswings three quarters ahead, expressed algebraically as follows.

\[ P(R_{t+3} = 1) = F(-0.152278 - 3.551372x_t) \]  

Figure 5.4 below shows the optimal forecast of the probability of recessions from running a probit model using historical data on the returns of the JSE ALSI lagged three quarters, as represented by the line. The graph does not show a clear relationship between the returns of the JSE ALSI and the business cycle, although the probability of recessions have reached values larger than 0.5 during each of the downswings, and surpassing the 0.65 probability mark during the 1981/1983, 1997/1999 (peaked at 0.80), and 2008/2009 downswings. However, the graph reflects two false signals, during 1988/1999 and 2002/2003, where the probability of recession was high, signalling future downswings, which did not occur.

Figure 5.4. Downswings and recession probabilities from 3rd quarter lag of the JSE ALSI
5.3.3. THE STATIC PROBIT MODEL AND THE FINANCIAL VARIABLES

The static probit model was estimated using both explanatory variables, the yield spread and returns of the JSE ALSI with forecast horizons ranging from one to eight quarters in order to determine whether the inclusion of both explanatory variables will increase the model's forecasting ability (details of the results can be found in Appendix B).

Table 5.5. In-sample static probit results using the yield curve spread and JSE ALSI

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spread</td>
<td>-0.311</td>
<td>-0.376</td>
<td>-0.368</td>
<td>-0.283</td>
<td>-0.200</td>
<td>-0.109</td>
<td>-0.073</td>
<td>-0.036</td>
</tr>
<tr>
<td>Prob</td>
<td>(0.000***), (0.000***), (0.000***), (0.000***), (0.017**), 0.100, 0.407</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>JSE ALSI</td>
<td>-0.836</td>
<td>-2.346</td>
<td>-3.723</td>
<td>-1.316</td>
<td>0.747</td>
<td>-0.230</td>
<td>0.729, 1.265</td>
<td></td>
</tr>
<tr>
<td>Prob</td>
<td>0.551</td>
<td>0.111</td>
<td>(0.010**), 0.307</td>
<td>0.533</td>
<td>0.840</td>
<td>0.527, 0.280</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike</td>
<td>1.087</td>
<td>0.983</td>
<td>0.975</td>
<td>1.121</td>
<td>1.251</td>
<td>1.353</td>
<td>1.377, 1.383</td>
<td></td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.156</td>
<td>1.052</td>
<td>1.045</td>
<td>1.191</td>
<td>1.322</td>
<td>1.424</td>
<td>1.448, 1.455</td>
<td></td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The yield spread was found to be statistically significant from the first to the sixth lag, whereas the returns of the JSE ALSI were found to be significant at a lag of three quarters. It is this horizon that reports the lowest Akaike and Schwarz criterion values. Consequently, the yield spread and JSE ALSI best forecast downswings three quarters ahead.

Figure 5.5 plots the probability estimates of the forecast of the spread and returns of the JSE ALSI at three quarters ahead. It may be observed that although none of the probabilities reach 1, for each downswing, each of the probability estimates reach a minimum value of 0.8, higher than both individual graphs of the spread and JSE ALSI from Figures 5.3 and 5.4, respectively, with the exception of the spread forecast for the 1984/1986 downswing. Moreover, the estimated probabilities remain low during periods of growth, and only one false signal was observed in 2003. Thus, it may appear that the inclusion of both explanatory variables may improve the model's forecasting ability, although this will be confirmed using the results from the Akaike, Schwarz criterion, and RMSE.
5.3.4. Evaluating the Static Probit Model’s Accuracy Across the Explanatory Variables

Table 5.6. Accuracy of the static probit models

<table>
<thead>
<tr>
<th></th>
<th>Yield Spread</th>
<th>JSE ALSI</th>
<th>Spread &amp; JSE ALSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.397044</td>
<td>0.471263</td>
<td>0.390344</td>
</tr>
</tbody>
</table>

Source: Estimations

The model with the yield spread alone and the model with both the spread and ALSI returns produce RMSE values that are close (results are can be found in Appendix E). The ALSI returns produce the highest RMSE value, thus confirming that share prices produce the least accurate result in comparison to the yield curve spread (Estrella & Mishkin, 1996). However, the model with the lowest RMSE determines the model that most accurately forecasts economic downswings, therefore the model with the spread and JSE ALSI not only produces higher probabilities, but most accurately predicts downswings when compared to models that only use the spread and share prices as explanatory variables. Consequently, it
may be suggested that including share prices when using the spread to forecast downswings improves the forecasting ability in the short-run, similar to Estrella and Mishkin’s (1998) findings.

The static probit model excludes the information found in the autocorrelation structure of the dependent or binary variable when forecasting recessions. Furthermore, the model makes the assumption that the random shocks are independent, identically distributed, normal random variables with a mean of zero. By adding a lag of the dependent or binary variable, previous states of the dummy variable will be taken into account, thus making the assumption that the random shocks are independent, identically distributed, normal random variables with a mean of zero more credible, as it removes serial correlation in the error term. The addition of a lagged dummy variable yields the dynamic probit model (Dueker, 1997: 44-45), the results of which will be discussed next.

5.4. THE DYNAMIC PROBIT MODEL

5.4.1. THE DYNAMIC PROBIT MODEL AND YIELD CURVE SPREAD

The static probit model is a time-series model that does not include the dynamic element of the dependent variable (Karunaratne, 2002). It excludes the information found in the autocorrelation structure of the dependent or binary variable in forecasting recessions (Dueker, 1997: 44). This may be improved by adding a lag of the dependent variable, resulting in the dynamic probit model. The addition of a lagged dummy variable to the static probit model removes serial correlation in the error term, and it gives more credibility to the assumption that \( \epsilon_t \) has a mean of zero, conditional on information across the time period \( t - k \) (Dueker, 1997).

The dynamic probit model is expressed algebraically as follows.

\[
P(R_t = 1) = F(\beta_0 + \beta_1 x_{t-k} + \beta_2 R_{t-k})
\]  

(3)

The model was run using the business cycle data provided by the SARB as the dummy recession variable. The yield curve spread was used as the explanatory variable along with a lagged recession variable. Probit models ranging from a forecast horizon of one to eight lags were run in order to determine the optimal lag structure of the model when predicting recessions using the dynamic probit model in South Africa. This would be determined by the model with the lowest Akaike and Schwarz criterion and statistical significance. The complete set of results can be found in Appendix C; these are further summarised in Table 5.7 below.
Table 5.7. In-sample dynamic probit forecast using the yield curve

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>-0.328</td>
<td>-0.342</td>
<td>-0.306</td>
<td>-0.263</td>
<td>-0.206</td>
<td>-0.140</td>
<td>-0.101</td>
<td>-0.057</td>
</tr>
<tr>
<td>Prob of $x_t$</td>
<td>(0.000***), (0.000***), (0.000***), (0.000***), (0.006***), (0.042**), 0.238</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$R_{t-k}$</td>
<td>2.829</td>
<td>1.729</td>
<td>0.940</td>
<td>0.354</td>
<td>-0.099</td>
<td>-0.329</td>
<td>-0.508</td>
<td>-0.442</td>
</tr>
<tr>
<td>Prob of $R_{t-k}$</td>
<td>(0.000***), (0.000***), (0.001***), 0.198, 0.717, 0.225, (0.064*), 0.104</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Akaike</td>
<td>0.474</td>
<td>0.718</td>
<td>0.933</td>
<td>1.107</td>
<td>1.246</td>
<td>1.334</td>
<td>1.358</td>
<td>1.376</td>
</tr>
<tr>
<td>Schwarz</td>
<td>0.543</td>
<td>0.787</td>
<td>1.002</td>
<td>1.177</td>
<td>1.316</td>
<td>1.404</td>
<td>1.429</td>
<td>1.447</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

From Table 5.7, it can be seen that the coefficients for the spread are negative, confirming the negative relationship between the yield curve spread and business cycle. Furthermore, these continue to be statistically significant from the first to the seventh lag. When compared to Table 5.2, the yield spread’s forecasting ability increases up to seven quarters, unlike the six quarters using the static probit. The lag of the dummy variable remains significant up to and including the third lag, after which time it becomes statistically insignificant and the sign changes from positive to negative from the fifth lag where it continues to be insignificant. This demonstrates that there is a positive, statistically significant relationship between the lag of the dummy variable and recessions. Therefore, a recent recession is likely to increase the probability of a future recession. The lag of the dummy variable however, is significant at the seventh lag, but the variable’s sign is contrary to what is expected. Moreover, based on the lowest Akaike and Schwarz criterion, the model that provides the most optimal forecast of recessions is one that forecasts recessions one quarter ahead, expressed algebraically below. Khomo and Aziakpono (2006) reported an optimal forecast horizon of six months, whereas Clay and Keeton (2011) reported four months, where both studies used the lowest RMSE to identify the optimal forecast horizon.

$$ P(R_t = 1) = F(-1.282151 - 0.327607x_{t-1} + 2.828718R_{t-1}) \quad (4) $$

Figure 5.6 below plots the graphs of the optimal forecast of the probability of recessions from running both the static and dynamic probit models using historical data on the yield curve spread lagged two
quarters and one quarter, respectively. The estimated probability from the static probit model is represented by the black line, whereas the estimated probability from the dynamic model is represented by the pink line. When running a model, the probability should be one during periods of downswings, and zero during periods of economic growth. Both graphs plot low probabilities of recession during periods of economic growth, the static model only estimates a probability of zero during the period between 1986/1989, unlike the dynamic model that estimates a probability of zero during each of the economic growth periods. Furthermore, although the static probit model predicts high probabilities above 0.7 for each of the downswings, the dynamic probit forecasts probabilities of 1 during the 1984/1986 and 1997/1999 recessions, and peak at 0.99 during the remaining 1981/1983, 1989/1993, and 2008/2009 recessions. The static probit model forecast resulted in a false prediction of a downswing in 2002/2003, where the estimated probability peaked at 0.84, unlike the dynamic probit which estimated a probability of 0.32. These results suggest that the dynamic probit may produce a better probability forecast when compared to the static probit model. However, Khomo & Aziakpono (2006), reported comparable results, observing a false signal in 2003 when estimating using both the static and dynamic probit model.

Figure 5.6. Downswings and recession probabilities of the static vs. dynamic probit forecasts -spread
In order to determine which explanatory variable provides a better forecast of recessions, the relationship between the JSE ALSI and the business cycle when forecasting with the dynamic probit model is discussed next.

5.4.2. THE DYNAMIC PROBIT MODEL AND JSE ALSI

A summary of the results obtained from running dynamic probit models using the JSE ALSI returns as the explanatory variables with lags ranging from one to eight quarters is presented in Table 5.8 below (a complete set of results can be found in Appendix C). The results obtained suggest that when running the model of the ALSI returns and recession variable with the same lag and differing lags, the recession variable produces the best results when lagged one quarter across all the lags of the ALSI returns, thus the table below is a summary of the ALSI lagged from one to eight quarters and the recession variable lagged one quarter.

**Table 5.8. In-sample dynamic probit results using the JSE ALSI returns**

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>-1.401</td>
<td>-3.251</td>
<td>-3.051</td>
<td>2.479</td>
<td>3.902</td>
<td>-1.639</td>
<td>2.853</td>
<td>2.218</td>
</tr>
<tr>
<td>Prob of $x_t$</td>
<td>0.409</td>
<td>(0.0564*)</td>
<td>(0.0718*)</td>
<td>0.166</td>
<td>(0.0256**)</td>
<td>0.313</td>
<td>0.119</td>
<td>0.204</td>
</tr>
<tr>
<td>$R_{t-1}$</td>
<td>2.749</td>
<td>2.805</td>
<td>2.725</td>
<td>2.947</td>
<td>3.035</td>
<td>2.756</td>
<td>2.963</td>
<td>2.865</td>
</tr>
<tr>
<td>Prob of $R_{t-1}$</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
<td>(0.000***):</td>
</tr>
<tr>
<td>Akaike</td>
<td>0.607</td>
<td>0.585</td>
<td>0.592</td>
<td>0.607</td>
<td>0.582</td>
<td>0.623</td>
<td>0.569</td>
<td>0.579</td>
</tr>
<tr>
<td>Schwarz</td>
<td>0.675</td>
<td>0.654</td>
<td>0.662</td>
<td>0.677</td>
<td>0.652</td>
<td>0.694</td>
<td>0.640</td>
<td>0.651</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

In determining the optimal lag structure of the model, the lag with the lowest Akaike and Schwarz criterion together with significant ALSI return and lagged dummy variables is one with a lag of five quarters for the ALSI return, and one quarter for the dummy recession variable. Thus, the ALSI return
provides optimal forecasting ability when using the dynamic probit model five quarters ahead, expressed algebraically:

\[ P(R_t = 1) = F(-1.708574 + 3.901622x_{t-5} + 3.034759R_{t-1}) \]  

(5)

The above relationships suggest that there is a positive relationship (unlike the static probit that demonstrates a negative relationship) between share prices and the probability of future downswings. Therefore, a decline in the returns of share prices is likely to result in a period of economic downswing, and rising share prices are likely to signal a recovering economy, or future economic growth. Furthermore, a positive relationship exists between a lagged recession variable and the probability of downswings, thus the current downswing period is likely to be followed by another period of economic downswing.

Figure 5.7 below plots the graphs of the optimal lag structures of the probability of recessions from running both the static and dynamic probit models using historical data on the JSE ALSI lagged three quarters for the static, and lagged five quarters for the dynamic, using the ALSI and one for the dummy variable, respectively.

![Figure 5.7. Downswings and recession probabilities of the static vs. dynamic probit forecasts –JSE ALSI](image-url)
The above graph suggests that in both cases, the estimated probability of recessions is higher during periods of economic downswings, and lower during periods of economic growth. Although, the graph suggests that the estimated probabilities of the dynamic probit are significantly higher than the static probit during periods of downswings and lower during periods of growth, with the peaks ranging from 0.94 to 0.98 during recessions and ranging from 0 to 0.05 during periods of growth. The static probit model resulted in false signals in 1988 and 2003, where the model estimated a high probability of recession, although no recession occurred. However, the dynamic probit model did not produce any false signals. These results suggest that the dynamic probit produces a better estimate of future economic downswings in comparison to the static probit model.

5.4.3. THE DYNAMIC PROBIT MODEL AND THE FINANCIAL VARIABLES

The dynamic probit model was estimated using the yield spread, returns of the JSE ALSI, and a lag of the dummy variable with mixed forecast horizons ranging from one to eight quarters in order to determine whether the inclusion of both the spread and ALSI returns as explanatory variables may increase the model’s forecasting ability (results can be found in Appendix C).

