Identifying the Future Directions of Australian Excess Stock Returns and Their Determinants Using Binary Models

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Abstract

The predictability of excess stock returns has been debated by researchers over time, with many studies proving that stock returns can be predicted to some extent. To enable an effective investment strategy, it is vital for investors to identify the future directions of stock returns and the factors causing directional changes. This study sought to determine whether Australian monthly excess stock return signs are predictable, and identify the key determinants of Australian monthly excess stock return directions. Three different binary models were considered to predict stock directions: discriminant, logistic and probit models. The predictive powers of benchmark static logistic and probit models were also compared with dynamic, autoregressive and dynamic autoregressive models. In order to identify the key determinants, this study considered various economic, international and financial factors, as well as past volatility measures of explanatory variables. It also tested a United States (US) binary recession indicator and Organisation for Economic Co-operation and Development (OECD) composite leading indicator as explanatory variables in the predictive models.

This study found that Australian monthly excess stock returns can be successfully predicted using the binary models considered in the study. The best binary predictive model recorded a 71 per cent average hit ratio in terms of forecasting accuracy. The goodness-of-fit measures and hit ratio indicated that three models—the discriminant, logistic and probit models—had similar predictive powers of monthly excess stock return signs. In addition, the statistic

logistic/probit models showed strong predicting ability, compared to the dynamic, autoregressive and dynamic autoregressive logistic/probit models.

In terms of the Australian monthly excess stock return signs, the following were identified as determinants: Standard and Poor (S&P) 500 monthly stock returns, Australian long-term interest rates (10-year bond rate), Australian short-term interest rates (three-month bank-accepted bill rate), monthly net exports and the volatility of the Australian dollar and US dollar exchange rate (measured by mean absolute deviation). Moreover, the findings showed that the US binary recession indicator and OECD composite leading indicator do not have predictive power for Australian monthly stock return signs.

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List of Abbreviations

ANOVA	Analysis of Variance
APT	Arbitrage Pricing Theory
ASX	Australian Security Exchange Limited
AUD	Australian Dollar
CAPM	Capital Asset Pricing Model
CC^2	Squared Canonical Correlation
CPI	Consumer Price Index
GDP	Gross Domestic Product
LR	Likelihood Ratio
MAD	Mean Absolute Deviation
NBER	National Bureau of Economic Research
NE	Net Export
OECD	Organisation for Economic Co-operation and Development
OLS	Ordinary Least Squares
PER	Price/Earnings Ratio
S&P	Standard and Poor
SD	Standard Deviation
U^2	Squared Return
US	United States
USD	US Dollar

Master by Research Declaration

'I, Chinthana Sanjeewa Bandara Hatangala, declare that the Master by Research thesis entitled *Identifying the Future Directions of Australian Excess Stock Returns and Their Determinants Using Binary Models* is no more than 60,000 words in length, including quotations and excluding tables, figures, appendices, bibliographies, references and footnotes. This thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.'

Signature   Date

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Finally, I dedicate this thesis to my caring, loving and supportive wife, Rukshala. It was a great comfort and relief to know that she was willing to manage our household activities, including caring for our little son, while I completed my thesis.

Publications Associated with Thesis

Hatangala C & Kulendran N 2014, 'Identifying the future directions of the Australian stock returns and their determinants using binary models', paper presented at the *31st Annual Pan-Pacific Conference*, 2–5 June, Sakai City, Osaka, Japan.

Chapter 1: Introduction

1.1 Research Background

Investor interest in stock market investments remains consistently high, despite the uncertainty of returns. This is largely due to the extra returns that can be earned from the stock market, in comparison to safer investments, such as government securities and bank deposits. The extra returns of stock investments are the expected return of stock investments that surpass the risk-free return (the return of government securities)—known as 'excess stock returns'. Generally, investors allocate a significant proportion of their funds to the stock market, and the proportion of investment varies depending on the future expectations of excess stock returns. Investors allocate a higher proportion of funds to stock investments when the expected excess stock returns are high. In contrast, funds are transferred to risk-free alternatives when the expected excess stock returns are low.

If future stock returns could be predicted, investors could determine the right time to buy and sell stocks in order to gain maximum profit or minimise possible losses. Therefore, reasonable prediction of value of stock returns or the direction of stock return cycles is vital for effective investment decision making. The stock returns that follow upwards or downwards trends (expansions or contractions) over periods have the main effect on equity investment decisions, as opposed to day-to-day changes in returns. These upwards and downwards trends are also known as 'bull' and 'bear' markets. According to Chauvet and

Potter (2001), in stock market terminology, bull (bear) markets correspond to periods of generally increasing (decreasing) market price.

In recent years, stock prices around the world have been very sensitive not only to corporate announcements, such as the release of financial results, dividend announcements and changes to boards of directors but also to macroeconomic changes. Since the Global Financial Crisis that began in mid-2007 in the United States (US), stock investors have become more alert of changes in economic conditions than ever before. Today’s stock prices not only reflect the expected financial performance of companies, but also quickly adjust to changes that occur in macroeconomic and international factors.

Various methods and econometric models have been developed to forecast the value and directional changes of stock returns. Based on this, two main types of forecasting models are identified in the literature: classification models and level estimation models. Classification models are used to predict the directional changes of stock returns, while level estimation models are used to predict the values of stock returns. Several studies have identified classification models as the better of these two types of model in terms of forecasting accuracy. Leung et al. (2000) demonstrated that the group of classification models is superior to the group of level estimation models in terms of forecasting stock market movements because classification models are able to generate higher trading profits than are level estimation models.

In previous studies, binary models have been widely used by researchers as classification models to predict the probabilities of recovery and contraction trends of stock returns, as well as the expected duration of those trends. A number of studies have demonstrated that binary models have better predictive power than level estimation models. For example, Leung et al. (2000), Nyberg (2008) and Hong and Chung (2003) used various multivariate binary classification models to predict stock returns, including linear discriminant analysis, logit, probit and probabilistic neural network models. Their empirical results suggested that the binary classification models outperformed the level estimation models, and that binary models are strong in predicting the direction of stock market movements and maximising returns from investment trading.

The explanatory variables used in binary models to predict stock returns have evolved over time, based on the success of those variables in making accurate predictions. Originally, the historical volatility of stock returns was used as an explanatory variable for sign predictions. However, recent studies have used various economic, international and financial variables as predictor variables on ground of the stronger relationship between economic conditions and stock market behaviours. The capital asset pricing model (CAPM) developed by Sharpe (1964), Lintner (1965) and Mossin (1966) and the arbitrage pricing theory (APT) developed by Ross (1976) can be used to determine the relationship between macroeconomic factors and share returns. Both the CAPM and APT explain that the prices of the securities are driven by systematic factors or market risk factors. According to these two models, systematic factors—which are mainly macroeconomic and international factors—determine the expected return for equity investments (required rate of return), which is then used for investment decision making. A lower (higher) required rate of returns give an indication that the stock prices are under-priced (overpriced).

Researchers have identified significant relationships between economic conditions and excess stock returns in many empirical studies. For example, Chauvet and Potter (1998) found a time-varying relationship between stock return and risk in regard to business cycle turning points. Fama and French (1989) and Whitelaw (1994) also found a significant dependency relationship in the conditional distribution of stock returns and business conditions. These studies have revealed that, when economic conditions are good, stock markets follow a bull-run, in which excess stock returns increase. In contrast, when economic conditions are bad, the market follows a bear-run, in which excess stock returns decrease. In another study, Chauvet and Potter (2000) established that a bear market generally begins a couple of months before an economic contraction, and ends before the trough of recession. Nyberg (2008) established that binary dynamic regression models can be successfully used to predict US monthly excess stock returns. His study also showed that models that used the binary recession indicator as an explanatory variable outperformed models that used only the financial variables.