Table 5.9. In-sample dynamic probit results using the yield curve spread and JSE ALSI

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Optimal (1:3:1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-1.285</td>
<td>-0.671</td>
<td>-0.289</td>
<td>-0.133</td>
<td>-0.035</td>
<td>0.048</td>
<td>0.045</td>
<td>-0.061</td>
<td>-1.213</td>
</tr>
<tr>
<td>Prob</td>
<td>0.000***</td>
<td>0.002***</td>
<td>0.156</td>
<td>0.491</td>
<td>0.855</td>
<td>0.795</td>
<td>0.807</td>
<td>0.739</td>
<td>0.000***</td>
</tr>
<tr>
<td>Spread</td>
<td>-0.328</td>
<td>-0.329</td>
<td>-0.314</td>
<td>-0.257</td>
<td>-0.207</td>
<td>-0.136</td>
<td>-0.111</td>
<td>-0.067</td>
<td>-0.344</td>
</tr>
<tr>
<td>Prob</td>
<td>0.001***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.008***</td>
<td>0.027**</td>
<td>0.169</td>
<td>0.000***</td>
</tr>
<tr>
<td>JSE ALSI</td>
<td>0.078</td>
<td>-3.009</td>
<td>-3.999</td>
<td>-1.225</td>
<td>0.720</td>
<td>-0.341</td>
<td>0.562</td>
<td>1.158</td>
<td>-3.841</td>
</tr>
<tr>
<td>Prob</td>
<td>0.975</td>
<td>0.1*</td>
<td>0.01**</td>
<td>0.345</td>
<td>0.550</td>
<td>0.767</td>
<td>0.629</td>
<td>0.327</td>
<td>0.061*</td>
</tr>
<tr>
<td>R_{t+k}</td>
<td>2.829</td>
<td>1.776</td>
<td>0.978</td>
<td>0.338</td>
<td>-0.089</td>
<td>-0.338</td>
<td>-0.493</td>
<td>-0.420</td>
<td>2.891</td>
</tr>
<tr>
<td>Prob</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.001***</td>
<td>0.221</td>
<td>0.745</td>
<td>0.215</td>
<td>0.074*</td>
<td>0.125</td>
<td>0.000***</td>
</tr>
<tr>
<td>Akaike</td>
<td>0.495</td>
<td>0.718</td>
<td>0.899</td>
<td>1.125</td>
<td>1.267</td>
<td>1.357</td>
<td>1.366</td>
<td>1.380</td>
<td>0.472</td>
</tr>
<tr>
<td>Schwarz</td>
<td>0.587</td>
<td>0.810</td>
<td>0.992</td>
<td>1.218</td>
<td>1.361</td>
<td>1.451</td>
<td>1.461</td>
<td>1.475</td>
<td>0.565</td>
</tr>
</tbody>
</table>

Source: Estimations
***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The above table reports the results of the probit model using both the spread and ALSI returns as explanatory variables along with the dummy variable lagged at each of the forecast horizons. The yield curve spread is found to be statistically significant up to and including a lag of seven quarters, whereas the ALSI returns are only significant at a lag of two and three quarters, and the dummy is found to add statistical significance up to and including a lag of three quarters. The model that reports the lowest Akaike and Schwarz criterion values is one that forecasts downswings at a lag of one quarter for both the spread and dummy recession variables, and a lag of three quarters for the JSE ALSI returns (i.e. 1:3:1), these results are also included in the table in the optimal column (1:3:1).

Figure 5.8 shows the probability estimates of the optimal lag structure of the spread and returns of the JSE ALSI at one and three quarters respectively for the dynamic probit model. The probability estimates reach 0.99 during the 1989/1993 and 2008/2009 recessions, and 1 during the remaining observed recessions. Moreover, the probabilities remain low during economic upswings, with estimated probabilities remaining below 0.1 on average. In 2003, a false signal was reported where the estimated probability of an economic downswing peaked at 0.62, thus predicting a downswing, which did not occur.
5.4.4. EVALUATING THE DYNAMIC PROBIT MODEL’S ACCURACY ACROSS THE EXPLANATORY VARIABLES

The evaluation tool used to determine which model best predicts recession in South Africa is the RMSE (results are can be found in Appendix E). It is widely used as it establishes how a model’s ability to predict may change across the time horizons (Khomo & Aziakpono, 2006: 13).

Table 5.10. Accuracy of the dynamic probit models

<table>
<thead>
<tr>
<th></th>
<th>Yield Spread</th>
<th>JSE ALSI</th>
<th>Spread &amp; JSE ALSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.247</td>
<td>0.263</td>
<td>0.250</td>
</tr>
</tbody>
</table>

Source: Estimations

The dynamic probit forecast produces RMSE results that are lower than those of the static probit model. In addition, when comparing the results of the forecast using the dynamic probit, the model with the lowest RMSE is the model that uses the yield curve spread. This is followed by the model that uses both the ALSI and spread as explanatory variables, although the relationship between the share prices and
the probability of economic downswings contradicts that of economic theory. This may suggest that share prices may not be a good indicator of economic activity. Furthermore, the RMSE results suggest that the ALSI returns produce more errors than the other models. Moreover, it can be observed that the yield curve spread most accurately forecasts economic downswings when estimating using the dynamic probit model, unlike the static probit which demonstrates that the inclusion of the ALSI returns increases the model’s forecasting ability in the short-run.

In an effort to improve the probit model’s forecasting ability, another extension of the probit model was proposed, one that allows the variance of the error term to change across the business cycle. The results from running this model will be discussed next.

5.5. THE BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL

5.5.1. THE BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL AND YIELD CURVE SPREAD

When forecasting recessions, a structural break in the economy may result in a shift in the relationship between the explanatory variable and the probability of recessions, resulting in a false signal or missed recession (Silvia, Bullard & Lai, 2008: 16). The static probit model is thus extended, resulting in a business cycle specific conditionally independent probit model, by permitting the variance of the error term to change with the business cycle and this may account for possible structural breaks that might exist in the link between the yield curve and the economy (Chauvet & Potter, 2005).

The business cycle specific conditionally independent probit model is expressed as follows:

\[ Y_t^* = \beta_0 + \beta_1 S_t - K + \sigma(t) \varepsilon_t \]

(6)

In order to estimate the business cycle specific model, the residuals of the optimal forecast model of the static probit model that forecasts the probability of recessions three quarters ahead were estimated, and the variance of each of the residuals at each quarter were calculated using the below formula:

\[ Var(X) \equiv E[(X - \mu)^2] \]

(7)

Where: \(X\) is defined as a random variable, in this case the residual; and \(\mu\) is the mean, or average.
Once the variance was estimated, it was used as a time series explanatory variable in addition to the yield curve spread in the probit model. The model was estimated with forecast horizons ranging from one to eight lags of the spread, the summary of the results can be seen below in Table 5.11 (complete results are in Appendix D).

Table 5.11. In-sample business cycle conditionally independent probit results using the yield spread

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Optimal (3:8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>( x_t )</td>
<td>-0.307</td>
<td>-0.383</td>
<td>-0.354</td>
<td>-0.280</td>
<td>-0.188</td>
<td>-0.122</td>
<td>-0.077</td>
<td>-0.054</td>
<td>-0.444</td>
</tr>
<tr>
<td>Prob of ( x_t )</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.012**</td>
<td>0.100</td>
<td>0.247</td>
<td>0.000***</td>
<td></td>
</tr>
<tr>
<td>( \sigma(t) \varepsilon_t )</td>
<td>0.322</td>
<td>0.192</td>
<td>0.345</td>
<td>0.253</td>
<td>0.204</td>
<td>-0.042</td>
<td>0.063</td>
<td>-0.607</td>
<td>-0.865</td>
</tr>
<tr>
<td>Prob of ( \sigma(t) \varepsilon_t )</td>
<td>0.623</td>
<td>0.785</td>
<td>0.621</td>
<td>0.709</td>
<td>0.753</td>
<td>0.947</td>
<td>0.919</td>
<td>0.343</td>
<td>0.264</td>
</tr>
<tr>
<td>Akaike</td>
<td>1.096</td>
<td>1.011</td>
<td>1.038</td>
<td>1.136</td>
<td>1.262</td>
<td>1.341</td>
<td>1.371</td>
<td>1.379</td>
<td>0.947</td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.166</td>
<td>1.081</td>
<td>1.108</td>
<td>1.207</td>
<td>1.332</td>
<td>1.412</td>
<td>1.442</td>
<td>1.451</td>
<td>1.019</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The spread is statistically significant up until the seventh quarter lag; however the variance of the error term is found to be insignificant over the above forecast horizon. The variance of the error term is found to be significant in a few instances where mixed lags between the spread and variance terms are used. Therefore, it may be suggested that the variance of the error term may not add significant predictive ability when forecasting downswings using the yield curve spread. The model with the lowest Akaike and Schwarz criterion is one with mixed lags (results in the optimal (3:8) column in the table), where the spread is lagged three quarters, and the variance of the error term is lagged eight quarters (3:8). The variance of the error term is nonetheless found to be statistically insignificant; therefore it may be concluded that the variance of the error term does not add predictive ability. The optimal lag structure of the model predicts downswings three and eight quarters ahead, expressed algebraically below.

\[
P(R_t = 1) = F(0.087217 - 0.444403 S_{t-3} - 0.864783 \varepsilon_{t-8})
\]  (8)

Equation (8) demonstrates an inverse relationship between the yield curve spread and the probability of downswings, which is supported by economic theory. Moreover, it is suggested that there is also a
negative relationship between the variance of the error term and the probability of downswings, thus suggesting that periods of high volatility are often followed by periods of less volatility; this variable was found to be insignificant in this model.

Figure 5.9. Downswings and recession probabilities of the static, dynamic & business cycle probit forecasts – yield curve spread

The above graph plots the optimal lag structures of the probability of recessions when using historical data of the yield curve spread lagged two and one quarter for the static and dynamic probit models, respectively. In addition to the static and dynamic probit models, the graph plots the business cycle conditionally independent probit model with the optimal lag structure of three quarters for the yield curve spread, and eight quarters for the variance of the error term. The dynamic probit produces higher probabilities of recession during periods of economic downswings, reaching 1 during the 1984/1986 and 1997/1999 recessions. Furthermore, the results of the dynamic probit model plot the lowest probability values during periods of economic growth, reaching values of zero between 1980/1981, 1986/1988, and briefly in 1995 and 2000. The static probit and business cycle probit models produce similar results. However, the static probit and business cycle probit models, peaked at 0.84 and 0.87 respectively, reporting a false signal of an economic downturn in 2003/2004. These results are supported by those of Khomo and Aziakpono (2006) who reported a false signal in 2003 with a probability of 0.84 using the
static probit model, and similarly predicted a false signal in 2003 using the dynamic probit model with
the yield curve spread as the explanatory variable.

The dynamic probit model on the other hand reported an estimated probability of 0.32 during this time.
Consequently, it may be suggested that a false signal may be circumvented when estimating using an in-
sample forecast of the dynamic probit model, by removing serial correlation in the error term.

These results will be compared to those of the business cycle probit that uses the JSE ALSI as the
explanatory variable, this follows next.

5.5.2. THE BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL
AND JSE ALSI

The model was run similarly to that of the spread, with mixed forecast horizons ranging from one to
eight lags, the summary of the results can be seen in Table 5.12 below (complete results are in Appendix
D).

Table 5.12. In-sample business cycle conditionally independent probit results using the JSE ALSI
returns

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Optimal (3:2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>-1.665</td>
<td>-2.744</td>
<td>-3.592</td>
<td>-1.932</td>
<td>0.126</td>
<td>-0.583</td>
<td>0.490</td>
<td>1.131</td>
<td>-3.770</td>
</tr>
<tr>
<td>Prob of $x_t$</td>
<td>0.152</td>
<td>0.021**</td>
<td>0.004***</td>
<td>0.102</td>
<td>0.914</td>
<td>0.614</td>
<td>0.672</td>
<td>0.337</td>
<td>0.002***</td>
</tr>
<tr>
<td>$\sigma(t)\varepsilon_t$</td>
<td>1.250</td>
<td>1.281</td>
<td>1.371</td>
<td>1.156</td>
<td>0.888</td>
<td>0.434</td>
<td>0.382</td>
<td>-0.361</td>
<td>1.398</td>
</tr>
<tr>
<td>Prob of $\sigma(t)\varepsilon_t$</td>
<td>0.034**</td>
<td>0.031**</td>
<td>0.022**</td>
<td>0.049**</td>
<td>0.129</td>
<td>0.453</td>
<td>0.511</td>
<td>0.548</td>
<td>0.019**</td>
</tr>
<tr>
<td>Akaike</td>
<td>1.337</td>
<td>1.311</td>
<td>1.280</td>
<td>1.346</td>
<td>1.385</td>
<td>1.395</td>
<td>1.393</td>
<td>1.383</td>
<td>1.274</td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.407</td>
<td>1.381</td>
<td>1.350</td>
<td>1.416</td>
<td>1.456</td>
<td>1.466</td>
<td>1.465</td>
<td>1.455</td>
<td>1.343</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at
a 10% level of significance.
The above results reveal a positive relationship between the variance of the error term and the business cycle, suggesting that the greater the instability, the greater the probability of recessions. The optimal lag structure of the model is one that forecasts economic downswings three and two quarters ahead (3:2) for the ALSI returns and variance of the error terms, respectively. It is at these horizons that the model reports the lowest Akaike and Schwarz criterion values:

\[
P(R_t = 1) = F(-0.382310 - 3.769641x_{t-3} + 1.370544\epsilon_{t-2})
\]

(9)

Figure 5.10. Downswings and recession probabilities of the static, dynamic and business cycle probit forecasts –JSE ALSI

Figure 5.10 plots the optimal forecast of the probability of recessions when using historical data of the returns of the JSE ALSI lagged three quarters for the static probit, five quarters for the dynamic probit, and three and two quarters for the business cycle conditionally independent probit model, three being the lag of the ALSI returns and two being the lag of the variance of the error term. The graph suggests that on average, the dynamic probit model forecast higher estimated probabilities of recession during recessions, unlike the results of the static and business cycle probit, which forecast similar results to each other. The business cycle probit forecast higher probability values in 2003/2004 when a recession was incorrectly estimated, and again in 1993 where the probability of recession peaked during the period when the economy was exiting a recession and entering into a period of economic growth. Along
with the false signals predicted by the business cycle model, the static probit model also incorrectly forecast downswings in 1988 and in 2003/2004.

5.5.3. THE BUSINESS CYCLE PROBIT MODEL AND THE FINANCIAL VARIABLES

The business cycle specific conditionally independent probit model was run using the yield spread and returns of the JSE ALSI with forecast horizons ranging from one to eight quarters, in order to determine whether the inclusion of both explanatory variables may increase the model’s forecasting ability (results can be found in Appendix D).

Table 5.13. In-sample business cycle probit results using the yield curve spread and JSE ALSI

<table>
<thead>
<tr>
<th>Forecast Horizon</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>Optimal (2:3:2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spread</td>
<td>-0.300</td>
<td>-0.372</td>
<td>-0.359</td>
<td>-0.274</td>
<td>-0.192</td>
<td>-0.121</td>
<td>-0.080</td>
<td>-0.059</td>
<td>-0.383</td>
</tr>
<tr>
<td>Prob</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.000***</td>
<td>0.013**</td>
<td>0.089*</td>
<td>0.209</td>
<td>0.000***</td>
<td></td>
</tr>
<tr>
<td>JSE ALSI</td>
<td>-0.831</td>
<td>-2.325</td>
<td>-3.683</td>
<td>-1.305</td>
<td>0.756</td>
<td>-0.270</td>
<td>0.694</td>
<td>1.263</td>
<td>-3.651</td>
</tr>
<tr>
<td>Prob</td>
<td>0.553</td>
<td>0.115</td>
<td>0.011**</td>
<td>0.311</td>
<td>0.528</td>
<td>0.813</td>
<td>0.547</td>
<td>0.282</td>
<td>0.011</td>
</tr>
<tr>
<td>$\sigma(t)\varepsilon_t$</td>
<td>0.321</td>
<td>0.108</td>
<td>0.246</td>
<td>0.245</td>
<td>0.208</td>
<td>-0.041</td>
<td>0.057</td>
<td>-0.623</td>
<td>0.253</td>
</tr>
<tr>
<td>Prob of $\sigma(t)\varepsilon_t$</td>
<td>0.625</td>
<td>0.880</td>
<td>0.735</td>
<td>0.718</td>
<td>0.748</td>
<td>0.948</td>
<td>0.927</td>
<td>0.333</td>
<td>0.722</td>
</tr>
<tr>
<td>Akaike</td>
<td>1.110</td>
<td>1.007</td>
<td>0.998</td>
<td>1.145</td>
<td>1.275</td>
<td>1.358</td>
<td>1.385</td>
<td>1.386</td>
<td>0.972</td>
</tr>
<tr>
<td>Schwarz</td>
<td>1.202</td>
<td>1.100</td>
<td>1.092</td>
<td>1.238</td>
<td>1.370</td>
<td>1.453</td>
<td>1.481</td>
<td>1.482</td>
<td>1.065</td>
</tr>
</tbody>
</table>

Source: Estimations

***Significant at a 1% level of significance, **significant at a 5% level of significance, and *significant at a 10% level of significance.

The model with the lowest Akaike and Schwarz criterion is one with the spread lagged two quarters, a lag of three quarters for the ALSI returns, and the variance of the error terms lagged two quarters, shown in the optimal (2:3:2) column in the table. Both the spread and returns of the ALSI are found to be statistically significant, but the variance of the error terms is found to be statistically insignificant, and is thus found not to have any predictive ability.
Figure 5.11 plots the probability estimates of the optimal forecast of the business cycle probit using the spread and returns of the JSE ALSI. The model forecasts lags of two, three and two quarters for the yield spread, ALSI returns and variance of the error terms, respectively. Although none of the probabilities produced an estimate of 1 during any of the recessions, the probability estimates produced a minimum of 0.83 during each of the recessions. Moreover, the estimated probabilities remained low during periods of economic upswings, reaching levels of zero during 1981 and 1987/1988. There was nonetheless a false signal in 2003/2004, as the probability of an economic downswing was forecast, although none was experienced.

Table 5.14. Accuracy of the business cycle probit models

<table>
<thead>
<tr>
<th></th>
<th>Yield Spread</th>
<th>JSE ALSI</th>
<th>Spread &amp; JSE ALSI</th>
</tr>
</thead>
<tbody>
<tr>
<td>RMSE</td>
<td>0.383</td>
<td>0.460</td>
<td>0.385</td>
</tr>
</tbody>
</table>

Source: Estimations

Table 5.14 suggests that the model that most accurately estimates future economic downswings is one that uses the yield curve, as it has the lowest RMSE. This is followed closely by the model that uses both
the yield spread and ALSI returns as explanatory variables, and finally, the ALSI returns produce the least accurate forecast of downswings (results are can be seen in Appendix E).

5.6. THE PROBIT MODEL’S ACCURACY IN FORECASTING RECESSIONS

Table 5.15 below is a summary of the accuracy of the static, dynamic, and business cycle probit models (results are can be found in Appendix E). These models were estimated by using the yield curve spread, and the JSE ALSI explanatory variables individually. This was followed by estimating each model using both explanatory variables in order to determine whether including both variables may increase the model’s forecasting ability.

Table 5.15. Accuracy of the probit models

<table>
<thead>
<tr>
<th></th>
<th>Yield Spread</th>
<th>JSE ALSI</th>
<th>Spread &amp; JSE ALSI</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Static</strong></td>
<td>0.397</td>
<td>0.471</td>
<td>0.390</td>
</tr>
<tr>
<td><strong>Dynamic</strong></td>
<td>0.247</td>
<td>0.263</td>
<td>0.250</td>
</tr>
<tr>
<td><strong>Business Cycle</strong></td>
<td>0.383</td>
<td>0.460</td>
<td>0.385</td>
</tr>
</tbody>
</table>

Source: Estimations

The above table suggests that the dynamic probit model produces the lowest RMSE across all of the estimated probit models. Second to the dynamic probit is the business cycle probit model, which demonstrates that the variations of the static probit model improve the model’s forecasting ability, although the results suggest that the variance of the error term does not add any predictive ability, as it is found to be statistically insignificant. Furthermore, the yield curve spread produces the lowest RMSE values across the dynamic and business cycle probit models. However, the addition of the ALSI returns increases the yield curve spread’s forecasting ability when estimating using the static probit model. Moreover, the model with the lowest RMSE is the dynamic probit model estimated using the yield curve spread; this would suggest that this is the model that most accurately estimates the probability of economic downswings. This is supported by the findings of Khomo and Aziakpono (2006) who reported that although they observed the results of the yield curve spread forecast to be similar when using the static and dynamic probit models, the dynamic probit produced a more accurate forecast of economic downswings in the short-run up to the first quarter. Moreover, they found that the yield curve spread
produced a better estimate of economic downswings than the share prices did. Clay and Keeton (2011) support these findings and demonstrate that the yield curve produces the best forecast when compared to share prices across both static and dynamic forecasting, and report that share prices alone provide little predictive ability in recession forecasting. Additionally, they believe that although the yield curve’s results are similar across the static and dynamic forecasts, the dynamic probit produces a better forecast of economic downswings.

It may be argued that the results from the in-sample forecast demonstrate that the dynamic probit model produces the most accurate forecast of economic downswings in South Africa over the specified period. Thus including the previous states of the business cycle improves the static probit model’s predictive ability, indicating that an economy’s previous business cycle phase influences its current state. Furthermore, the yield curve continues to produce the best forecast of economic downswings in South Africa when compared to share prices across all three probit models, although including share prices increases the yield curve’s forecasting ability when forecasting using the static probit model. It may therefore be argued that economic downswings in South Africa are more accurately forecast when predicting using the dynamic probit model and the yield curve spread.

5.7. CONCLUSION

The results of forecasting economic downswings in South Africa using the yield curve spread and share prices are presented in this chapter. To begin with, a discussion on the data, namely the yield curve spread and JSE ALSI was presented, followed by a discussion on the results of estimating recessions using the three probit models. The results demonstrate that the yield curve spread produces the lowest RMSE when estimating using the dynamic and business cycle probit models; however, the lowest reported RMSE for the static probit is one that is estimated using the yield curve spread and JSE ALSI returns.

The JSE ALSI produced inconsistent results as a positive relationship between the business cycle and share prices was observed when estimating using the dynamic probit model; this relationship contradicts economic theory. Therefore, it may be argued that share prices may not be a good indicator of economic activity in South Africa.
Similarly, the variance of the error term of the optimal lag structure of the business cycle probit model estimated using the yield curve spread was found to be statistically insignificant, hence it may be concluded that the variance of the error term may not add any predictive ability when estimating using the yield curve spread. It has however been shown that the variance of the error term adds predictive ability when estimating using share prices.

The results suggest that the yield curve continues to produce the most accurate forecast in comparison to share prices across the static, dynamic, and business cycle probit models, although share prices increase the ability of the yield curve spread to forecast economic downswings when estimating using the static probit model. Additionally, the dynamic probit model most accurately predicts downswings across the three probit models, as the results of the dynamic probit model forecast observe the lowest RMSE values. Thus, it is has been observed that the addition of the lag of the recession variable to the static probit model results in a more accurate forecast of future economic downswings. This is because the dynamic probit model takes into account the information available in the autocorrelation structure of the binary variable.

Consequently, it has been demonstrated that the model that most accurately forecasts economic downswings in South Africa is the dynamic probit model estimated using the yield curve spread, thus including the previous business cycle phases increases the static probit model's forecasting ability.
CHAPTER SIX
SUMMARY OF FINDINGS, LIMITATIONS, POLICY IMPLICATIONS, AND RECOMMENDATIONS FOR FUTURE RESEARCH

6.1. SUMMARY OF FINDINGS OF THE YIELD CURVE SPREAD’S ABILITY TO FORECAST RECESSIONS

This study looked at a comparative analysis of the probit model’s ability to forecast South African economic downswings using the yield curve spread and share prices as explanatory variables. The findings of the study have been evaluated against the three main objectives set out in the introduction.

The first objective outlined was an analysis of the relationship between the term structure of interest rates, or the yield curve spread and the business cycle versus the relationship between share prices and the business cycle. The yield curve spread produced the lowest RMSE results across the static, dynamic, and business cycle probit models when judged against the JSE ALSI. These forecast results demonstrate that the yield curve spread continues to produce more accurate forecasts of future economic downswings in South Africa in comparison to share prices. Furthermore, the dynamic probit results reported some inconsistent findings that reported a positive relationship between share prices and economic downswings, which contradicts economic theory. Consequently it may be argued that share prices provide little information about the business cycle, and therefore future economic downswings in South Africa.

The second objective outlined was with regard to the implication of including both explanatory variables in a single forecasting model. The findings from the static probit model produced the lowest RMSE when including both variables, thus share prices improve the yield curve spread’s ability to forecast South African economic downswings, but this was found to be the case only when predicting using the static probit model. The yield curve spread continues to produce more accurate forecasts when using the dynamic models.

The final objective was to identify the most appropriate model to forecast economic downswings with the South African business cycle in mind. This would involve a comparative analysis of the results across all three probit models. The results of the in-sample forecasting reveal that the dynamic probit model produces the most accurate forecast of economic downswings. Thus, it may be argued that including the dynamic term improves the model’s forecasting ability, as it removes serial correlation in the error terms and moreover, including the information from the previous business cycle phases in the current
forecast improves the model’s ability to predict future downswings. In addition, the dynamic probit model estimated using the yield curve spread produced the most accurate forecast of South African downswings, demonstrated by the low probability estimate of 0.32, unlike the static and business cycle probit models that produced false signals of recessions, with reported probability estimates of 0.84 and 0.87 respectively in 2003.

Therefore, it may be concluded that the yield curve spread continues to produce the best forecast of recessions, and the addition of a lag of the binary variable resulting in the dynamic probit model improves the models forecasting ability, thus producing the most accurate forecast of South African economic downswings.

6.2. LIMITATIONS OF THIS STUDY

The focus of this dissertation is to produce an in-sample analysis of share prices and the yield curve spread’s ability to forecast recessions in South Africa comparatively across three different probit models. As this is an in-sample analysis, it looks only at the various models’ ability to fit the existing data, and thus does not look at using this data to identify the next possible recession period. Therefore, it may be useful to run an out-of sample comparative analysis across the same probit models and explanatory variables, in order to identify which of these models is likely to most accurately identify the next possible recession.

6.3. POLICY IMPLICATIONS AND RECOMMENDATIONS FOR FUTURE RESEARCH

Although share prices were found to increase the yield curve spread’s ability to predict recessions in South Africa when forecasting using the static probit model, the yield curve spread alone continues to produce the most accurate forecast of recessions when running the dynamic probit model. The ability to accurately forecast recessions is important in a country like South Africa that is characterised by high levels of poverty, unemployment, and a significant income gap between the rich and the poor. It is thus important to identify a possible future recession in order to mitigate the potential losses that may arise.

These findings may be used by government to reduce the possible impact of a future recession by adjusting the current fiscal policy, or monetary policy through the SARB. As the research was based on
in-sample forecasting, it may be valuable to run out-of-sample predictions in order for the government and the SARB to accurately identify the next possible recession in order to adjust their policies so that these may have maximum impact at such time that the potential recession is identified to commence.

The findings of this study suggest that the dynamic probit model and yield curve spread produce the most accurate forecast of recessions in South Africa. Although these results are observed using in-sample forecasting, it may be useful to run out-of-sample forecasting using the three probit models in order to accurately identify when a potential recession might occur. Moreover, as the yield curve has been found to continuously produce the most accurate forecast, rather than running complex econometric modeling, the slope of the yield curve alone may be used to interpret the expected economic environment, as a positively sloped yield curve suggests a growing economy and an inverted yield curve suggests a future recession.
REFERENCES


**APPENDIX A: UNIT ROOT TESTS FOR THE RECESSION, YIELD CURVE SPREAD AND JSE ALSI VARIABLES**

**YIELD CURVE SPREAD**

Null Hypothesis: SPREAD has a unit root  
Exogenous: Constant  
Lag Length: 2 (Automatic - based on SIC, maxlag=12)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-4.044507</td>
</tr>
</tbody>
</table>

Test critical values:  
1% level: -3.485115  
5% level: -2.885450  
10% level: -2.579598  


Null Hypothesis: SPREAD is stationary  
Exogenous: Constant  
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th>LM-Stat.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Kwiatkowski-Phillips-Schmidt-Shin test statistic</td>
</tr>
</tbody>
</table>

Asymptotic critical values*:  
1% level: 0.739000  
5% level: 0.463000  
10% level: 0.347000  

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)

**JSE ALSI RETURNS**

Null Hypothesis: RALSI has a unit root  
Exogenous: Constant  
Lag Length: 0 (Automatic - based on SIC, maxlag=12)

<table>
<thead>
<tr>
<th>t-Statistic</th>
<th>Prob.*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Augmented Dickey-Fuller test statistic</td>
<td>-8.770136</td>
</tr>
</tbody>
</table>

Test critical values:  
1% level: -3.484653  
5% level: -2.885249  
10% level: -2.579491  

Null Hypothesis: RALSI is stationary  
Exogenous: Constant  
Bandwidth: 8 (Newey-West automatic) using Bartlett kernel

<table>
<thead>
<tr>
<th>LM-Stat.</th>
<th>Kwiatkowski-Phillips-Schmidt-Shin test statistic</th>
<th>0.055657</th>
</tr>
</thead>
<tbody>
<tr>
<td>Asymptotic critical values*:</td>
<td>1% level</td>
<td>0.739000</td>
</tr>
<tr>
<td></td>
<td>5% level</td>
<td>0.463000</td>
</tr>
<tr>
<td></td>
<td>10% level</td>
<td>0.347000</td>
</tr>
</tbody>
</table>

*Kwiatkowski-Phillips-Schmidt-Shin (1992, Table 1)
### APPENDIX B: STATIC PROBIT MODEL RESULTS

#### YIELD CURVE SPREAD

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/12/12    Time: 22:42  
Sample (adjusted): 1980Q2 2010Q4  
Included observations: 123 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.025329</td>
<td>0.132731</td>
<td>-0.190832</td>
<td>0.8487</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.319212</td>
<td>0.059621</td>
<td>-5.354012</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>McFadden R-squared</th>
<th>0.227318</th>
<th>Mean dependent var</th>
<th>0.390244</th>
</tr>
</thead>
<tbody>
<tr>
<td>S.D. dependent var</td>
<td>0.489800</td>
<td>S.E. of regression</td>
<td>0.418901</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>1.066147</td>
<td>Sum squared resid</td>
<td>21.23281</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.111874</td>
<td>Log likelihood</td>
<td>-63.56806</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>1.084721</td>
<td>Deviance</td>
<td>127.1361</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>164.5388</td>
<td>Restr. log likelihood</td>
<td>-82.26942</td>
</tr>
<tr>
<td>LR statistic</td>
<td>37.40272</td>
<td>Avg. log likelihood</td>
<td>-0.516813</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Obs with Dep=0     75    Total obs     123
Obs with Dep=1     48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/12/12    Time: 22:43  
Sample (adjusted): 1980Q2 2010Q4  
Included observations: 123 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.25329</td>
<td>0.132731</td>
<td>-0.190832</td>
<td>0.8487</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.319212</td>
<td>0.059621</td>
<td>-5.354012</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>McFadden R-squared</th>
<th>0.293707</th>
<th>Mean dependent var</th>
<th>0.393443</th>
</tr>
</thead>
<tbody>
<tr>
<td>S.D. dependent var</td>
<td>0.490528</td>
<td>S.E. of regression</td>
<td>0.400339</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>0.979592</td>
<td>Sum squared resid</td>
<td>19.23251</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.025559</td>
<td>Log likelihood</td>
<td>-57.75510</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>0.998262</td>
<td>Deviance</td>
<td>115.5102</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>163.5442</td>
<td>Restr. log likelihood</td>
<td>-81.77210</td>
</tr>
<tr>
<td>LR statistic</td>
<td>48.03401</td>
<td>Avg. log likelihood</td>
<td>-0.473402</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0.000000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Obs with Dep=0     74    Total obs     122
Obs with Dep=1     48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/12/12   Time: 22:44
Sample (adjusted): 1980Q4 2010Q4
Included observations: 121 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.022361</td>
<td>0.137862</td>
<td>0.162197</td>
<td>0.8712</td>
</tr>
<tr>
<td>SPREAD(-3)</td>
<td>-0.366049</td>
<td>0.065209</td>
<td>-5.613512</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.274392  Mean dependent var 0.396694
S.D. dependent var 0.491246  S.E. of regression 0.403270
Akaike info criterion 1.007765  Sum squared resid 19.35259
Schwarz criterion 1.053976  Log likelihood -58.96979
Hannan-Quinn criter. 1.026533  Deviance 117.9396
Restr. deviance 162.5389  Restr. log likelihood -81.26947
LR statistic 44.59936  Avg. log likelihood -0.487354
Prob(LR statistic) 0.000000