The current study was motivated by the above studies as well as the limited attention devoted to predicting Australian excess stock return directions using binary models. Also, no previous studies have used dynamic binary models to predict Australian stock market directions. Thus, the main objectives of this study were to predict Australian monthly excess stock return signs using binary models, and identify the key contributory factors that determine monthly stock return directions in Australia. This study used three binary models—discriminant, logistic regression and probit regression models—to predict the monthly directions of excess stock returns. In addition to benchmark static logistic and probit models, this study used dynamic, autoregressive and dynamic autoregressive models for sign forecasting. Autoregressive models and dynamic autoregressive models (new dynamic models) were proposed by Kauppi and Saikkonen (2008) to predict US recession periods.

This study tested various economic, financial and international variables as explanatory variables of predictive models to identify the key determinants of Australian monthly excess stock return directions. This study also tested how different past volatility measures of selected predictor variables can be used in binary models to forecast stock returns. US binary recession indicators were first used by Nyberg (2008) to predict US stock market directions, and were tested in the current study as an explanatory variable to forecast Australian stock market directions. Further, the Organisation for Economic Co-operation and Development (OECD) index for Australia—a composite leading indicator intended to forecast Australian future economic activity—was tested as an explanatory variable to predict excess stock return signs.

1.2 Australian Stock Market and S&P/ASX 200 Index

The Australian Security Exchange Limited (ASX) is one of the major security exchanges operating in the world. The ASX was ranked as one of the top 15 largest stock exchanges as of 1 January 2015, with a market capitalisation of over US$1.5 trillion. The ASX has operated for over 150 years, and currently has around 2,200 listed companies and issuers. The major index Standard and Poor (S&P)/ASX 200 consists of the top 200 companies, based on the highest market capitalisation. This index was introduced in 2000 at value equal to the previous major index—the ASX All Ordinaries. The ASX All Ordinaries index consists of market capitalisation of the top 500 companies, and still runs parallel to the S&P/ASX 200. However, the S&P/ASX 200 is considered the major index to represent Australian stock exchange movements. This study sought to predict the monthly movements of the S&P/ASX 200 index. Figure 1.1 illustrates the perfectly positive relationship between the ASX All Ordinaries and S&P/ASX 200 index.

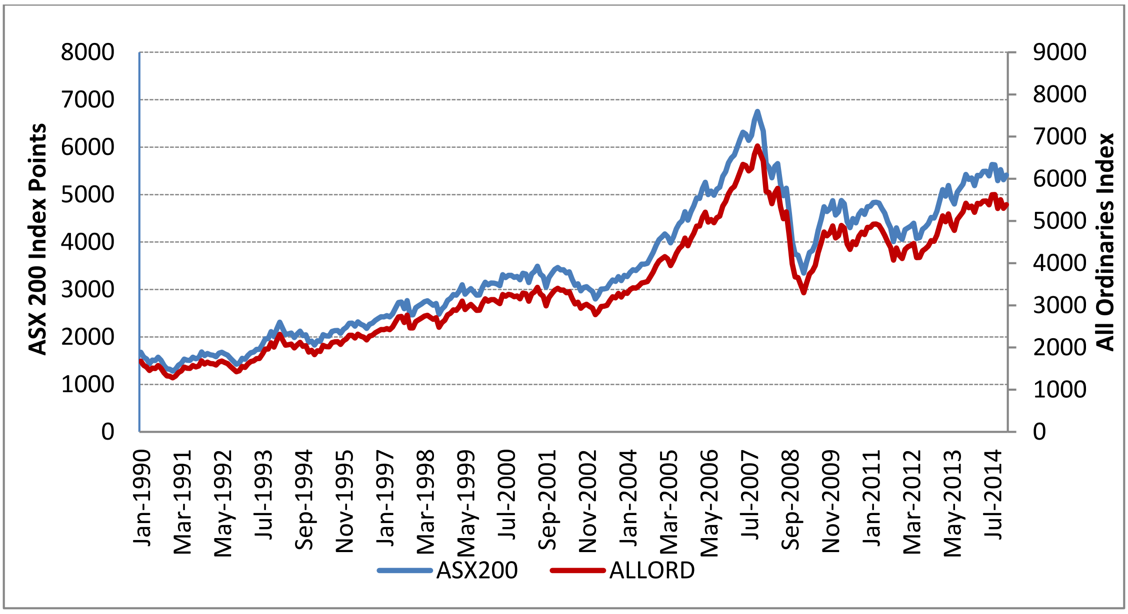

Figure 1.1: ASX All Ordinaries Index and S&P/ASX 200 Index, January 1990 to December 2014

Source: DX Database & www.rba.gov.au/statistic.

1.3 Aims of the Study

The main aim of this study was to predict the directional change in Australian monthly excess stock returns using binary models, and identify the key contributory factors that determine the monthly directions of excess stock returns in Australia. The specific aims of the study were as follows:

1. To assess the forecasting accuracy of three binary models—discriminant, logistic and probit models—for predicting Australian monthly excess stock return signs.
2. To measure the success of using developed binary models—such as dynamic logit/probit, autoregressive and dynamic autoregressive models—in predicting Australian excess stock returns, in comparison to benchmark static models.
3. To identify the major economic and financial factors that are significant in predicting Australian stock return signs.
4. To determine how international stock markets, such as the S&P 500 index and MSCI world index, affect the monthly direction of Australian stock returns.
5. To evaluate the effect of US economic indicators on the monthly direction of Australian stock returns.
6. To measure the effect of leading economic indicators—such as the OECD indicator and US recession indicator (dates defined by the US National Bureau of Economic Research)—on Australian stock return directions.
7. To examine the use of different past volatility measures of predictor variables—such as the mean absolute deviation (MAD), standard deviation (SD) and squared return (U^2)—in predicting directional changes in Australian stock returns.

1.4 Research Problem

This study examined the following research questions.

1.4.1 Research Question 1

Are the directions of monthly Australian excess stock returns predictable using discriminant, logistic and probit models?

1.4.2 Research Question 2

Do the developed dynamics probit/logit, autoregressive and dynamic autoregressive models offer better predicting results than benchmark static models in predicting Australian excess stock return signs?

1.4.3 Research Question 3

What are the key economic and financial factors that drive excess stock return directions?

1.4.4 Research Question 4

Are global stock market movements significant in predicting Australian excess stock return signs?

1.4.5 Research Question 5

Which US economic indicators are significant in predicting Australian excess stock return signs?

1.4.6 Research Question 6

What is the effect of leading economic indicators—such as the OECD indicator and US recession indicator—on the directions of Australian excess stock return signs?

1.4.7 Research Question 7

Which volatility measures of predictor variables can be used to forecast excess stock return directions using binary regression models?

1.5 Contribution to Knowledge (Academic Contribution)

Classification models have been widely used by scholars around the world to predict the directions of growth cycles, such as business, stock return and tourism growth cycles. A number of studies have shown that binary classification models compare favourably with other predictive models—such as level estimation models—in predicting growth cycles. Although some studies have used binary models to forecast the directions of international indices, such as the S&P 500, only a few studies have used binary models to predict the future directions of Australian excess stock returns.

This study focused on assessing the ability of three major binary models—discriminant, logistic and probit models—to predict the monthly directions of Australian excess stock returns. To the best of the researcher's knowledge, this is the first study to use dynamic binary models to predict Australian stock market directions. This study sought to assess how new dynamic logistic and probit models introduced by Kauppi and Saikkonen (2008) can be used to predict Australian monthly excess stock return signs.

In order to predict the directions of excess stock returns, this study identified the key factors driving monthly directional changes by testing various economic, financial and international variables. This study also sought to identify how volatility measures of some predictor variables—including the ASX 200, S&P500, MSCI and foreign exchange rate—are significant in predicting excess stock return signs. It tested three different volatility measures (MAD, SD and U^2) of selected predictor variables to assess their predictive power for Australian excess stock return signs. This type of analysis is important to study how predictive power changes when considering the volatility of predictor variables, and to assess the effectiveness of different volatility measures to predict ASX returns.

In addition, this study employed business cycle leading indicators—such as the OECD index and US binary recession indicators—as explanatory variables to evaluate their predictive ability for Australian excess stock return directions. To the best of the researcher's knowledge, no previous study has used business cycle leading indicators to predict Australian excess stock return directions.

1.6 Statement of Significance (Practical Contribution)

Investors around the world make the larger portion of their investments in stock markets, either by investing directly or through institutional investors. Thus, it is important for investors to have accurate information about future stock market movements so they can maximise their portfolio returns and minimise potential risk. In particular, the expected turnaround in excess stock return directions has a significant effect on the timing of investment decisions and asset allocation. Therefore, accurate predictions of directional changes are central to effective investment decision making. However, very little attention is devoted in the literature to studying the ability to predict Australian excess stock return directions, and to identifying the key contributory factors that determine the directions of excess stock returns in Australia. Against this background, this study makes an important contribution to stakeholders—such as investors, equity analysts, fund managers, researchers and investment policy makers—who are interested in the future directions of Australian excess stock returns and the key factors driving those directions.

1.7 Conceptual Framework

Figure 1.2 explains the conceptual framework of this research. It indicates how Australian monthly excess stock return signs were predicted, and how determinants were identified. Three binary models—discriminant, logistic and probit models—were used to forecast monthly signs. Developed logistic/probit models such as dynamic, autoregressive and dynamic autoregressive models were also tested alongside basic static models. In order to identify the key determinants of monthly excess stock return directions, possible economic, financial and international variables, as well as volatility measurements of selected variables, were considered. To test the significance of the binary models and identify the determinants of stock return directions, this study considered several diagnosis tests, including hypothesis tests. The classification results (hit ratio) were used to measure both the in-sample and out-of-sample forecasting accuracy of the predictive models.

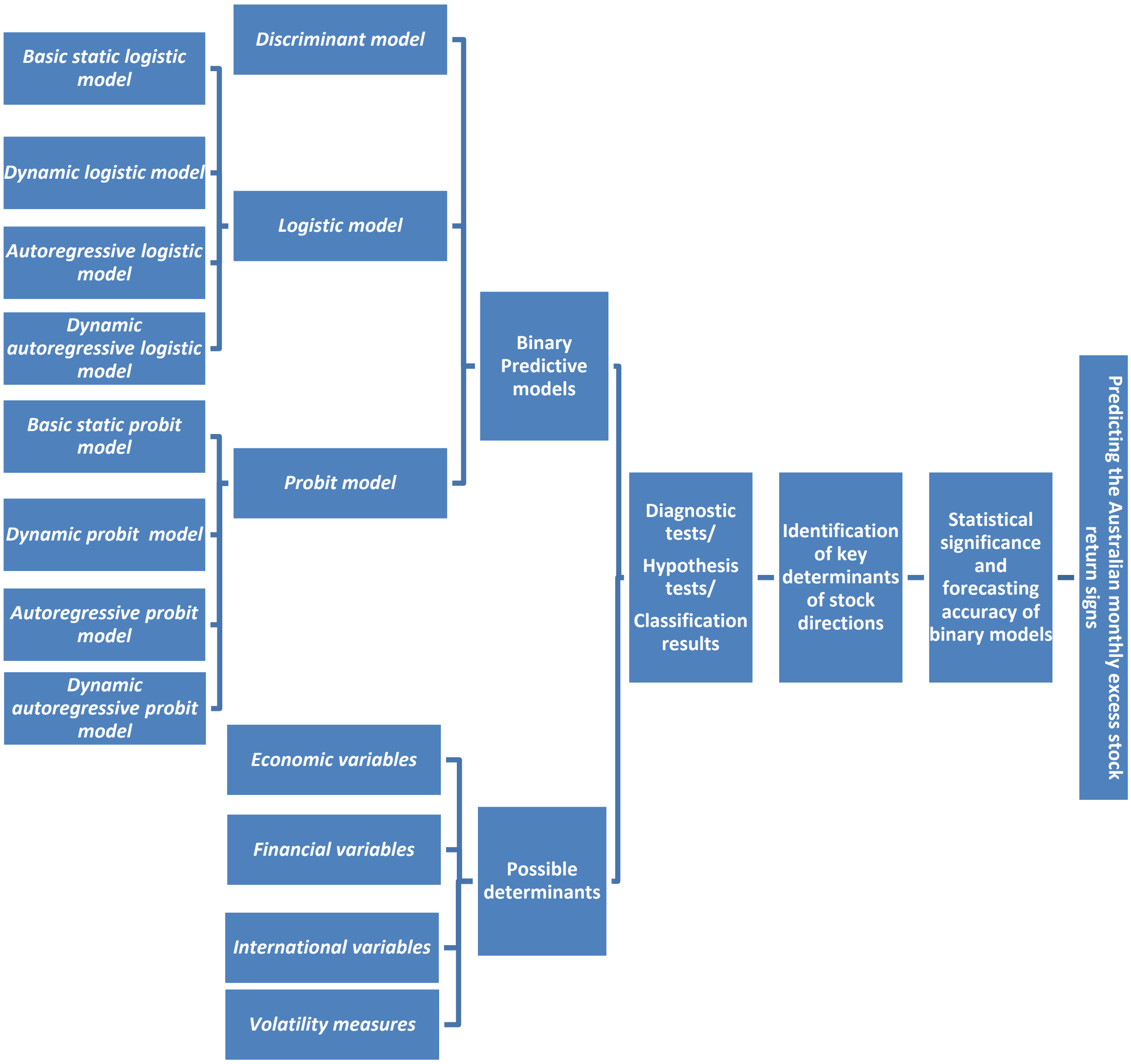

Figure 1.2: Conceptual Framework

1.8 Thesis Outline

This section describes the outline of the thesis, as shown in Figure 1.3.