Obs with Dep=0 73  Total obs 121
Obs with Dep=1 48

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/12/12   Time: 22:44
Sample (adjusted): 1981Q1 2010Q4
Included observations: 120 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.004875</td>
<td>0.133908</td>
<td>-0.036408</td>
<td>0.9710</td>
</tr>
<tr>
<td>SPREAD(-4)</td>
<td>-0.290720</td>
<td>0.056551</td>
<td>-5.140813</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.204201  Mean dependent var 0.400000
S.D. dependent var 0.491952  S.E. of regression 0.424428
Akaike info criterion 1.104497  Sum squared resid 21.25642
Schwarz criterion 1.150955  Log likelihood -64.26982
Hannan-Quinn criter. 1.123364  Deviance 128.5396
Restr. deviance 161.5228  Restr. log likelihood -80.76140
LR statistic 32.98317  Avg. log likelihood -0.535582
Prob(LR statistic) 0.000000

Obs with Dep=0 72  Total obs 120
Obs with Dep=1 48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/12/12   Time: 22:45
Sample (adjusted): 1981Q2 2010Q4
Included observations: 119 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.062157</td>
<td>0.128628</td>
<td>-0.483233</td>
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<td>SPREAD(-5)</td>
<td>-0.198391</td>
<td>0.048951</td>
<td>-4.05217</td>
<td>0.0001</td>
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McFadden R-squared 0.112898  Mean dependent var 0.403361
S.D. dependent var 0.492646  S.E. of regression 0.455690
Akaike info criterion 1.230049  Sum squared resid 24.29549
Schwarz criterion 1.276757  Log likelihood -71.18794
Hannan-Quinn criter. 1.249016  Deviance 142.3759
Restr. deviance 160.4956  Restr. log likelihood -80.24778
LR statistic 18.11967  Avg. log likelihood -0.598218
Prob(LR statistic) 0.000021

Obs with Dep=0 71  Total obs 119
Obs with Dep=1 48

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/12/12   Time: 22:45
Sample (adjusted): 1981Q3 2010Q4
Included observations: 118 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.125649</td>
<td>-0.992649</td>
<td>0.3209</td>
</tr>
<tr>
<td>SPREAD(-6)</td>
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<td>0.044997</td>
<td>-2.523483</td>
<td>0.0116</td>
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McFadden R-squared 0.041103  Mean dependent var 0.406780
S.D. dependent var 0.493328  S.E. of regression 0.481477
Akaike info criterion 1.329685  Sum squared resid 26.89110
Schwarz criterion 1.376645  Log likelihood -76.45140
Hannan-Quinn criter. 1.348752  Deviance 152.9028
Restr. deviance 159.4556  Restr. log likelihood -79.72847
LR statistic 6.554142  Avg. log likelihood -0.647893
Prob(LR statistic) 0.010464

Obs with Dep=0 70  Total obs 118
Obs with Dep=1 48

---
**Dependent Variable: RECESSION**  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/12/12   Time: 22:46  
Sample (adjusted): 1981Q4 2010Q4  
Included observations: 117 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tr>
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<td>SPREAD(-7)</td>
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<td>McFadden R-squared</td>
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<td>S.D. dependent var</td>
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<td></td>
<td>27.81674</td>
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<tr>
<td>Schwarz criterion</td>
<td>1.418354</td>
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<tr>
<td>Hannan-Quinn criter.</td>
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<td></td>
<td>156.4231</td>
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<td>Restr. deviance</td>
<td>158.4067</td>
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<td></td>
<td>-79.20335</td>
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<tr>
<td>LR statistic</td>
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<tr>
<td>Prob(LR statistic)</td>
<td>0.159007</td>
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</tr>
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</table>

Obs with Dep=0  69  Total obs  117  
Obs with Dep=1  48

---

**Dependent Variable: RECESSION**  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/12/12   Time: 22:52  
Sample (adjusted): 1982Q1 2010Q4  
Included observations: 116 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<tr>
<td>SPREAD(-8)</td>
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<td>McFadden R-squared</td>
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<td>S.D. dependent var</td>
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<td>Akaike info criterion</td>
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<tr>
<td>Schwarz criterion</td>
<td>1.429401</td>
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<td>Hannan-Quinn criter.</td>
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<td>Restr. deviance</td>
<td>156.6124</td>
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<td>LR statistic</td>
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<td></td>
<td>-0.673721</td>
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<tr>
<td>Prob(LR statistic)</td>
<td>0.578249</td>
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</tr>
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</table>

Obs with Dep=0  69  Total obs  116  
Obs with Dep=1  47

---

87
GRANGER CAUSALITY TEST

Pairwise Granger Causality Tests
Date: 10/26/13   Time: 17:32
Sample: 1980Q1 2010Q4
Lags: 2

Null Hypothesis: Obs F-Statistic Prob.

| RECESSION does not Granger Cause SPREAD | 122 | 1.95655 | 0.1459 |
| SPREAD does not Granger Cause RECESSIO | 8.04086 | 0.0005 |

JSE ALSI RETURNS

Dependent Variable: RECESSIO
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/14/12   Time: 19:48
Sample (adjusted): 1980Q3 2010Q4
Included observations: 122 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.218888</td>
<td>0.120535</td>
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<tr>
<td>RALSI(-1)</td>
<td>-1.708847</td>
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</tr>
<tr>
<td>McFadden R-squared</td>
<td>0.013633</td>
<td>Mean dependent var</td>
<td>0.393443</td>
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<tr>
<td>S.D. dependent var</td>
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<td>S.E. of regression</td>
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<td>Akaike info criterion</td>
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</tr>
<tr>
<td>Schwarz criterion</td>
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<td>Log likelihood</td>
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</tr>
<tr>
<td>Hannan-Quinn criterion</td>
<td>1.373709</td>
<td>Deviance</td>
<td>161.3146</td>
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<tr>
<td>Restr. deviance</td>
<td>163.5442</td>
<td>Restr. log likelihood</td>
<td>-81.77210</td>
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</tr>
<tr>
<td>LR statistic</td>
<td>2.229556</td>
<td>Avg. log likelihood</td>
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</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0.135393</td>
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</tr>
</tbody>
</table>

| Obs with Dep=0 | 74 | Total obs | 122 |
| Obs with Dep=1 | 48 |             |     |
## Dependent Variable: RECESSION
### Method: ML - Binary Probit (Quadratic hill climbing)
**Date:** 11/14/12   **Time:** 19:49
**Sample (adjusted):** 1980Q4 - 2010Q4
**Included observations:** 121 after adjustments
**Convergence achieved after 3 iterations**
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>0.1312</td>
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<tr>
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<td>1.172623</td>
<td>-2.337194</td>
<td>0.0194</td>
</tr>
</tbody>
</table>

- **McFadden R-squared:** 0.034246
- **S.D. dependent var:** 0.91246
- **Akaike info criterion:** 1.330353
- **Schwarz criterion:** 1.376564
- **Hannan-Quinn criter.:** 1.349121
- **Resr. deviance:** 162.5389
- **LR statistic:** 5.566240
- **Prob(LR statistic):** 0.018310

- **Obs with Dep=0:** 73
- **Total obs:** 121
- **Obs with Dep=1:** 48

## Dependent Variable: RECESSION
### Method: ML - Binary Probit (Quadratic hill climbing)
**Date:** 11/14/12   **Time:** 19:49
**Sample (adjusted):** 1981Q1 - 2010Q4
**Included observations:** 120 after adjustments
**Convergence achieved after 3 iterations**
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.2159</td>
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<td>1.208243</td>
<td>-2.939286</td>
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</table>

- **McFadden R-squared:** 0.055882
- **S.D. dependent var:** 0.491952
- **Akaike info criterion:** 1.304138
- **Schwarz criterion:** 1.350956
- **Hannan-Quinn criter.:** 1.323005
- **Resr. deviance:** 161.5228
- **LR statistic:** 9.026232
- **Prob(LR statistic):** 0.002661

- **Obs with Dep=0:** 72
- **Total obs:** 120
- **Obs with Dep=1:** 48
## Dependent Variable: RECESSION

**Method:** ML - Binary Probit (Quadratic hill climbing)

- **Date:** 11/14/12  
- **Time:** 19:50

- **Sample (adjusted):** 1981Q2 2010Q4
- **Included observations:** 119 after adjustments
- **Convergence achieved after 3 iterations**

**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
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<table>
<thead>
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<th>Value</th>
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<tr>
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<td>S.D. dependent var</td>
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<tr>
<td>Akaike info criterion</td>
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<tr>
<td>Schwarz criterion</td>
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</tr>
<tr>
<td>Hannan-Quinn criterion</td>
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<tr>
<td>Residual deviance</td>
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<tr>
<td>LR statistic</td>
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<td>Prob(LR statistic)</td>
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<td>Mean dependent var</td>
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<td>Sum squared resid</td>
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<td>Deviance</td>
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<td>Deviance</td>
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</tr>
<tr>
<td>Avg. log likelihood</td>
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</tr>
<tr>
<td>Avg. log likelihood</td>
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</tr>
<tr>
<td>Obs with Dep=0</td>
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<td>Total obs</td>
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<td>Obs with Dep=1</td>
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## Dependent Variable: RECESSION

**Method:** ML - Binary Probit (Quadratic hill climbing)

- **Date:** 11/14/12  
- **Time:** 19:51

- **Sample (adjusted):** 1981Q3 2010Q4
- **Included observations:** 118 after adjustments
- **Convergence achieved after 3 iterations**

**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
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<td>1.165258</td>
<td>0.048044</td>
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<table>
<thead>
<tr>
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<tr>
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<td>S.D. dependent var</td>
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<td>Akaike info criterion</td>
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<td>Schwarz criterion</td>
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<td>Hannan-Quinn criterion</td>
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<td>Residual deviance</td>
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<td>LR statistic</td>
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<tr>
<td>Prob(LR statistic)</td>
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<td>S.E. of regression</td>
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<td>Sum squared resid</td>
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<td>Deviance</td>
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<tr>
<td>Log likelihood</td>
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<tr>
<td>Deviance</td>
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<td>Avg. log likelihood</td>
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<tr>
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<tr>
<td>Obs with Dep=1</td>
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Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/14/12   Time: 19:51
Sample (adjusted): 1981Q4 2010Q4
Included observations: 117 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<td>1.157394</td>
<td>-0.478253</td>
<td>0.6325</td>
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McFadden R-squared 0.001445  Mean dependent var 0.410256
S.D. dependent var 0.493996  S.E. of regression 0.495670
Akaike info criterion 1.386136  Sum squared resid 28.25426
Schwarz criterion 1.433352  Log likelihood -79.08894
Hannan-Quinn crit. 1.405305  Deviance 158.1779
Restr. deviance 158.4067  Restr. log likelihood -79.20335
LR statistic 0.228825  Avg. log likelihood -0.675974
Prob(LR statistic) 0.632396

Obs with Dep=0 69  Total obs 117
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/14/12   Time: 19:52
Sample (adjusted): 1982Q1 2010Q4
Included observations: 116 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
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<td>0.123151</td>
<td>-2.080755</td>
<td>0.0375</td>
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<td>RALSI(-7)</td>
<td>0.523725</td>
<td>1.160444</td>
<td>0.451314</td>
<td>0.6518</td>
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</tbody>
</table>

McFadden R-squared 0.001304  Mean dependent var 0.410256
S.D. dependent var 0.493996  S.E. of regression 0.495670
Akaike info criterion 1.382829  Sum squared resid 28.25426
Schwarz criterion 1.433352  Log likelihood -79.08894
Hannan-Quinn crit. 1.405305  Deviance 158.1779
Restr. deviance 158.4067  Restr. log likelihood -79.20335
LR statistic 0.228825  Avg. log likelihood -0.675974
Prob(LR statistic) 0.632396

Obs with Dep=0 69  Total obs 116
Obs with Dep=1 47

91
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/14/12   Time: 19:52
Sample (adjusted): 1982Q2 2010Q4
Included observations: 115 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
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<td>1.172927</td>
<td>1.004265</td>
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McFadden R-squared 0.006575  Mean dependent var 0.400000
S.D. dependent var 0.492042  S.E. of regression 0.491852
Akaike info criterion 1.371956  Sum squared resid 27.33681
Schwarz criterion 1.419694  Log likelihood -76.88748
Hannan-Quinn criter. 1.391333  Deviance 153.7750
Restr. deviance 154.7927  Restr. log likelihood -77.39634
LR statistic 1.017716  Avg. log likelihood -0.668187
Prob(LR statistic) 0.313061

Obs with Dep=0 69  Total obs 115
Obs with Dep=1 46

THE YIELD CURVE SPREAD AND RETURNS OF THE JSE ALSI

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 11/15/12   Time: 20:21
Sample (adjusted): 1980Q3 2010Q4
Included observations: 122 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.000811</td>
<td>0.139034</td>
<td>-0.005833</td>
<td>0.9953</td>
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<tr>
<td>SPREAD(-1)</td>
<td>-0.310767</td>
<td>0.060175</td>
<td>-5.164386</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-1)</td>
<td>-0.836346</td>
<td>1.403728</td>
<td>-0.595803</td>
<td>0.5513</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.0225452  Mean dependent var 0.393443
S.D. dependent var 0.490528  S.E. of regression 0.420965
Akaike info criterion 1.087482  Sum squared resid 21.08816
Schwarz criterion 1.156434  Log likelihood -63.33643
Hannan-Quinn criter. 1.115488  Deviance 126.6729
Restr. deviance 163.5442  Restr. log likelihood -81.77210
LR statistic 36.87134  Avg. log likelihood -0.519151
Prob(LR statistic) 0.000000

Obs with Dep=0 74  Total obs 122
Obs with Dep=1 46

92
**Dependent Variable: RECESSION**
**Method: ML - Binary Probit (Quadratic hill climbing)**

Date: 11/15/12   Time: 20:22  
Sample (adjusted): 1980Q4 2010Q4  
Included observations: 121 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.077744</td>
<td>0.146121</td>
<td>0.532051</td>
<td>0.5947</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.376253</td>
<td>0.067827</td>
<td>-5.547241</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-2)</td>
<td>-2.346026</td>
<td>1.473756</td>
<td>-1.591869</td>
<td>0.1114</td>
</tr>
</tbody>
</table>

**McFadden R-squared** 0.305239  
**Mean dependent var** 0.396694  
**S.D. dependent var** 0.491246  
**S.E. of regression** 0.396694  
**Akaike info criterion** 0.982857  
**Sum squared resid** 18.56922  
**Schwarz criterion** 1.052174  
**Log likelihood** -56.46282  
**Hannan-Quinn criter.** 1.421109  
**Deviance** 112.9256  
**Restr. deviance** 162.5389  
**Restr. log likelihood** -81.26947  
**LR statistic** 49.61329  
**Avg. log likelihood** -0.466635  
**Prob(LR statistic)** 0.000000

<table>
<thead>
<tr>
<th>Obs with Dep=0</th>
<th>73</th>
<th>Total obs</th>
<th>121</th>
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</thead>
<tbody>
<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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<td></td>
</tr>
</tbody>
</table>

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**Dependent Variable: RECESSION**
**Method: ML - Binary Probit (Quadratic hill climbing)**

Date: 11/15/12   Time: 20:23  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.142488</td>
<td>0.151202</td>
<td>0.942366</td>
<td>0.3460</td>
</tr>
<tr>
<td>SPREAD(-3)</td>
<td>-0.366219</td>
<td>0.067705</td>
<td>-5.438592</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-3)</td>
<td>-3.723428</td>
<td>1.450781</td>
<td>-2.566498</td>
<td>0.0103</td>
</tr>
</tbody>
</table>

**McFadden R-squared** 0.312863  
**Mean dependent var** 0.396694  
**S.D. dependent var** 0.491246  
**S.E. of regression** 0.395316  
**Akaike info criterion** 0.974902  
**Sum squared resid** 18.28418  
**Schwarz criterion** 1.044590  
**Log likelihood** -55.49414  
**Hannan-Quinn criter.** 1.003203  
**Deviance** 110.9883  
**Restr. deviance** 161.5228  
**Restr. log likelihood** -81.26947  
**LR statistic** 50.53452  
**Avg. log likelihood** -0.462451  
**Prob(LR statistic)** 0.000000

<table>
<thead>
<tr>
<th>Obs with Dep=0</th>
<th>72</th>
<th>Total obs</th>
<th>120</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs with Dep=1</td>
<td>48</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/15/12   Time: 20:24  
Sample (adjusted): 1981Q2 2010Q4  
Included observations: 119 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.031433</td>
<td>0.138782</td>
<td>0.226493</td>
<td>0.8208</td>
</tr>
<tr>
<td>SPREAD(-4)</td>
<td>-0.282969</td>
<td>0.057009</td>
<td>-4.963627</td>
<td>0.0000</td>
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<tr>
<td>RALSI(-4)</td>
<td>-1.315562</td>
<td>1.287775</td>
<td>-1.021578</td>
<td>0.3070</td>
</tr>
</tbody>
</table>

McFadden R-squared | 0.206556 | Mean dependent var | 0.403361 |
S.D. dependent var  | 0.492646 | S.E. of regression  | 0.427038 |
Akaike info criterion | 1.120540 | Sum squared resid   | 21.15397 |
Schwarz criterion   | 1.190602 | Log likelihood      | -63.67214 |
Hannan-Quinn criter. | 1.148990 | Deviance             | 127.3443 |
Restr. deviance     | 160.4956  | Restr. log likelihood| -80.24778 |
LR statistic        | 33.15126  | Avg. log likelihood  | -0.535060 |
Prob(LR statistic)  | 0.000000  |                     |          |

Obs with Dep=0     | 71        | Total obs            | 119      |
Obs with Dep=1     | 48        |                       |          |

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Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 11/15/12   Time: 20:25  
Sample (adjusted): 1981Q3 2010Q4  
Included observations: 118 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.078742</td>
<td>0.132399</td>
<td>-0.594728</td>
<td>0.5520</td>
</tr>
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<td>SPREAD(-5)</td>
<td>-0.199885</td>
<td>0.049753</td>
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<tr>
<td>RALSI(-5)</td>
<td>0.746925</td>
<td>1.199367</td>
<td>0.622766</td>
<td>0.5334</td>
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</tbody>
</table>

McFadden R-squared | 0.111596 | Mean dependent var | 0.406780 |
S.D. dependent var  | 0.493328 | S.E. of regression  | 0.457184 |
Akaike info criterion | 1.251374 | Sum squared resid   | 24.03695 |
Schwarz criterion   | 1.321815  | Log likelihood      | -70.83105 |
Hannan-Quinn criter. | 1.279975 | Deviance             | 141.6621 |
Restr. deviance     | 159.4569  | Restr. log likelihood| -79.72847 |
LR statistic        | 17.79484  | Avg. log likelihood  | -0.600263 |
Prob(LR statistic)  | 0.000137  |                     |          |

Obs with Dep=0     | 70        | Total obs            | 118      |
Obs with Dep=1     | 48        |                       |          |

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University of Johannesburg
**Dependent Variable: RECESSION**  
**Method: ML - Binary Probit (Quadratic hill climbing)**  
**Date: 11/15/12   Time: 20:26**  
**Sample (adjusted): 1981Q4 2010Q4**  
**Included observations: 117 after adjustments**  
**Convergence achieved after 3 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.116380</td>
<td>0.128618</td>
<td>-0.904850</td>
<td>0.3655</td>
</tr>
<tr>
<td>SPREAD(-6)</td>
<td>-0.109193</td>
<td>0.045526</td>
<td>-2.398488</td>
<td>0.0165</td>
</tr>
<tr>
<td>RALSI(-6)</td>
<td>-0.229958</td>
<td>1.140888</td>
<td>-0.201560</td>
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<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
<th>Description</th>
<th>Prob.</th>
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<tbody>
<tr>
<td>McFadden R-squared</td>
<td>0.038610</td>
<td>Mean dependent var</td>
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<tr>
<td>S.D. dependent var</td>
<td>0.493996</td>
<td>S.E. of regression</td>
<td>0.485357</td>
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<tr>
<td>Akaike info criterion</td>
<td>1.352912</td>
<td>Sum squared resid</td>
<td>26.85516</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.423737</td>
<td>Log likelihood</td>
<td>-76.14534</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>1.381666</td>
<td>Deviance</td>
<td>152.2907</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>158.4067</td>
<td>Restr. log likelihood</td>
<td>-79.20335</td>
</tr>
<tr>
<td>LR statistic</td>
<td>6.116030</td>
<td>Avg. log likelihood</td>
<td>-0.650815</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0.046981</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Obs with Dep=0</td>
<td>69</td>
<td>Total obs</td>
<td>117</td>
</tr>
<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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<td></td>
</tr>
</tbody>
</table>

**Dependent Variable: RECESSION**  
**Method: ML - Binary Probit (Quadratic hill climbing)**  
**Date: 01/17/13   Time: 20:10**  
**Sample (adjusted): 1982Q1 2010Q4**  
**Included observations: 116 after adjustments**  
**Convergence achieved after 3 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.189453</td>
<td>0.129297</td>
<td>-1.465249</td>
<td>0.1429</td>
</tr>
<tr>
<td>SPREAD(-7)</td>
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<td>0.728967</td>
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<td>0.632130</td>
<td>0.5273</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
<th>Description</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>McFadden R-squared</td>
<td>0.018680</td>
<td>Mean dependent var</td>
<td>0.405172</td>
</tr>
<tr>
<td>S.D. dependent var</td>
<td>0.493055</td>
<td>S.E. of regression</td>
<td>0.490182</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>1.376610</td>
<td>Sum squared resid</td>
<td>27.15151</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.447824</td>
<td>Log likelihood</td>
<td>-76.84341</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>1.405519</td>
<td>Deviance</td>
<td>153.6868</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>156.6124</td>
<td>Restr. log likelihood</td>
<td>-78.30618</td>
</tr>
<tr>
<td>LR statistic</td>
<td>2.925535</td>
<td>Avg. log likelihood</td>
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</tr>
<tr>
<td>Prob(LR statistic)</td>
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<tr>
<td>Obs with Dep=0</td>
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<td>Total obs</td>
<td>116</td>
</tr>
<tr>
<td>Obs with Dep=1</td>
<td>47</td>
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Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/17/13   Time: 20:10
Sample (adjusted): 1982Q2 2010Q4
Included observations: 115 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
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<td>0.131747</td>
<td>-1.939201</td>
<td>0.0525</td>
</tr>
<tr>
<td>SPREAD(-8)</td>
<td>-0.036475</td>
<td>0.043977</td>
<td>-0.829422</td>
<td>0.4069</td>
</tr>
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<td>RALSI(-8)</td>
<td>1.264527</td>
<td>1.169851</td>
<td>1.080930</td>
<td>0.2797</td>
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<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
<th>Description</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>McFadden R-squared</td>
<td>0.011016</td>
<td>Mean dependent var</td>
<td>0.400000</td>
</tr>
<tr>
<td>S.D. dependent var</td>
<td>0.492042</td>
<td>S.E. of regression</td>
<td>0.491671</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>1.383370</td>
<td>Sum squared resid</td>
<td>27.07491</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>1.454977</td>
<td>Log likelihood</td>
<td>-76.54377</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>1.412435</td>
<td>Deviance</td>
<td>153.0875</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>154.7927</td>
<td>Restr. log likelihood</td>
<td>-77.39634</td>
</tr>
<tr>
<td>LR statistic</td>
<td>1.705153</td>
<td>Avg. log likelihood</td>
<td>-0.665598</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
<td>0.426315</td>
<td></td>
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</tr>
<tr>
<td>Obs with Dep=0</td>
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</tr>
<tr>
<td>Obs with Dep=1</td>
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<td></td>
</tr>
</tbody>
</table>
APPENDIX C: DYNAMIC PROBIT MODEL RESULTS

YIELD CURVE SPREAD

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/13/13   Time: 15:56
Sample (adjusted): 1980Q2 2010Q4
Included observations: 123 after adjustments
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-1.282151</td>
<td>0.255785</td>
<td>-5.012621</td>
<td>0.0000</td>
</tr>
<tr>
<td>SPREAD(-1)</td>
<td>-0.327607</td>
<td>0.093308</td>
<td>-3.511031</td>
<td>0.0004</td>
</tr>
<tr>
<td>RECESSION(-1)</td>
<td>2.828718</td>
<td>0.410194</td>
<td>6.896050</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.681848
Mean dependent var 0.390244
S.D. dependent var 0.489800
S.E. of regression 0.250537
Akaike info criterion 0.474376
Sum squared resid 7.532242
Schwarz criterion 0.542966
Log likelihood -26.17415
Hannan-Quinn criter. 0.502237
Deviance 52.34830
Restr. deviance 164.5388
Restr. log likelihood -82.26942
LR statistic 112.1905
Avg. log likelihood -0.212798
Prob(LR statistic) 0.000000

Obs with Dep=0 75
Total obs 123
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/13/13   Time: 15:57
Sample (adjusted): 1980Q3 2010Q4
Included observations: 122 after adjustments
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.773571</td>
<td>0.210803</td>
<td>-3.669649</td>
<td>0.0002</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.341822</td>
<td>0.077263</td>
<td>-4.421412</td>
<td>0.0000</td>
</tr>
<tr>
<td>RECESSION(-2)</td>
<td>1.728836</td>
<td>0.314588</td>
<td>5.495550</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.501073
Mean dependent var 0.393443
S.D. dependent var 0.490528
S.E. of regression 0.250537
Akaike info criterion 0.474376
Sum squared resid 7.532242
Schwarz criterion 0.542966
Log likelihood -26.17415
Hannan-Quinn criter. 0.502237
Deviance 52.34830
Restr. deviance 164.5388
Restr. log likelihood -82.26942
LR statistic 112.1905
Avg. log likelihood -0.212798
Prob(LR statistic) 0.000000

Obs with Dep=0 74
Total obs 122
Obs with Dep=1 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 15:58  
Sample (adjusted): 1980Q4 2010Q4  
Included observations: 121 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-2.152935</td>
<td>0.0313</td>
</tr>
<tr>
<td>SPREAD(-3)</td>
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<td>-4.594742</td>
<td>0.0000</td>
</tr>
<tr>
<td>RECESSION(-3)</td>
<td>0.939509</td>
<td>0.283778</td>
<td>3.310715</td>
<td>0.0009</td>
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</tbody>
</table>

McFadden R-squared: 0.342295  
S.D. dependent var: 0.396694  
S.E. of regression: 0.374604  
Sum squared resid: 16.55875  
Log likelihood: -53.45132  
Deviance: 106.9026  
Restr. deviance: 162.5389  
Restr. log likelihood: -81.26947  
Avg. log likelihood: -0.441746  
Prob(LR statistic): 0.000000  
Obs with Dep=0: 73  
Total obs: 121  
Obs with Dep=1: 48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 15:59  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.176072</td>
<td>0.188897</td>
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<td>-0.263112</td>
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<td>-4.418597</td>
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<td>0.354056</td>
<td>0.274851</td>
<td>1.288175</td>
<td>0.1977</td>
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McFadden R-squared: 0.214385  
Mean dependent var: 0.396694  
S.E. of regression: 0.420616  
Sum squared resid: 20.69940  
Log likelihood: -63.44734  
Deviance: 126.8947  
Restr. deviance: 161.5228  
Restr. log likelihood: -80.76140  
Avg. log likelihood: -0.528728  
Prob(LR statistic): 0.000000  
Obs with Dep=0: 72  
Total obs: 120  
Obs with Dep=1: 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 16:00  
Sample (adjusted): 1981Q2 2010Q4  
Included observations: 119 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<td>0.185066</td>
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<td>0.272218</td>
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<td>0.7170</td>
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McFadden R-squared 0.113720  
S.D. dependent var 0.492646  
Akaike info criter. 1.245748  
Schwarz criterion 1.315809  
Hannan-Quinn criter. 1.274197  
Restr. deviance 160.4956  
LR statistic 18.25160  
Prob(LR statistic) 0.000109

Obs with Dep=0 71  
Obs with Dep=1 48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 16:00  
Sample (adjusted): 1981Q3 2010Q4  
Included observations: 118 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
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<th>Prob.</th>
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<tr>
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<td>0.050831</td>
<td>-2.757245</td>
<td>0.0058</td>
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<td>RECESSION(-6)</td>
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<td>0.271325</td>
<td>-1.213695</td>
<td>0.2249</td>
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McFadden R-squared 0.050478  
S.D. dependent var 0.493328  
Akaike info criter. 1.333965  
Schwarz criterion 1.404406  
Hannan-Quinn criter. 1.362566  
Restr. deviance 159.4569  
LR statistic 18.049095  
Prob(LR statistic) 0.017872

Obs with Dep=0 70  
Obs with Dep=1 48

---

99
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 16:01  
Sample (adjusted): 1981Q4 2010Q4  
Included observations: 117 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
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<th>Variable</th>
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<td>-0.508098</td>
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McFadden R-squared 0.034761  Mean dependent var 0.410256  
S.D. dependent var 0.493996  S.E. of regression 0.487438  
Akaike info criterion 1.358123  Sum squared resid 27.08597  
Schwarz criterion 1.428948  Log likelihood -76.45020  
Hannan-Quinn criter. 1.386877  Deviance 152.9004  
Restr. deviance 158.4067  Restr. log likelihood -79.20335  
LR statistic 5.506314  Avg. log likelihood -0.653420  
Prob(LR statistic) 0.063726

Obs with Dep=0 69  Total obs 117
Obs with Dep=1 48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/13/13   Time: 16:02  
Sample (adjusted): 1982Q1 2010Q4  
Included observations: 116 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<td>0.272104</td>
<td>-1.624111</td>
<td>0.1044</td>
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McFadden R-squared 0.019134  Mean dependent var 0.405172  
S.D. dependent var 0.493055  S.E. of regression 0.491482  
Akaike info criterion 1.375998  Sum squared resid 27.29567  
Schwarz criterion 1.447211  Log likelihood -76.80787  
Hannan-Quinn criter. 1.404906  Deviance 153.6157  
Restr. deviance 156.6124  Restr. log likelihood -79.30618  
LR statistic 2.996610  Avg. log likelihood -0.662137  
Prob(LR statistic) 0.223509

Obs with Dep=0 69  Total obs 116
Obs with Dep=1 47
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/15/13   Time: 19:02
Sample (adjusted): 1980Q4 2010Q4
Included observations: 121 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>RALSI(-2)</td>
<td>-3.251113</td>
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<td>-1.907772</td>
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<tr>
<td>RECESSION(-1)</td>
<td>2.05064</td>
<td>0.351734</td>
<td>7.97437</td>
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McFadden R-squared: 0.584224
Mean dependent var: 0.393443
S.D. dependent var: 0.490528
S.E. of regression: 0.276172
Akaike info criterion: 0.606539
Sum squared resid: 9.076255
Schwarz criterion: 0.675491
Log likelihood: -33.99890
Hannan-Quinn criter.: 0.634545
Deviance: 67.99779
Restr. deviance: 163.5442
Restr. log likelihood: -81.77210
LR statistic: 95.54641
Avg. log likelihood: -0.278679
Prob(LR statistic): 0.000000
Obs with Dep=0: 74
Obs with Dep=1: 48
Total obs: 122

Obs with Dep=0: 73
Obs with Dep=1: 48
Total obs: 121
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/15/13   Time: 19:11
Sample (adjusted): 1981Q1 2010Q4
Included observations: 120 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
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<tr>
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<th>Coefficient</th>
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McFadden R-squared 0.597229  Mean dependent var 0.400000
S.D. dependent var 0.491952  S.E. of regression 0.275711
Akaike info criterion 0.592139  Sum squared resid 8.893957
Schwarz criterion 0.661826  Log likelihood -32.52835
Hannan-Quinn criter. 0.620439  Deviance 65.05670
Restr. deviance 161.5228  Restr. log likelihood -80.76140
LR statistic 96.46610  Avg. log likelihood -0.271070
Prob(LR statistic) 0.000000