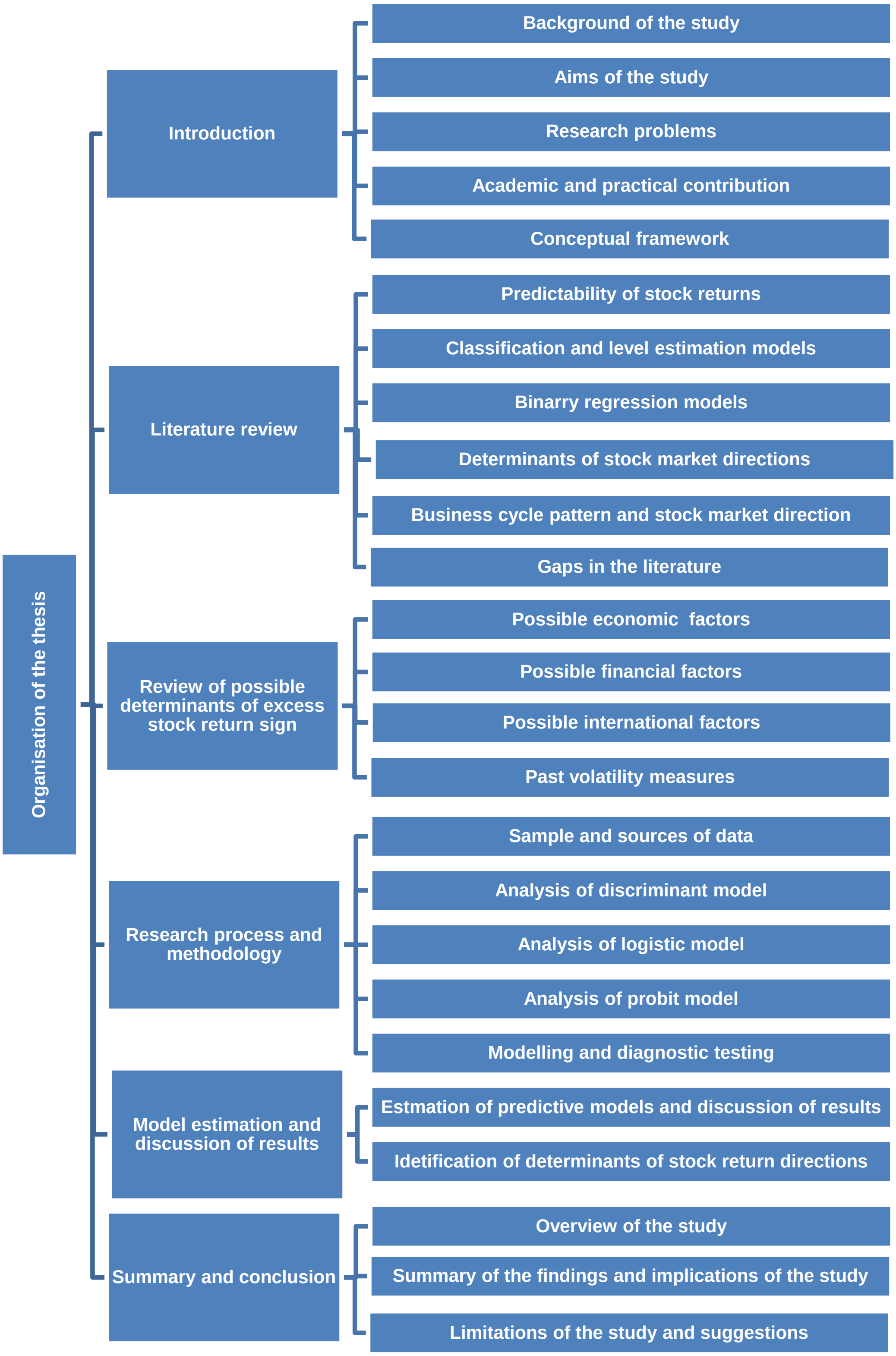

Figure 1.3: Thesis Outline

Chapter 1: Introduction

The first chapter introduces the research. It explains the study background, aims, research problems, and academic and practical contributions. It also discusses the thesis's conceptual framework and structure.

Chapter 2: Literature Review

The literature review chapter presents a comprehensive review of past studies related to forecasting the directions of stock returns and the key determinants of stock return future directions. This chapter comprises sections that discuss previous studies testing the predictability of stock returns, a comparison of classification models and level estimation models for stock return predictions, the theoretical background for identifying the determinants of stock return directions, the relationship between business cycle patterns and stock market directions, economic international and fundamental financial factors for predicting stock returns, and the use of leading economic indicators to forecast stock directions. Finally, this chapter discusses the gaps in the relevant literature.

Chapter 3: Review of Possible Determinants of Excess Stock Return Signs

This chapter discusses the possible determinants of Australian monthly stock return signs. Each of the variables discussed in this chapter are tested as explanatory variables in predictive binary models. This chapter discusses explanatory variables, including various economic, international and financial variables, and some of the volatility measurements of the selected variables.

Chapter 4: Research Process and Methodology

Chapter 4 discusses the research process and methodology used to predict Australian monthly excess stock return signs and identify the key determinants. Further, it discusses the sample and sources of data collected for the study. It explains the three binary models employed—discriminant, logistic and probit models—and the developed dynamic logistic/probit models. It also discusses the modelling and diagnostic tests used for the discriminant, logistic and probit models.

Chapter 5: Model Estimation and Discussion of Results

Chapter 5 presents the results of the estimated binary predictive models. It identifies the best binary models for predicting Australian monthly stock returns, based on goodness-of-fit measures and forecasting accuracy (hit ratio). It also identifies the determinants of the monthly directions of stock returns.

Chapter 6: Summary and Conclusion

Chapter 6 summarises and concludes the study. It presents an overview of the study, summarises the study findings and discusses the study implications. It also explains the limitations of the study, presents suggestions for future research and concludes the thesis.

Chapter 2: Literature Review

2.1 Introduction

This chapter reviews the literature related to predicting stock returns and their determinants, comprising six sections. The first section discusses previous studies that tested the predictability of stock returns. The second section explains previous studies' use of classification models and level estimation models to forecast stock returns. The third section discusses previous studies' use of binary models as level estimation models to predict stock signs. The fourth section discusses the literature that studied the determinants of excess stock returns and the theoretical background of identifying determinants. It also reviews the existing literature related to the possible determinants of stock market returns, including economic factors, international factors, the volatility of past returns and fundamental financial factors. The final section identifies the gaps in the literature and summarises the chapter.

2.2 Is the Direction of Stock Return Changes Predictable?

Much attention has been devoted to the predictability of stock market returns by various stakeholders, such as investors, institutional investors, fund managers and investment analysts, in order to maximise investment returns and minimise potential loses. If stock returns—particularly excess stock returns (stock returns that exceed the risk-free return)—can be predicted, investors can effectively time the buying and selling of stocks to help achieve their financial goals.

The efficient market hypothesis implies that stock price movements are based on the random walk hypothesis and are unpredictable. However, theories and studies supported the efficient market hypothesis (that is stock returns are unpredictable) has been revised by new empirical findings in recent years. New empirical findings have revealed that market directions are predictable and that past prices, past volatility and other independent determinants can be used to forecast future stock price movements, to some extent. For example, Breen et al. (1989) developed a forecasting model based on the negative relationship between stock index returns and treasury bill interest rates, and assessed the forecasting ability of stock returns. This study used two market timing tests—the Cumby-Modest and Henriksson-Merton tests—to demonstrate that treasury bill returns can forecast changes in the distribution of stock index excess returns.

In another study, Hong and Chung (2003) proposed a model-free omnibus statistical procedure to determine whether the direction of change in an economic variable is predictable, using the history of its past changes. They applied the model-free test procedures to five daily US stock price indices, and found positive evidence that the direction of excess stock returns is predictable using past excess stock returns. Moreover, Christoffersen and Diebold (2006) analytically demonstrated that the asset return sign probability forecast is most sensitive to changes in volatility. They showed that sign forecast ability appears strongest at intermediate horizons of two or three months using a realistically calibrated simulation exercise. Cochrane (1999) surveyed and demonstrated that price variables such as price/earnings and book/market can be used to infer the market expectation of future returns. He also addressed the issue of predictability of stock returns, and expressed that he could not agree with the views of returns are independent overtime. Thus, based on this review of past studies, a number of outcomes have demonstrated that stock returns are predictable, to some extent.