Obs with Dep=0 72  Total obs 120
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/15/13   Time: 19:15
Sample (adjusted): 1981Q2 2010Q4
Included observations: 119 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

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<th>Variable</th>
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<th>z-Statistic</th>
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<td>RALSI(-4)</td>
<td>2.479251</td>
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<td>2.947452</td>
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McFadden R-squared 0.587248  Mean dependent var 0.403361
S.D. dependent var 0.492646  S.E. of regression 0.276924
Akaike info criterion 0.607100  Sum squared resid 8.895697
Schwarz criterion 0.677162  Log likelihood -33.12245
Hannan-Quinn criter. 0.635550  Deviance 66.24490
Restr. deviance 160.4956  Restr. log likelihood -80.24778
LR statistic 94.25065  Avg. log likelihood -0.278340
Prob(LR statistic) 0.000000

Obs with Dep=0 71  Total obs 119
Obs with Dep=1 48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/15/13   Time: 19:20
Sample (adjusted): 1981Q3 2010Q4
Included observations: 118 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
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<tr>
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McFadden R-squared 0.607183  Mean dependent var 0.406780
S.D. dependent var 0.493328  S.E. of regression 0.266414
Akaike info criterion 0.581672  Sum squared resid 8.162307
Schwarz criterion 0.652114  Log likelihood -31.31867
Hannan-Quinn criter. 0.610274  Deviance 62.63735
Restr. deviance 159.4569  Restr. log likelihood -79.72847
LR statistic 96.81959  Avg. log likelihood -0.265412
Prob(LR statistic) 0.000000

Obs with Dep=0 70  Total obs 118
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/15/13   Time: 19:25
Sample (adjusted): 1981Q4 2010Q4
Included observations: 117 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
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<tr>
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<th>Prob.</th>
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<tbody>
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McFadden R-squared 0.607183  Mean dependent var 0.406780
S.D. dependent var 0.493328  S.E. of regression 0.266414
Akaike info criterion 0.581672  Sum squared resid 8.162307
Schwarz criterion 0.652114  Log likelihood -31.31867
Hannan-Quinn criter. 0.610274  Deviance 62.63735
Restr. deviance 159.4569  Restr. log likelihood -79.72847
LR statistic 96.81959  Avg. log likelihood -0.265412
Prob(LR statistic) 0.000000

Obs with Dep=0 69  Total obs 117
Obs with Dep=1 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/15/13  Time: 19:33  
Sample (adjusted): 1982Q1 2010Q4  
Included observations: 116 after adjustments  
Convergence achieved after 5 iterations  
Covariance matrix computed using second derivatives

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
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<td>McFadden R-squared</td>
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<td>mean dependent var</td>
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<tr>
<td>S.D. dependent var</td>
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<td>S.E. of regression</td>
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<td>Akaike info criterion</td>
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<td>Schwarz criterion</td>
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<td>0.597537</td>
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<tr>
<td>Resstr. deviance</td>
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<tr>
<td>Prob(LR statistic)</td>
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Obs with Dep=0 69  Total obs 116

Obs with Dep=1 47

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/15/13  Time: 19:42  
Sample (adjusted): 1982Q2 2010Q4  
Included observations: 115 after adjustments  
Convergence achieved after 5 iterations  
Covariance matrix computed using second derivatives

<table>
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<th>Std. Error</th>
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<td>0.608352</td>
<td>mean dependent var</td>
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</tr>
<tr>
<td>S.D. dependent var</td>
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<td>S.E. of regression</td>
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<tr>
<td>Akaike info criterion</td>
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<td>sum squared resid</td>
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</tr>
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<td>Schwarz criterion</td>
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<td>log likelihood</td>
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<td>Hannan-Quinn criter.</td>
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<tr>
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<td>restr. log likelihood</td>
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</tr>
<tr>
<td>LR statistic</td>
<td>94.16851</td>
<td>avg. log likelihood</td>
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<tr>
<td>Prob(LR statistic)</td>
<td>0.000000</td>
<td></td>
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</tr>
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</table>

Obs with Dep=0 69  Total obs 115

Obs with Dep=1 46
THE YIELD CURVE SPREAD AND RETURNS OF THE JSE ALSI

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 04/28/13   Time: 13:48
Sample (adjusted): 1980Q3 2010Q4
Included observations: 122 after adjustments
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
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<td>0.0000</td>
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<tr>
<td>SPREAD(-1)</td>
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<td>-3.32962</td>
<td>0.0009</td>
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<td>0.412267</td>
<td>6.862372</td>
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McFadden R-squared 0.679942  Mean dependent var 0.393443
S.D. dependent var 0.490528  S.E. of regression 0.252650
Akaake info criterion 0.494620  Sum squared resid 7.532197
Schwarz criterion 0.586556  Log likelihood -26.17185
Hannan-Quinn criter. 0.531962  Deviance 52.34369
Restr. deviance 163.5442  Restr. log likelihood -81.77210
LR statistic 111.2005  Avg. log likelihood -0.214523
Prob(LR statistic) 0.000000

Obs with Dep=0 74  Total obs 122
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 04/28/13   Time: 13:50
Sample (adjusted): 1981Q1 2010Q4
Included observations: 120 after adjustments
Convergence achieved after 5 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>RALSI(-3)</td>
<td>-3.841370</td>
<td>2.051577</td>
<td>-1.872399</td>
<td>0.0612</td>
</tr>
<tr>
<td>RECESSION(-1)</td>
<td>2.891038</td>
<td>0.442144</td>
<td>6.538681</td>
<td>0.0000</td>
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</table>

McFadden R-squared 0.699023  Mean dependent var 0.390000
S.D. dependent var 0.491952  S.E. of regression 0.253798
Akaake info criterion 0.471788  Sum squared resid 7.471942
Schwarz criterion 0.564705  Log likelihood -24.30731
Hannan-Quinn criter. 0.509522  Deviance 48.61462
Restr. deviance 161.5228  Restr. log likelihood -80.76140
LR statistic 112.9082  Avg. log likelihood -0.202561
Prob(LR statistic) 0.000000

Obs with Dep=0 72  Total obs 120
Obs with Dep=1 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 04/28/13   Time: 14:03  
Sample (adjusted): 1980Q4 2010Q4  
Included observations: 121 after adjustments  
Convergence achieved after 5 iterations  
Covariance matrix computed using second derivatives  

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.671215</td>
<td>0.216931</td>
<td>-3.094142</td>
<td>0.0020</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.328959</td>
<td>0.075767</td>
<td>-4.341702</td>
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</tr>
<tr>
<td>RALSI(-2)</td>
<td>-3.008799</td>
<td>1.826797</td>
<td>-1.647035</td>
<td>0.0996</td>
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<tr>
<td>RECESSION(-2)</td>
<td>1.775532</td>
<td>0.327552</td>
<td>5.420607</td>
<td>0.0000</td>
</tr>
</tbody>
</table>

McFadden R-squared | 0.514812 | Mean dependent var | 0.396694  
S.D. dependent var | 0.491246 | S.E. of regression | 0.319835  
Akaike info criterion | 0.717867 | Sum squared resid | 11.96844  
Schwarz criterion | 0.810290 | Log likelihood | -39.43098  
Hannan-Quinn criter. | 0.755404 | Deviance | 78.86195  
Restr. deviance | 162.5389 | Restr. log likelihood | -81.26947  
LR statistic | 83.67698 | Avg. log likelihood | -0.325876  
Prob(LR statistic) | 0.000000 |

Obs with Dep=0 | 73 | Total obs | 121  
Obs with Dep=1 | 48 |

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 04/28/13   Time: 14:24  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives  

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>0.0000</td>
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<tr>
<td>RALSI(-3)</td>
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<td>-2.585642</td>
<td>0.0097</td>
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<tr>
<td>RECESSION(-3)</td>
<td>0.978279</td>
<td>0.295875</td>
<td>3.306388</td>
<td>0.0009</td>
</tr>
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</table>

McFadden R-squared | 0.381919 | Mean dependent var | 0.400000  
S.D. dependent var | 0.491952 | S.E. of regression | 0.371011  
Akaike info criterion | 0.898618 | Sum squared resid | 15.96729  
Schwarz criterion | 0.991534 | Log likelihood | -49.91707  
Hannan-Quinn criter. | 0.936352 | Deviance | 99.83413  
Restr. deviance | 161.5228 | Restr. log likelihood | -80.76140  
LR statistic | 61.68867 | Avg. log likelihood | -0.415976  
Prob(LR statistic) | 0.000000 |

Obs with Dep=0 | 72 | Total obs | 120  
Obs with Dep=1 | 48 |
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/22/13   Time: 23:34
Sample (adjusted): 1981Q2 2010Q4
Included observations: 119 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.133375</td>
<td>0.193745</td>
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<tr>
<td>SPREAD(-4)</td>
<td>-0.257251</td>
<td>0.059874</td>
<td>-4.296537</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-4)</td>
<td>-1.224837</td>
<td>1.295692</td>
<td>-0.945315</td>
<td>0.3445</td>
</tr>
<tr>
<td>RECESSION(-4)</td>
<td>0.337986</td>
<td>0.276136</td>
<td>1.223983</td>
<td>0.2210</td>
</tr>
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</table>

McFadden R-squared: 0.215808
Mean dependent var: 0.403361
S.D. dependent var: 0.492646
Akaiake info criterion: 1.124868
Schwarz criterion: 1.218284
Hannan-Quinn criter.: 1.162801
Rest. deviance: 160.4956
LR statistic: 34.63627

Obs with Dep=0: 71
Total obs: 119
Obs with Dep=1: 48

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/23/13   Time: 00:00
Sample (adjusted): 1981Q3 2010Q4
Included observations: 118 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.034742</td>
<td>0.189417</td>
<td>-0.183414</td>
<td>0.8545</td>
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<tr>
<td>SPREAD(-5)</td>
<td>-0.206903</td>
<td>0.054468</td>
<td>-3.798623</td>
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<tr>
<td>RALSI(-5)</td>
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<td>1.203356</td>
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<td>0.5497</td>
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<tr>
<td>RECESSION(-5)</td>
<td>-0.088584</td>
<td>0.272599</td>
<td>-0.324960</td>
<td>0.7452</td>
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</tbody>
</table>

McFadden R-squared: 0.112261
Mean dependent var: 0.406780
S.D. dependent var: 0.493328
Akaiake info criterion: 1.267425
Schwarz criterion: 1.361346
Hannan-Quinn criter.: 1.305560
Rest. deviance: 159.4569
LR statistic: 17.90081

Obs with Dep=0: 70
Total obs: 118
Obs with Dep=1: 48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/23/13   Time: 00:30
Sample (adjusted): 1981Q4 2010Q4
Included observations: 117 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>0.184956</td>
<td>0.259882</td>
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<tr>
<td>SPREAD(-6)</td>
<td>-0.135876</td>
<td>0.051183</td>
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<td>0.0079</td>
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<tr>
<td>RALSI(-6)</td>
<td>-0.340677</td>
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<td>-0.296009</td>
<td>0.7672</td>
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<tr>
<td>RECESSION(-6)</td>
<td>-0.337500</td>
<td>0.271869</td>
<td>-1.241405</td>
<td>0.2145</td>
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</tbody>
</table>

McFadden R-squared: 0.048485
Mean dependent var: 0.410256
S.E. of regression: 0.485152

Obs with Dep=0: 69
Total obs: 117
Obs with Dep=1: 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/23/13   Time: 01:07
Sample (adjusted): 1982Q1 2010Q4
Included observations: 116 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.184813</td>
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<td>0.0273</td>
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<tr>
<td>RALSI(-7)</td>
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<td>1.164698</td>
<td>0.482752</td>
<td>0.6293</td>
</tr>
<tr>
<td>RECESSION(-7)</td>
<td>-0.492823</td>
<td>0.275915</td>
<td>-1.786144</td>
<td>0.0741</td>
</tr>
</tbody>
</table>

McFadden R-squared: 0.039557
Mean dependent var: 0.405172
S.E. of regression: 0.486674

Obs with Dep=0: 69
Total obs: 116
Obs with Dep=1: 47

UNIVERSITY
OF
JOHANNESBURG
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/23/13   Time: 01:46
Sample (adjusted): 1982Q2 2010Q4
Included observations: 115 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
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<td>0.182598</td>
<td>-0.333551</td>
<td>0.7387</td>
</tr>
<tr>
<td>SPREAD(-8)</td>
<td>-0.067195</td>
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<td>-1.374522</td>
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</tr>
<tr>
<td>RALSI(-8)</td>
<td>1.157619</td>
<td>1.180920</td>
<td>0.980269</td>
<td>0.3270</td>
</tr>
<tr>
<td>RECESSION(-8)</td>
<td>-0.420433</td>
<td>0.273704</td>
<td>-1.536086</td>
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</tr>
</tbody>
</table>

McFadden R-squared: 0.026525
Mean dependent var: 0.400000
S.D. dependent var: 0.492042
S.E. of regression: 0.489609
Akaike info criterion: 1.379885
Sum squared resid: 26.60855
Schwarz criterion: 1.475361
Log likelihood: -75.34341
Hannan-Quinn criter.: 1.418639
Deviance: 150.6868
Restr. deviance: 154.7927
Restr. log likelihood: -77.39634
LR statistic: 4.105870
Avg. log likelihood: -0.655160
Prob(LR statistic): 0.250257

Obs with Dep=0: 69
Total obs: 115
Obs with Dep=1: 46
### APPENDIX D: BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL RESULTS

#### YIELD CURVE SPREAD

**Dependent Variable:** RECESSION  
**Method:** ML - Binary Probit (Quadratic hill climbing)  
**Date:** 01/20/13  **Time:** 17:56  
**Sample (adjusted):** 1980Q4 2010Q4  
**Included observations:** 121 after adjustments  
**Convergence achieved after 4 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.088074</td>
<td>0.186224</td>
<td>-0.472947</td>
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<tr>
<td>SPREAD(-1)</td>
<td>-0.307082</td>
<td>0.062134</td>
<td>-4.942270</td>
<td>0.0000</td>
</tr>
<tr>
<td>BCVAR(-1)</td>
<td>0.321763</td>
<td>0.654378</td>
<td>0.491707</td>
<td>0.6229</td>
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</table>

<table>
<thead>
<tr>
<th>McFadden R-squared</th>
<th>Mean dependent var</th>
<th>0.220747</th>
<th>0.396694</th>
</tr>
</thead>
<tbody>
<tr>
<td>S.D. dependent var</td>
<td>S.E. of regression</td>
<td>0.491246</td>
<td>0.423841</td>
</tr>
<tr>
<td>Akaike info criterion</td>
<td>Sum squared resid</td>
<td>1.096354</td>
<td>21.19770</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>Log likelihood</td>
<td>1.165672</td>
<td>-63.32944</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>Deviance</td>
<td>1.124507</td>
<td>126.6589</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>Restr. log likelihood</td>
<td>162.5389</td>
<td>-81.26947</td>
</tr>
<tr>
<td>LR statistic</td>
<td>Avg. log likelihood</td>
<td>35.88005</td>
<td>-0.52384</td>
</tr>
<tr>
<td>Prob(LR statistic)</td>
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<td>0.000000</td>
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</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Obs with Dep=0</th>
<th>73</th>
<th>Total obs</th>
<th>121</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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<td></td>
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</tbody>
</table>