2.3 Level Estimation and Classification Models for Stock Return Predictions

In reviewing previous studies that addressed the predictability of excess stock returns, two main branches of predictive models were identified. Some research used level estimation models that forecast the value of excess stock returns, while others used classification models that predict the directions of stock indices. However, in recent years, there has been a growing focus on predicting the directions of share returns or market indices, rather than predicting exact values.

For example, Leung et al. (2000) emphasised the importance of accurate predictions of the direction of change in stock market returns to develop an effective market trading strategy. They argued that forecasting the level or value of return—even with a small forecast error—may not be as useful as accurately predicting the direction of movement (or sign of return) for profitable trading. Their study applied classification models that predict direction based on probability—such as linear discriminant analysis, logit, probit and probabilistic neural network models—and compared them with level estimation models, such as exponential smoothing, multivariate transfer function, vector autoregression with Kalman filter, and multi-layered feedforward neural network models. Their empirical study strongly suggested that classification models that predict stock market directions based on probability outperform level estimation models that forecast the stock market's level—both in terms of the accuracy of predicting the directions of stock market movement, and maximising returns from investment trading.

In another study, Enke and Thawornwong (2005) examined the effectiveness of the neural network level estimation and neural network classification models. They concluded that the trading strategies guided by neural network classification models generate higher profits under the same risk exposure than the buy-and-hold strategy, as well as the level estimation forecast of neural network. In addition, based on conventional forecast error magnitude criteria, Leitch and Tanner (1991) found that predicting the direction of change in profitability is the best criterion for investment decisions, rather than forecasting profit based on values.

2.4 Using Binary Regression Models as Classification Models for Sign Predictions

Various predictive models have been used by scholars to predict turning points in growth cycles, such as business, excess stock returns and tourism growth rate cycles. However, recent empirical studies by Chauvet and Potter (2005), Kauppi and Saikkonen (2008) and Nyberg (2010) indicated that business cycle forecasts are more accurate when using binary classification models. A number of studies have demonstrated that binary models compare favourably to their level estimation counterparts. Leung et al. (2000) used various multivariate binary classification models to predict stock returns—including parametric linear discriminant analysis, logit and probit, and non-parametric probabilistic neural networks—and compared these with level-based forecasting models. Their empirical results suggested that the binary classification models outperformed the level estimation models, and that the binary models were strong in predicting the direction of the stock market movement and maximising returns from investment trading.

Hong and Chung (2003) also examined the out-of-sample profitability of a class of binary logistic models for directional forecasts of excess returns, and found that trading rules based on logistic forecast models could earn significantly higher risk-adjusted returns than trades based on the buy-and-hold strategy. In another study, Nyberg (2008) studied the predictive power of dynamic binary probit models developed over a period of time, and found that the number of correct signs (hit ratio) of US monthly returns and investment returns were higher when using dynamic probit models, as opposed to their level estimation counterparts.

2.5 Determinants of Excess Stock Return Directions

Determinants used to forecast excess stock return directions have evolved over time. Initially, the past volatility of stock returns was used by researchers to forecast stock directions. However, due to the strong relationship between business cycle patterns and stock market directions, researchers have recently used various economic and international variables to predict stock directions. Previous studies have also positively tested fundamental financial variables for stock return forecasting. The following discussion examines the theories that explain the relationship between determinants and stock returns, and how researchers have successfully used various determinants to forecast stock directions.

2.5.1 Theoretical Background to Identify Determinants of Excess Stock Return Directions

The CAPM, APT and dividend discount model can be used to explain the relationship between economic activity and stock market direction. These are further reviewed in the following sections.

2.5.1.1 *CAPM*

The CAPM developed by Sharpe (1964), Lintner (1965) and Mossin (1966) explains the relationship between macroeconomic forces and share returns. The CAPM explains the price of securities built on the relationship between the expected return of the stock (E[r]) and market risk. Market risk arises due to changes in macroeconomic variables, and these changes affect stock returns as per the model. The CAPM model explains stocks returns as $E(r) = r_f + \beta (r_m - r_f)$, where r_f is the risk-free interest rate, $(r_m - r_f)$ is the market risk premium and β (beta) is the sensitivity of stock returns to market risk. The market risk premium changes due to changes in macroeconomic variables, and these changes then affect stock returns and market price.

2.5.1.2 *APT*

The APT is the core idea of Ross (1976), and explains the relationship between macroeconomic forces and share returns. The APT explains that the price of securities is driven by a few systematic factors (macroeconomic factors). The model is explained as ($E[r] = r_f + \beta_1 f_1 + \beta_2 f_2, \ldots$), where the betas ($\beta_1, \beta_2 \ldots$) are the stock sensitivity to each market risk factor ($f_1, f_2 \ldots$). The APT (a single index model) is more general than the CAPM when understanding the relationship between stock returns and market forces.

2.5.1.3 *Dividend Discount Model*

The dividend discount model developed by Gordon and Shapiro (1956) can also be used to express the relationship between economic forces and stock prices. The dividend discount model is defined with the formula:

$$Stock\ \mathrm{Price} = \sum_{t=1}^{\infty} \frac{D_t}{(1+k)^n}$$

where D_t is the expected dividend stream and k is the required rate of return. According to this model, the systematic economic forces that influence corporate earnings (D_t/cash flows) and required rate of return (risk-free rate and market risk premium) determine the share price and excess stock returns.

2.5.2 Past Volatility of Stock Returns to Forecast Future Directions

A number of previous studies have demonstrated that the past volatility of stock returns can be successfully used to predict future stock returns, to some extent. Hong and Chung (2003) produced strong evidence that the directions of excess stock returns can be predicted using past excess stock returns, particularly in the case of large excess stock returns. Their study demonstrated that the direction and level of past excess stock returns can successfully be used to predict the direction of future excess stock returns with any other significant variables. Further, they indicated that volatility and the past distribution of returns, such as skewness and kurtosis, can be used to forecast the direction of excess stock returns. Christoffersen and Diebold (2006) also studied the relationship between asset return volatility and asset return sign forecasts, and found that sign probability forecasts are most sensitive to changes in volatility at an intermediate level (two to three months). In another study, Breen et al. (1989) demonstrated that a positive expected excess return—or the probability of an up market—is a function of conditional variance of past returns.

2.5.3 Business Cycle Pattern and Market Directions

A number of previous studies have identified the condition of the economy as the most critical factor for predicting excess stock returns. Fama and French (1989) found a clear business cycle pattern for expected returns on common stocks. They stressed that expected returns are low near peaks and high near troughs of the business cycle. Further, they identified that expected returns contain a risk premium that is related to longer-term aspects of the business condition, and revealed that changes to the risk premium are stronger for stocks as business conditions change.

Chauvet and Potter (1998) demonstrated that the business cycle pattern is also evident in the conditional expectation and variance of value-weighted excess return. They revealed that, around the beginning of a recession, stock market volatility increases considerably, thereby reflecting great uncertainty associated with these periods, while expected returns decrease in anticipation of a decrease in earnings. Further, they stressed that, towards the end of a recession, expected returns have their highest value in anticipation of the economic recovery, and volatility is still very high in anticipation of the end of the contraction. In fact, they found that conditional volatility is at its highest values near peaks and troughs of the business cycle. Thus, during times of high volatility, investors might move back and switch from stock to bond, thereby driving changes in expected returns and the direction of the relationship, depending on the stage of the economy.

2.5.3.1 *Economic and International Factors to Forecast Future Stock Directions*

Many scholars have discussed how changes in various macroeconomic factors affect excess stock returns. Previous studies have tested various macroeconomic variables as predictive variables to forecast stock returns. Fama and Schwert (1977) estimated the extent to which stock returns are predictable using the expected and unexpected components of the inflation rate during the period 1953 to 1971. They used the Consumer Price Index (CPI) and returns on an equally weighted portfolio and value-weighted portfolio of New York Stock Exchange stocks. They found that common stock returns are negatively related to the expected component of inflation and are probably related to the unexpected component of inflation. In another study, Breen et al. (1989) constructed a forecasting model based on the negative correlation between stock index returns and treasury bill interest rates, and concluded that treasury bill returns can successfully forecast changes in the distribution of stock index excess returns.

When Chen et al. (1986) studied the relationship between macroeconomic factors and stock returns, they also found that macroeconomic factors have some predictive power for stock returns—such as changes in aggregate production, inflation, short-term interest rates, the slope of term structure (measured by the return differences between long- and short-term government bonds) and the risk premium (measured by the return differences between low-and high-grade bonds). Further, they concluded that stock returns are exposed to systematic economic news and priced in accordance with their exposures. Chen (1991) showed that state variables—such as the lagged production growth rate, term premium and short-term interest rate—are reliable indicators of recent and future economic growth. Chen further revealed that excess market returns are negatively correlated with recent economic growth and positively correlated with expected future economic growth.

In another study, Pesaran and Timmermann (1995) examined the predictive power of various economic factors over the monthly stock return change, such as the treasury bill rate, treasury bond rate, industrial output, inflation and money supply. They examined the period between 1954 and 1992, and concluded that predictability seemed quite low during relatively calm markets, and increased when the market was more volatile. A study by Whitelaw (1994) stated that the economic variables such as bond yield spread, interest spread between commercial papers and one year treasury yield, and dividend yield combinedly provides reasonable evidence of predictability in both returns and their volatility. Based on US excess stock returns forecast, Campbell and Thompson (2008) demonstrated that macroeconomic variables—such as short- and long-term interest rates, level of consumption and stock market valuation ratios—provide a better out-of-sample prediction than the historical average return forecast.

Kazi (2009) identified systematic risk factors and their influence on returns in the Australian stock market, and concluded that some systematic risk factors are dominant for Australian stock market price movements, especially in the long term. The study suggested that, in the long term, Australian stock market returns are influenced by systematic risk factors, such as interest rates, corporate profitability, industrial production and (to a lesser extent) global market movements. In the short term, it is adjusted each quarter by its own performance, interest rates and global stock movements of the previous quarter.

Kearney and Daly (1998) examined how the conditional volatility of Australian stock market returns is related to the conditional volatility of financial and business cycle variables. They estimated the conditional volatility of stock market returns using the generalised least squares model, examining monthly data over the period of 1972 to January 1994. They found a strong association between the conditional volatility of money supply and conditional volatility of Australian stock market returns. Further, they revealed that the conditional volatilities of inflation and interest rates are directly associated with stock market volatility. They also found that current account deficits, industrial production and money supply are indirectly associated with stock market volatility. However, they found no evidence of a statistically significant relationship between foreign exchange markets and the Australian stock market.

Jain et al. (2011) studied how changes in interest and exchange rates affect Australian banking sectors' stock returns. They found that an increase in short-term interest rates had a statistically significant negative effect on the stock returns of four major banks, while appreciation in the Australian dollar (AUD) generates an increase in banking stock returns.

Shamsuddin and Kim (2003) examined the integration of the Australian stock market with two leading trading partners—the US and Japan—prior to and following the Asian financial crisis. They found that there was a long-term relationship between the Australian, US and Japanese markets prior to the crisis; however, the US influence on the Australian market diminished in the post-crisis period even though US influence on Japan remained at a modest level. They also found that the Australian market became more independent with country's own factors after the financial crisis.

Di Lorio and Faff (2000) examined the foreign currency exposure of Australian equities market major sectors using AUD/USD factor return in an augmented market model. Their results were quite mixed, with nine industries showing significant exchange rate exposure—oil and gas, solid fuels, alcohol and tobacco, chemicals, engineering and retail, food and households goods, property trust and building materials.

2.5.3.2 *Leading Economic Indicators to Forecast Future Stock Directions*

In addition to the various economic and international factors, leading financial indicators used to measure overall economic activity have been used by researchers to predict stock return directions. For example, Chauvet and Potter (1998) used leading financial indicators to forecast the state of stock markets and excess returns, and found that leading indicators have very good within-sample forecasting performance, compared to alternative models. Kulendran and Wong (2011) used composite leading indicators as explanatory variables in logit and probit models to predict the turning points of Hong Kong's inboundtourism growth cycle. They stressed the importance of using separate composite leading indicators for each source market in future research.

The recession dates defined by National Bureau of Economic Research (NBER) in the US is one of the leading indicators used to identify US business cycle patterns. Nyberg (2008) studied the ability of dynamic probit models to predict the direction of monthly US excess stock returns signs. Nyberg introduced a binary recession indicator that was estimated based on NBER recession dates as an explanatory variable in the predictive model. This was the first time this approach had been used to forecast stock return signs. The study employed and extended new dynamic probit models proposed by Kauppi and Saikkonen (2008). The empirical results showed that, when these models used the six-month recession forecast as an explanatory variable, they outperformed other predictive models that used only financial variables as explanatory variables.

2.5.4 Fundamental Financial Variables to Forecast Future Stock Directions

Several studies have examined the relationship between stock returns and fundamental financial variables. For example, Basu (1977) studied the relationship between the investment performance of equity securities and their price/earnings ratios (PERs). They concluded that low price/earnings portfolios earned superior returns on a risk-adjusted basis, and highlighted that the relationship between the investment performance of equity securities and their PERs seems valid. Fama and French (1992) demonstrated that the size of the firm and book-to-market equity capture the cross-sectional variation in average stock returns. Chen (1991) showed that the market dividend price ratio alone with some state variables is a reliable indicator of recent and future economic growth, whereby economic growth is positively correlated to excess stock returns. Cochrane (1999) found that the expected return on individual securities and the market as a whole varies slowly over time; thus, the market expectation of returns can be tracked by watching the price/dividend ratio, PER or book/market ratio. Pesaran and Timmermann (1995) examined the predictive power of various economic factors—including earnings per share and dividend yield over monthly stock return change—and concluded that variables have a predictive power over stock returns. In addition, Whitelaw (1994) stated that dividend yield can be used to predict variation in both returns and their volatility. Kazi (2009) suggested that, in the long term, Australian stock market returns are influenced by only a few factors, which include dividend yield.

2.6 Gaps in the Literature and Chapter Summary

Previous studies have revealed that stock market directions are predictable and classification models can be successfully used to predict stock directions. However, while classification binary models have been successfully used to predict the directions of global stock indices, such as the S&P 500, this review of past studies has indicated that little attention has been devoted to predicting the directions of Australian excess stock returns using classification models, such as logistic, probit and discriminant models. In the literature, the developed binary models—such as dynamic probit/logistic and autoregressive probit/logistic models—have indicated improved results in predicting stock returns, compared to static models. Therefore, it could be interesting to determine how these developed binary models can be applied to predicting Australian stock directions.