**Second Table:**

**Dependent Variable:** RECESSION  
**Method:** ML - Binary Probit (Quadratic hill climbing)  
**Date:** 01/20/13  **Time:** 17:57  
**Sample (adjusted):** 1981Q1 2010Q4  
**Included observations:** 120 after adjustments  
**Convergence achieved after 4 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
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<td>-5.347512</td>
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<td>0.191792</td>
<td>0.701659</td>
<td>0.273340</td>
<td>0.7846</td>
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<table>
<thead>
<tr>
<th>McFadden R-squared</th>
<th>Mean dependent var</th>
<th>0.286052</th>
<th>0.400000</th>
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<tbody>
<tr>
<td>S.D. dependent var</td>
<td>S.E. of regression</td>
<td>0.491952</td>
<td>0.405267</td>
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<tr>
<td>Akaike info criterion</td>
<td>Sum squared resid</td>
<td>1.010990</td>
<td>19.21620</td>
</tr>
<tr>
<td>Schwarz criterion</td>
<td>Log likelihood</td>
<td>1.080677</td>
<td>-57.65940</td>
</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>Deviance</td>
<td>1.039290</td>
<td>115.3188</td>
</tr>
<tr>
<td>Restr. deviance</td>
<td>Restr. log likelihood</td>
<td>161.5228</td>
<td>-80.76140</td>
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<tr>
<td>LR statistic</td>
<td>Avg. log likelihood</td>
<td>46.20400</td>
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<tr>
<td>Prob(LR statistic)</td>
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<td>0.000000</td>
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<table>
<thead>
<tr>
<th>Obs with Dep=0</th>
<th>72</th>
<th>Total obs</th>
<th>120</th>
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</thead>
<tbody>
<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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<td></td>
</tr>
</tbody>
</table>
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 17:58
Sample (adjusted): 1981Q2 2010Q4
Included observations: 119 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-5.234379</td>
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<td>0.345237</td>
<td>0.698472</td>
<td>0.494274</td>
<td>0.6211</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.267663
S.D. dependent var 0.492646
Akaikes info criter. 1.038124
Schwarz criterion 1.108186
Hannan-Quinn criter. 1.066574
Restr. deviance 160.4956
LR statistic 42.95879
Prob(LR statistic) 0.000000

Obs with Dep=0 71
Total obs 119

Obs with Dep=1 48

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 18:12
Sample (adjusted): 1982Q3 2010Q4
Included observations: 114 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.087217</td>
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<td>-0.444403</td>
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<td>-0.864783</td>
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</table>

McFadden R-squared 0.333040
S.D. dependent var 0.490952
Akaikes info criter. 0.947452
Schwarz criterion 1.019457
Hannan-Quinn criter. 1.066574
Restr. deviance 152.9469
LR statistic 42.95879
Prob(LR statistic) 0.000000

Obs with Dep=0 69
Total obs 114

Obs with Dep=1 45
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 17:58
Sample (adjusted): 1981Q3 2010Q4
Included observations: 118 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
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<td>SPREAD(-4)</td>
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<td>0.373729</td>
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<p>| | | | | |</p>
<table>
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<tr>
<th></th>
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</tr>
</thead>
<tbody>
<tr>
<td>McFadden R-squared</td>
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<td>Mean dependent var</td>
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<td>S.D. dependent var</td>
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<tr>
<td>Akaike info criterion</td>
<td>1.136228</td>
<td>Sum squared resid</td>
<td>21.19357</td>
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<tr>
<td>Schwarz criterion</td>
<td>1.206669</td>
<td>Log likelihood</td>
<td>-64.03745</td>
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</tr>
<tr>
<td>Hannan-Quinn criter.</td>
<td>1.164829</td>
<td>Deviance</td>
<td>128.0749</td>
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<tr>
<td>Restr. deviance</td>
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<td>Restr. log likelihood</td>
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<tr>
<td>LR statistic</td>
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<td>Avg. log likelihood</td>
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<tr>
<td>Prob(LR statistic)</td>
<td>0.000000</td>
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<tr>
<td>Obs with Dep=0</td>
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<td>Total obs</td>
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<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 17:59
Sample (adjusted): 1981Q4 2010Q4
Included observations: 117 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
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<td>-0.547320</td>
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<td>0.645549</td>
<td>0.315390</td>
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<tr>
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<tbody>
<tr>
<td>McFadden R-squared</td>
<td>0.106056</td>
<td>Mean dependent var</td>
<td>0.410256</td>
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<tr>
<td>S.D. dependent var</td>
<td>0.493996</td>
<td>S.E. of regression</td>
<td>0.460904</td>
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<td>Akaike info criterion</td>
<td>1.261596</td>
<td>Sum squared resid</td>
<td>24.21729</td>
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<tr>
<td>Schwarz criterion</td>
<td>1.332421</td>
<td>Log likelihood</td>
<td>-70.80339</td>
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<td>Hannan-Quinn criter.</td>
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<td>Deviance</td>
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<td>Restr. deviance</td>
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<td>Prob(LR statistic)</td>
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<tr>
<td>Obs with Dep=0</td>
<td>69</td>
<td>Total obs</td>
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<tr>
<td>Obs with Dep=1</td>
<td>48</td>
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</table>
**Dependent Variable: RECESSION**

**Method:** ML - Binary Probit (Quadratic hill climbing)

**Date:** 01/20/13   **Time:** 17:59

**Sample (adjusted):** 1982Q1 2010Q4

**Included observations:** 116 after adjustments

**Convergence achieved after 3 iterations**

**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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</thead>
<tbody>
<tr>
<td>C</td>
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<td>0.169507</td>
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<td>-0.121601</td>
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<td>0.628004</td>
<td>-0.066676</td>
<td>0.9468</td>
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</tbody>
</table>

**McFadden R-squared** 0.045209  **Mean dependent var** 0.405172

**S.D. dependent var** 0.493055  **S.E. of regression** 0.482059

**Akaike info criterion** 1.340794  **Sum squared resid** 26.25906

**Schwarz criterion** 1.412007  **Log likelihood** -74.76604

**Hannan-Quinn criter.** 1.369702  **Deviance** 149.5321

**Restr. deviance** 156.6124  **Restr. log likelihood** -78.30618

**LR statistic** 7.080276  **Avg. log likelihood** -0.644535

**Prob(LR statistic)** 0.029009

**Obs with Dep=0** 69  **Total obs** 116

**Obs with Dep=1** 47

---

**Dependent Variable: RECESSION**

**Method:** ML - Binary Probit (Quadratic hill climbing)

**Date:** 01/20/13   **Time:** 18:00

**Sample (adjusted):** 1982Q2 2010Q4

**Included observations:** 115 after adjustments

**Convergence achieved after 3 iterations**

**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>0.169438</td>
<td>-1.127896</td>
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<td>SPREAD(-7)</td>
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<td>BCVAR(-7)</td>
<td>0.063153</td>
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<td>0.101805</td>
<td>0.9189</td>
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</table>

**McFadden R-squared** 0.020325  **Mean dependent var** 0.400000

**S.D. dependent var** 0.492042  **S.E. of regression** 0.489387

**Akaike info criterion** 1.370840  **Sum squared resid** 26.82393

**Schwarz criterion** 1.423047  **Log likelihood** -75.82328

**Hannan-Quinn criter.** 1.399904  **Deviance** 151.6466

**Restr. deviance** 156.7124  **Restr. log likelihood** -78.46818

**LR statistic** 3.146132  **Avg. log likelihood** -0.659333

**Prob(LR statistic)** 0.207408

**Obs with Dep=0** 69  **Total obs** 115

**Obs with Dep=1** 46
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 18:00
Sample (adjusted): 1982Q3 2010Q4
Included observations: 114 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
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<tr>
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<td>BCVAR(-8)</td>
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<td>0.3434</td>
</tr>
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</table>

McFadden R-squared 0.011264  Mean dependent var 0.394737
S.D. dependent var 0.490952  S.E. of regression 0.492102
Akaike info criterion 1.379160  Sum squared resid 26.88021
Schwarz criterion 1.451165  Log likelihood -75.61209
Hannan-Quinn criter. 1.408382  Deviance 151.2242
Restr. deviance 152.9469  Restr. log likelihood -76.47346
LR statistic 1.722741  Avg. log likelihood -0.663264
Prob(LR statistic) 0.422583

Obs with Dep=0 69  Total obs 114
Obs with Dep=1 45

JSE ALSI RETURNS

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 19:23
Sample (adjusted): 1980Q4 2010Q4
Included observations: 121 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
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<tr>
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<td>1.249784</td>
<td>0.590482</td>
<td>2.116547</td>
<td>0.0343</td>
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</table>

McFadden R-squared 0.041300  Mean dependent var 0.396694
S.D. dependent var 0.491246  S.E. of regression 0.481491
Akaike info criterion 1.337406  Sum squared resid 27.35640
Schwarz criterion 1.406723  Log likelihood -77.91307
Hannan-Quinn criter. 1.365558  Deviance 155.8261
Restr. deviance 162.5389  Restr. log likelihood -81.26947
LR statistic 6.712799  Avg. log likelihood -0.643910
Prob(LR statistic) 0.034861

Obs with Dep=0 73  Total obs 121
Obs with Dep=1 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/20/13   Time: 19:24  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>1.281150</td>
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<td>2.155641</td>
<td>0.0311</td>
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</table>

McFadden R-squared 0.062995  Mean dependent var 0.400000  
S.D. dependent var 0.491952  S.E. of regression 0.475142  
Akaike info criterion 1.311230  Sum squared resid 26.41392  
Schwarz criterion 1.380917  Log likelihood -75.67380  
Hannan-Quinn criter. 1.339530  Deviance 151.3476  
Restr. deviance 161.5228  Restr. log likelihood -80.76140  
LR statistic 10.17521  Avg. log likelihood -0.630615  
Prob(LR statistic) 0.006173

Obs with Dep=0 72  Total obs 120  
Obs with Dep=1 48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/20/13   Time: 19:36  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<td>2.353104</td>
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</table>

McFadden R-squared 0.090909  Mean dependent var 0.400000  
S.D. dependent var 0.491952  S.E. of regression 0.466187  
Akaike info criterion 1.273658  Sum squared resid 25.42767  
Schwarz criterion 1.343345  Log likelihood -73.41947  
Hannan-Quinn criter. 1.301958  Deviance 146.8389  
Restr. deviance 161.5228  Restr. log likelihood -80.76140  
LR statistic 14.68387  Avg. log likelihood -0.611829  
Prob(LR statistic) 0.000648

Obs with Dep=0 72  Total obs 120  
Obs with Dep=1 48
Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/20/13   Time: 19:25  
Sample (adjusted): 1981Q2 2010Q4  
Included observations: 119 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tr>
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<td>-3.592496</td>
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<td>1.370544</td>
<td>0.598517</td>
<td>2.289900</td>
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</table>

McFadden R-squared          0.088512  
S.D. dependent var          0.492646  
Akaike info criterion       1.279746  
Schwarz criterion           1.349808  
Hannan-Quinn criter.        1.308196  
Restr. deviance             160.4956  
LR statistic                14.20581  
Prob(LR statistic)          0.000823  

Obs with Dep=0  71  Total obs  119  
Obs with Dep=1  48

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 01/20/13   Time: 19:25  
Sample (adjusted): 1981Q3 2010Q4  
Included observations: 118 after adjustments  
Convergence achieved after 3 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Std. Error</th>
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<th>Prob.</th>
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<tbody>
<tr>
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McFadden R-squared          0.041850  
S.D. dependent var          0.493328  
Akaike info criterion       1.345624  
Schwarz criterion           1.416065  
Hannan-Quinn criter.        1.374225  
Restr. deviance             159.4569  
LR statistic                6.673278  
Prob(LR statistic)          0.035556  

Obs with Dep=0  70  Total obs  118  
Obs with Dep=1  48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 19:26
Sample (adjusted): 1981Q4 2010Q4
Included observations: 117 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
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<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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McFadden R-squared 0.014768   Mean dependent var 0.410256
S.D. dependent var 0.493996    S.E. of regression 0.493434
Akaike info criterion 1.385191  Sum squared resid 27.75638
Schwarz criterion 1.456016       Log likelihood -78.03365
Hannan-Quinn criter. 1.413945    Deviance 156.0673
Restr. deviance 158.4067       Restr. log likelihood -79.20335
LR statistic 2.339402       Avg. log likelihood -0.666954
Prob(LR statistic) 0.310460

Obs with Dep=0 69  Total obs 117
Obs with Dep=1 48

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 19:26
Sample (adjusted): 1982Q1 2010Q4
Included observations: 116 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>0.433984</td>
<td>0.578767</td>
<td>0.749842</td>
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McFadden R-squared 0.005304   Mean dependent var 0.405172
S.D. dependent var 0.493055    S.E. of regression 0.495721
Akaike info criterion 1.394670  Sum squared resid 27.76855
Schwarz criterion 1.465884       Log likelihood -77.89087
Hannan-Quinn criter. 1.423579    Deviance 155.7817
Restr. deviance 156.6124       Restr. log likelihood -78.30618
LR statistic 0.830616       Avg. log likelihood -0.671473
Prob(LR statistic) 0.660137

Obs with Dep=0 69  Total obs 116
Obs with Dep=1 47

117
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 19:26
Sample (adjusted): 1982Q2 2010Q4
Included observations: 115 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
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<tr>
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</table>

McFadden R-squared 0.003897  Mean dependent var 0.400000
S.D. dependent var 0.492042  S.E. of regression 0.495070
Akaike info criterion 1.392952  Sum squared resid 27.45060
Schwarz criterion 1.464559  Log likelihood -77.09473
Hannan-Quinn criter. 1.422017  Deviance 154.1895
Restr. deviance 154.7927  Restr. log likelihood -77.39634
LR statistic 0.603230  Avg. log likelihood -0.670389
Prob(LR statistic) 0.739623

Obs with Dep=0 69  Total obs 115
Obs with Dep=1 46

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 01/20/13   Time: 19:27
Sample (adjusted): 1982Q3 2010Q4
Included observations: 114 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
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<tbody>
<tr>
<td>C</td>
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<td>0.157548</td>
<td>-1.560682</td>
<td>0.1186</td>
</tr>
<tr>
<td>RALSI(-8)</td>
<td>1.131016</td>
<td>1.178823</td>
<td>0.959445</td>
<td>0.3373</td>
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<tr>
<td>BCVAR(-8)</td>
<td>-0.368022</td>
<td>0.599819</td>
<td>-0.601551</td>
<td>0.5475</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.008562  Mean dependent var 0.394737
S.D. dependent var 0.490952  S.E. of regression 0.492598
Akaike info criterion 1.382784  Sum squared resid 26.93446
Schwarz criterion 1.454789  Log likelihood -75.81870
Hannan-Quinn criter. 1.422017  Deviance 154.1895
Restr. deviance 154.7927  Restr. log likelihood -77.39634
LR statistic 0.603230  Avg. log likelihood -0.670389
Prob(LR statistic) 0.519565

Obs with Dep=0 69  Total obs 114
Obs with Dep=1 45
THE YIELD CURVE SPREAD AND RETURNS OF THE JSE ALSI

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 04/28/13   Time: 18:07  
Sample (adjusted): 1980Q4 2010Q4  
Included observations: 121 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
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<tbody>
<tr>
<td>C</td>
<td>-0.064166</td>
<td>0.190868</td>
<td>-0.336180</td>
<td>0.7367</td>
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<tr>
<td>SPREAD(-1)</td>
<td>-0.300485</td>
<td>0.062471</td>
<td>-4.810014</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-1)</td>
<td>-0.831013</td>
<td>1.400408</td>
<td>-0.593408</td>
<td>0.5529</td>
</tr>
<tr>
<td>BCVAR(-1)</td>
<td>0.320815</td>
<td>0.656339</td>
<td>0.488795</td>
<td>0.6250</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.222897  Mean dependent var 0.396694  
S.D. dependent var 0.491246  S.E. of regression 0.424219  
Akaike info criterion 1.109996  Sum squared resid 21.0551  
Schwarz criterion 1.202419  Log likelihood -63.15476  
Hannan-Quinn criter. 1.147533  Deviance 126.3095  
Restr. deviance 162.5389  Restr. log likelihood -81.26947  
LR statistic 36.22941  Avg. log likelihood -0.521940  
Prob(LR statistic) 0.000000

Obs with Dep=0 73  Total obs 121  
Obs with Dep=1 48

---

Dependent Variable: RECESSION  
Method: ML - Binary Probit (Quadratic hill climbing)  
Date: 04/28/13   Time: 18:08  
Sample (adjusted): 1981Q1 2010Q4  
Included observations: 120 after adjustments  
Convergence achieved after 4 iterations  
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.056839</td>
<td>0.203109</td>
<td>0.279843</td>
<td>0.7796</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.371678</td>
<td>0.071147</td>
<td>-5.224081</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-2)</td>
<td>-2.324519</td>
<td>1.476307</td>
<td>-1.574550</td>
<td>0.1154</td>
</tr>
<tr>
<td>BCVAR(-2)</td>
<td>0.108174</td>
<td>0.715460</td>
<td>0.151195</td>
<td>0.8798</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.301379  Mean dependent var 0.396694  
S.D. dependent var 0.491952  S.E. of regression 0.424219  
Akaike info criterion 1.007027  Sum squared resid 18.54620  
Schwarz criterion 1.099944  Log likelihood -66.42164  
Hannan-Quinn criter. 1.147533  Deviance 128.3095  
Restr. deviance 162.5389  Restr. log likelihood -81.26947  
LR statistic 36.22941  Avg. log likelihood -0.521940  
Prob(LR statistic) 0.000000

Obs with Dep=0 72  Total obs 120  
Obs with Dep=1 48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 04/28/13   Time: 18:29
Sample (adjusted): 1981Q1 2010Q4
Included observations: 120 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.061191</td>
<td>0.204251</td>
<td>0.299585</td>
<td>0.7645</td>
</tr>
<tr>
<td>SPREAD(-2)</td>
<td>-0.383203</td>
<td>0.074025</td>
<td>-5.176661</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-3)</td>
<td>-3.651378</td>
<td>1.440324</td>
<td>-2.535108</td>
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<tr>
<td>BCVAR(-2)</td>
<td>0.253357</td>
<td>0.710775</td>
<td>0.356451</td>
<td>0.7215</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.327597  Mean dependent var 0.061191
S.D. dependent var 0.491952  S.E. of regression 0.204251
Akaike info criterion 0.971737  Sum squared resid 17.80418
Schwarz criterion 1.064653  Log likelihood -54.30421
Hannan-Quinn criter. 1.009471  Deviance 108.6084
Restr. deviance 161.5228  Restr. log likelihood -80.76140
LR statistic 52.91438  Avg. log likelihood -0.452535
Prob(LR statistic) 0.000000

Obs with Dep=0 72  Total obs 120
Obs with Dep=1 48

---

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 04/28/13   Time: 18:08
Sample (adjusted): 1981Q2 2010Q4
Included observations: 119 after adjustments
Convergence achieved after 4 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.095182</td>
<td>0.205578</td>
<td>0.462994</td>
<td>0.6434</td>
</tr>
<tr>
<td>SPREAD(-3)</td>
<td>-0.359343</td>
<td>0.071014</td>
<td>-5.06176</td>
<td>0.0000</td>
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<tr>
<td>RALSI(-3)</td>
<td>-3.682817</td>
<td>1.450645</td>
<td>-2.538744</td>
<td>0.0111</td>
</tr>
<tr>
<td>BCVAR(-3)</td>
<td>0.245961</td>
<td>0.726137</td>
<td>0.338726</td>
<td>0.7348</td>
</tr>
</tbody>
</table>

McFadden R-squared 0.309559  Mean dependent var 0.095182
S.D. dependent var 0.491952  S.E. of regression 0.205578
Akaike info criterion 0.971737  Sum squared resid 17.80418
Schwarz criterion 1.064653  Log likelihood -54.30421
Hannan-Quinn criter. 1.009471  Deviance 108.6084
Restr. deviance 161.5228  Restr. log likelihood -80.76140
LR statistic 52.91438  Avg. log likelihood -0.452535
Prob(LR statistic) 0.000000

Obs with Dep=0 71  Total obs 119
Obs with Dep=1 48
### Table 1: Probit Results for RECESSION

**Dependent Variable:** RECESSION  
**Method:** ML - Binary Probit (Quadratic hill climbing)  
**Date:** 06/17/13  **Time:** 14:13  
**Sample (adjusted):** 1981Q3 2010Q4  
**Included observations:** 118 after adjustments  
**Convergence achieved after 4 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable (Lag)</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.012861</td>
<td>0.186754</td>
<td>-0.068868</td>
<td>0.9451</td>
</tr>
<tr>
<td>SPREAD(-4)</td>
<td>-0.274496</td>
<td>0.059639</td>
<td>-4.602598</td>
<td>0.0000</td>
</tr>
<tr>
<td>RALSI(-4)</td>
<td>-1.305362</td>
<td>1.288338</td>
<td>-1.013214</td>
<td>0.3110</td>
</tr>
<tr>
<td>BCVAR(-4)</td>
<td>0.245428</td>
<td>0.679529</td>
<td>0.361174</td>
<td>0.7180</td>
</tr>
</tbody>
</table>

- **McFadden R-squared:** 0.203226  
- **Mean dependent var:** 0.406780  
- **S.E. of regression:** 0.430088  
- **Akaike info criterion:** 1.144501  
- **Sum squared resid:** 21.08721  
- **Schwarz criterion:** 1.238423  
- **Log likelihood:** -63.52557  
- **Hannan-Quinn criter.:** 1.182636  
- **Deviance:** 127.0511  
- **Restr. deviance:** 159.4569  
- **Restr. log likelihood:** -79.72847  
- **LR statistic:** 32.40579  
- **Avg. log likelihood:** -0.538352  
- **Prob(LR statistic):** 0.000000

- **Obs with Dep=0:** 70  
- **Total obs:** 118

### Table 2: Probit Results for RECESSION

**Dependent Variable:** RECESSION  
**Method:** ML - Binary Probit (Quadratic hill climbing)  
**Date:** 06/17/13  **Time:** 14:39  
**Sample (adjusted):** 1981Q4 2010Q4  
**Included observations:** 117 after adjustments  
**Convergence achieved after 3 iterations**  
**Covariance matrix computed using second derivatives**

<table>
<thead>
<tr>
<th>Variable (Lag)</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>0.114484</td>
<td>0.176865</td>
<td>-0.647297</td>
<td>0.5174</td>
</tr>
<tr>
<td>SPREAD(-5)</td>
<td>-0.192204</td>
<td>0.052102</td>
<td>-3.689000</td>
<td>0.0002</td>
</tr>
<tr>
<td>RALSI(-5)</td>
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<td>1.199018</td>
<td>0.630521</td>
<td>0.5284</td>
</tr>
<tr>
<td>BCVAR(-5)</td>
<td>0.207576</td>
<td>0.646479</td>
<td>0.321087</td>
<td>0.7481</td>
</tr>
</tbody>
</table>

- **McFadden R-squared:** 0.108586  
- **Mean dependent var:** 0.410256  
- **S.E. of regression:** 0.460630  
- **Akaike info criterion:** 1.275265  
- **Sum squared resid:** 23.97638  
- **Schwarz criterion:** 1.369698  
- **Log likelihood:** -70.60299  
- **Hannan-Quinn criter.:** 1.313604  
- **Deviance:** 141.2060  
- **Restr. deviance:** 158.4067  
- **Restr. log likelihood:** -79.20335  
- **LR statistic:** 17.20072  
- **Avg. log likelihood:** -0.603444  
- **Prob(LR statistic):** 0.000643

- **Obs with Dep=0:** 69  
- **Total obs:** 117

- **Obs with Dep=1:** 48
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/17/13   Time: 15:13
Sample (adjusted): 1982Q1 2010Q4
Included observations: 116 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>-0.116979</td>
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<td>SPREAD(-6)</td>
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<td>RALSI(-6)</td>
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<td>1.140782</td>
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<td>BCVAR(-6)</td>
<td>-0.041330</td>
<td>0.627989</td>
<td>-0.065814</td>
<td>0.9475</td>
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</tbody>
</table>

McFadden R-squared 0.045567
S.D. dependent var 0.493055
Akaike info criterion 1.357552
Schwarz criterion 1.452503
Hannan-Quinn criter. 1.396097
Restr. deviance 156.6124
LR statistic 7.136335
Prob(LR statistic) 0.067677

Obs with Dep=0 69
Obs with Dep=1 47
Total obs 116

Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/17/13   Time: 18:28
Sample (adjusted): 1982Q2 2010Q4
Included observations: 115 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
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<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
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<td>0.171846</td>
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<td>0.2286</td>
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<tr>
<td>SPREAD(-7)</td>
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</tr>
<tr>
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<tr>
<td>BCVAR(-7)</td>
<td>0.056742</td>
<td>0.621459</td>
<td>0.091305</td>
<td>0.9273</td>
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McFadden R-squared 0.022673
S.D. dependent var 0.492042
Akaike info criterion 1.385070
Schwarz criterion 1.480546
Hannan-Quinn criter. 1.423824
Restr. deviance 154.7927
LR statistic 3.509579
Prob(LR statistic) 0.319522

Obs with Dep=0 69
Obs with Dep=1 46
Total obs 115
Dependent Variable: RECESSION
Method: ML - Binary Probit (Quadratic hill climbing)
Date: 06/17/13  Time: 19:13
Sample (adjusted): 1982Q3 2010Q4
Included observations: 114 after adjustments
Convergence achieved after 3 iterations
Covariance matrix computed using second derivatives

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>Std. Error</th>
<th>z-Statistic</th>
<th>Prob.</th>
</tr>
</thead>
<tbody>
<tr>
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<td>-0.851090</td>
<td>0.3947</td>
</tr>
<tr>
<td>SPREAD(-8)</td>
<td>-0.059102</td>
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<tr>
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<td>0.642888</td>
<td>-0.968941</td>
<td>0.3326</td>
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McFadden R-squared 0.018883  Mean dependent var 0.394737
S.D. dependent var 0.490952  S.E. of regression 0.490721
Akaike info criterion 1.386481  Sum squared resid 26.48875
Schwarz criterion 1.482488  Log likelihood -75.02940
Hannan-Quinn criter. 1.425445  Deviance 150.0588
Restr. deviance 152.9469  Restr. log likelihood -76.47346
LR statistic 2.888122  Avg. log likelihood -0.658153
Prob(LR statistic) 0.409198

Obs with Dep=0 69  Total obs 114
Obs with Dep=1 45
### APPENDIX E: RMSE RESULTS

#### STATIC PROBIT MODEL & YIELD CURVE SPREAD

Forecast: RECESSIONF2_RMSE  
Actual: RECESSION  
Forecast sample: 1980Q1 2010Q4  
Adjusted sample: 1980Q3 2010Q4  
Included observations: 122

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
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</thead>
<tbody>
<tr>
<td>Root Mean Squared Error</td>
<td>0.397044</td>
</tr>
<tr>
<td>Mean Absolute Error</td>
<td>0.314460</td>
</tr>
<tr>
<td>Mean Absolute Percentage Error</td>
<td>16.01692</td>
</tr>
<tr>
<td>Theil Inequality Coefficient</td>
<td>0.358468</td>
</tr>
<tr>
<td>Bias Proportion</td>
<td>0.000219</td>
</tr>
<tr>
<td>Variance Proportion</td>
<td>0.265842</td>
</tr>
<tr>
<td>Covariance Proportion</td>
<td>0.733939</td>
</tr>
</tbody>
</table>

#### STATIC PROBIT MODEL & JSE ALSI RETURNS

Forecast: RECESSIONF3_RMSE  
Actual: RECESSION  
Forecast sample: 1980Q1 2010Q4  
Adjusted sample: 1981Q1 2010Q4  
Included observations: 120

<table>
<thead>
<tr>
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<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
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</tr>
<tr>
<td>Mean Absolute Error</td>
<td>0.444411</td>
</tr>
<tr>
<td>Mean Absolute Percentage Error</td>
<td>22.29839</td>
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<tr>
<td>Theil Inequality Coefficient</td>
<td>0.447916</td>
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<tr>
<td>Bias Proportion</td>
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</tr>
<tr>
<td>Variance Proportion</td>
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</tr>
<tr>
<td>Covariance Proportion</td>
<td>0.422511</td>
</tr>
</tbody>
</table>

#### THE STATIC PROBIT MODEL, YIELD CURVE SPREAD AND RETURNS OF THE JSE ALSI

Forecast: RECESSIONF3_3_RMSE  
Actual: RECESSION  
Forecast sample: 1980Q1 2010Q4  
Adjusted sample: 1981Q1 2010Q4  
Included observations: 120

<table>
<thead>
<tr>
<th>Metric</th>
<th>Value</th>
</tr>
</thead>
<tbody>
<tr>
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<tr>
<td>Mean Absolute Error</td>
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</tr>
<tr>
<td>Mean Absolute Percentage Error</td>
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</tr>
<tr>
<td>Theil Inequality Coefficient</td>
<td>0.346545</td>
</tr>
<tr>
<td>Bias Proportion</td>
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</tr>
<tr>
<td>Variance Proportion</td>
<td>0.248614</td>
</tr>
<tr>
<td>Covariance Proportion</td>
<td>0.751278</td>
</tr>
</tbody>
</table>
DYNAMIC PROBIT MODEL & YIELD CURVE SPREAD

Forecast: RECESSIONF1_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1980Q2 2010Q4
Included observations: 123

Root Mean Squared Error 0.247463
Mean Absolute Error 0.121929
Mean Absolute Percentage Error 5.912793
Theil Inequality Coefficient 0.205884
  Bias Proportion 0.000220
  Variance Proportion 0.070786
  Covariance Proportion 0.928993

DYNAMIC PROBIT MODEL & JSE ALSI RETURNS

Forecast: RECESSIONF5_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1981Q3 2010Q4
Included observations: 118

Root Mean Squared Error 0.263006
Mean Absolute Error 0.143204
Mean Absolute Percentage Error 6.876390
Theil Inequality Coefficient 0.215661
  Bias Proportion 0.000466
  Variance Proportion 0.094814
  Covariance Proportion 0.904720

THE DYNAMIC PROBIT MODEL, YIELD CURVE SPREAD AND RETURNS OF THE JSE ALSI

Forecast: RECESSIONF1_3_1_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1981Q1 2010Q4
Included observations: 120

Root Mean Squared Error 0.249532
Mean Absolute Error 0.118816
Mean Absolute Percentage Error 5.810644
Theil Inequality Coefficient 0.204414
  Bias Proportion 0.000109
  Variance Proportion 0.059736
  Covariance Proportion 0.940155
BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL & YIELD CURVE SPREAD

Forecast: RECESSIONF3_8_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1982Q3 2010Q4
Included observations: 114

Root Mean Squared Error 0.383160
Mean Absolute Error 0.294248
Mean Absolute Percentage Error 15.02102
Theil Inequality Coefficient 0.342312
  Bias Proportion 0.000259
  Variance Proportion 0.242158
  Covariance Proportion 0.757582

BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL & JSE ALSI RETURNS

Forecast: RECESSIONF3_2_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1981Q1 2010Q4
Included observations: 120

Root Mean Squared Error 0.460323
Mean Absolute Error 0.423192
Mean Absolute Percentage Error 21.30123
Theil Inequality Coefficient 0.432803
  Bias Proportion 0.000038
  Variance Proportion 0.489846
  Covariance Proportion 0.510116

BUSINESS CYCLE SPECIFIC CONDITIONALLY INDEPENDENT PROBIT MODEL, YIELD CURVE SPREAD & JSE ALSI RETURNS

Forecast: RECESSIONF2_3_2_RMSE
Actual: RECESSION
Forecast sample: 1980Q1 2010Q4
Adjusted sample: 1981Q1 2010Q4
Included observations: 120

Root Mean Squared Error 0.385186
Mean Absolute Error 0.296864
Mean Absolute Percentage Error 15.23214
Theil Inequality Coefficient 0.342041
  Bias Proportion 0.000408
  Variance Proportion 0.243532
  Covariance Proportion 0.756061