Business cycle patterns in regard to stock market directions have been considered in previous studies, with various macroeconomic, financial and international factors identified as determinants of stock directions. Although some researchers have used leading indicators as predictor variables in binary models to forecast business cycles and global stock market directions, there has been no such study related to the Australian stock market. Thus, the current study used an OECD indicator to predict Australian stock directions. The Australian OECD indicator is a designed composite leading indicator for Australia to measure the country's economic activity and identify early signals of turning points in economic activity. The study by Nyberg (2008) used a US binary recession indicator (based on recession dates defined by the NBER) for the first time to forecast US stock directions, and concluded that recession indicators are a useful predictor variable. Considering the strong association between the US economy and Australian stock market, the current study also sought to test a US recession indicator for the first time to predict Australian stock directions.

Several previous studies have used the historical volatility of stock returns as predictor variables to forecast future stock returns. However, only a limited number of studies have tested how different measurements of the volatility of predictor variables affect forecasting accuracy. Thus, this study tested three different volatility measures—MAD, SD and U^2—to assess the predictive power of excess stock return signs. The next chapter will further review and discuss possible determinants of Australian stock market directions.

Chapter 3: Review of Possible Determinants of Australian Excess Stock Return Signs

3.1 Introduction

The latter part of the previous chapter presented a review of the various determinants of stock market directions, and how these determinants have evolved over time. This chapter discusses the possible determinants that were examined in this study to predict Australian monthly excess stock return signs.

3.2 Selecting Possible Determinants of Australian Monthly Stock Directions

This study used past studies and theories to select the possible determinants of Australian stock return directions. Past volatility of stock returns was commonly used by researchers as the predictor variable at early years of testing stock market predictions. However, researchers later identified the strong influence of macroeconomic forces on stock return directions, and these are now widely used to predict stock returns. In addition to the literature, theories such as the CAPM, asset pricing model and dividend growth model can be used to identify the relationships between stock market returns and economic forces. In this study, the possible determinants were identified under four categories: economic factors, financial factors, international factors and past volatility measures. The following sections discuss the direct and indirect relationships between each selected variable and Australian stock market behaviour.

3.2.1 Interest Rates

The interest rates of an economy play a critical role in investment strategy and asset allocation decisions. Interest rates are the key indicator of the rate of return on debt investments, including government securities. Given their role in investment decisions, it is important to identify what relationship exists between interest rates and excess stock returns.

Excess return (r_t) is the investment return of equity investments that exceeds the risk-free interest rate. The risk-free interest rate (r_f) is a fragment of the formula used to calculate excess stock returns ($r_t = \text{Ln}\ (P_t/P_{t-1}) - r_f$) and, when the risk-free interest rate is low, the excess return is high, and vice versa. In addition, the CAPM used to explain the required rate of return ($RRR = r_f + \beta\ [r_m - r_f]$) can be used to identify the relationship between interest rates and investment decision making. When r_f is high, there is a higher required rate of return for investments compared to the expected returns of the investment, and vice versa. If the expected return does not meet or exceed the required return, the investment should not proceed.

From another perspective, lower interest rates improve the future earnings and cash flows of companies. Especially for high-geared companies, the cost of borrowing will be low in low-interest-rate scenarios, which improves the company’s profits. Also, when the future interest rate outlook is positive or remains at lower levels, consumer spending improves and business confidence is boosted, which helps improve stock prices.

In addition, interest rate changes can cause shifting investments between debt securities and equity securities by investors. Low interest rates decrease the attractiveness of debt security investments, such as bonds (market price increase), which moves investors to the equity market to earn more returns. Investments by foreign investors also affect the interest rate in Australia—low interest rates in Australia compared to the international market increase foreign investor confidence in Australian businesses.

The inverse relationship between interest rates and stock returns has been explained in several previous studies. Alam and Uddin (2009) studied the relationship between interest rates and stock returns in 15 stock markets, including the Australian stock market, based on time series and panel regression. They concluded that interest rates have a strong negative relationship with all the stock markets they reviewed. Campbell (1987), Whitelaw (1994), Kazi (2009) and Erdugan (2012) all found that interest rates can be used successfully to forecast stock returns, with both short- and long-term interest rates and term structures considered successful predictive variables of stock return directions.

To measure the effect of interest rates on the monthly directional changes of Australian excess returns, this study considered different measures of interest rates:

- short-term interest rates (three-month bank-accepted bill rate for Australia)
- long-term interest rate (10-year bond yield for Australia)
- first difference between short-term interest rate
- first difference between long-term interest rate

- term spread (difference between a 10-year bond yield and three-month bank-accepted bill rate).

Figure 3.1 illustrates the relationship between the ASX 200 index and Australian short- and long-term interest rates. This illustration indicates that an inverse relationship existed between interest rates and the ASX 200 index from 1990 to 2014.

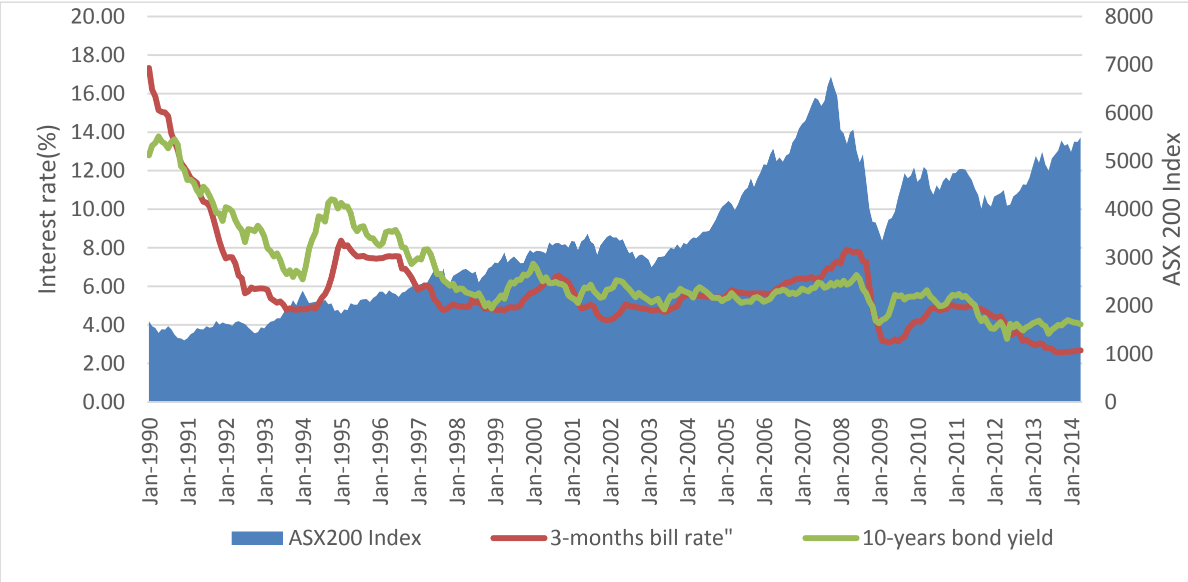

Figure 3.1: Monthly Movements of Australian 10-year Bond Yield, 3-month Bank-accepted Bill Rate and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.2 Foreign Exchange Rate

The exchange rate between the AUD and other currencies is determined by the demand for and supply of the AUD as a result of international activities with foreign countries. The AUD is one of the critical factors influencing the earnings of domestic companies, depending on their exposure to international trade. Companies who do not engage in much international trade and are mainly focused on the Australian market benefit from depreciation of the AUD against other currencies. Depreciation of the AUD favourably affects these companies because foreign goods and services are relatively expensive for domestic buyers. However, when the AUD appreciates against foreign currencies, imported products are cheaper for domestic buyers, which adversely affects domestic companies who are less involved in international trade.

Changes in the foreign exchange rate also play an important role in the level of foreign investments in the local share market. In Australia, a significant proportion of the stock market is owned by offshore investors, and their reaction is an important factor determining the direction of Australian stock returns. The Australian share market is not attractive to international investors when the AUD is trading at high levels compared to the domestic currencies of foreign investors. In contrast, when the AUD is trading at low levels, international investors' interest in buying Australian shares increases, and stocks become more attractive to foreign investors.

A number of researchers have discussed the significant relationship between the stock market and exchange rates, including Jorion (1991), Bodnar and Gentry (1993) and Dominguez and Tesar (2001). Donnelly and Sheehy (1996) found a relationship between foreign exchange rates and the stock price of large exporters in the United Kingdom, and suggested that there is a lag value relationship between stock markets and exchange rates. Di Lorio and Faff (2000) also found that significant US dollar (USD) exchange rate exposure was evident in the Australian stock market, although their results were mixed (positive or negative exposure) for different industry categories in the stock market.

In the current study, the exchange rate between the AUD and USD (AUD/USD) and the AUD and Chinese renminbi (AUD/REN) were considered predictive variables of binary models. The US exchange rate is an international standard unit of currency, and the also US is the second-largest trading partner of Australia an over a period of time. The Chinese renminbi exchange rate was also considered a predictor variable, given China's involvement with the Australian economy, with China being Australia's largest trading partner in terms of both imports and exports. Figures 3.2 and 3.3 demonstrate the relationship between the ASX 200 index and the two exchange rates. Both the AUD and Chinese renminbi display a negative relationship with the ASX 200 over the period considered, but a positive relationship during recession time from 2007 to 2009.

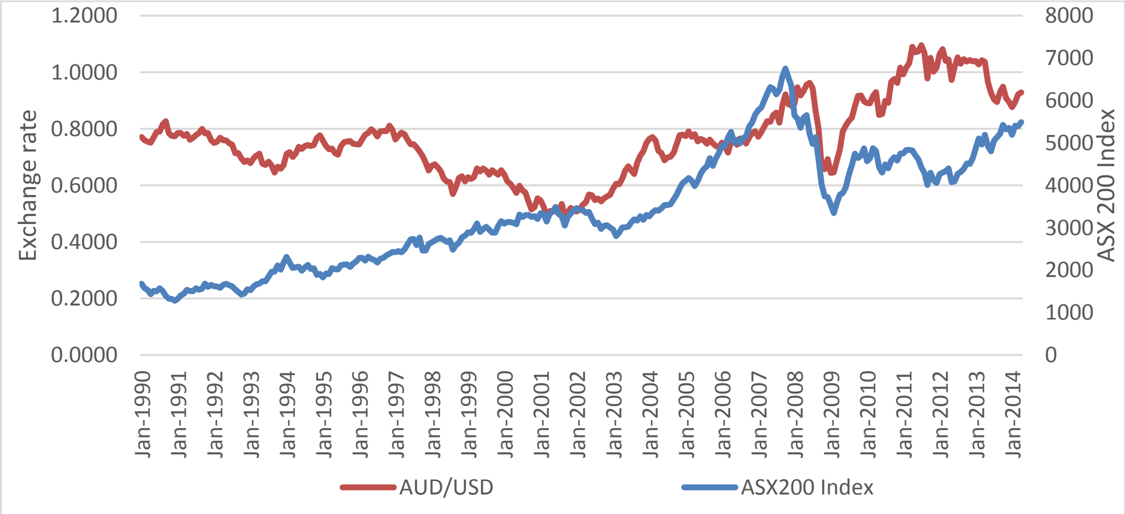

Figure 3.2: Monthly Movements of Exchange Rate between AUD/USD and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

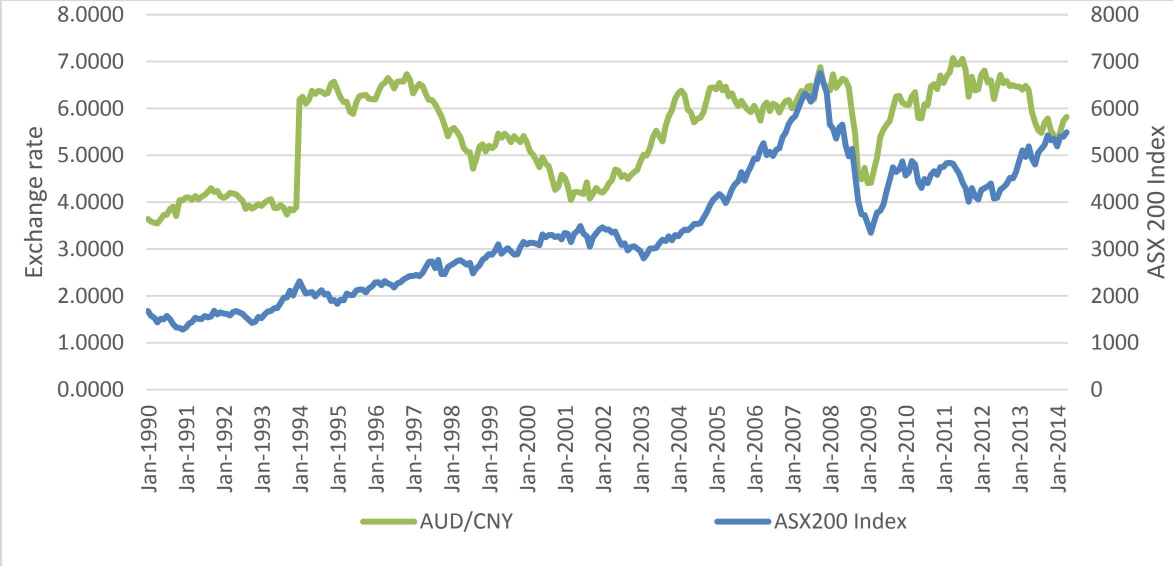

Figure 3.3: Monthly Movements of Exchange Rate between AUD/Chinese Renminbi and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.3 Export and Imports

Australia is one of the leading suppliers of natural resources to the world market, and is ranked in the top 20 economies in terms of global trade. From 2014 to 2015, the value of total exports of goods and services was recorded as AUD$318.7bn, which accounted for over two per cent of the country's gross domestic product (GDP), with China, Japan and the US the three major trading partners. The net export (NE) is the difference between a country's export and import of goods and services. Positive NE (trade surplus) is considered favourable for a country's economic growth. Balassa (1986), Ram (1985) and Tyler (1981) highlighted the positive relationship between export growth and level of economic development. The current study tested the monthly exports, imports and NEs (exports − imports) as predictive variables of ASX 200 monthly returns, considering the high exposure of Australian listed companies to international trade.

Figure 3.4 displays a positive relationship between exports and the ASX 200 index, while Figure 3.5 displays a negative relationship between NEs and the ASX 200 index. Figure 3.5 also indicates higher fluctuations in monthly Australian NEs, with more positive monthly NEs reported after 2008, in comparison to the previous 18 years.

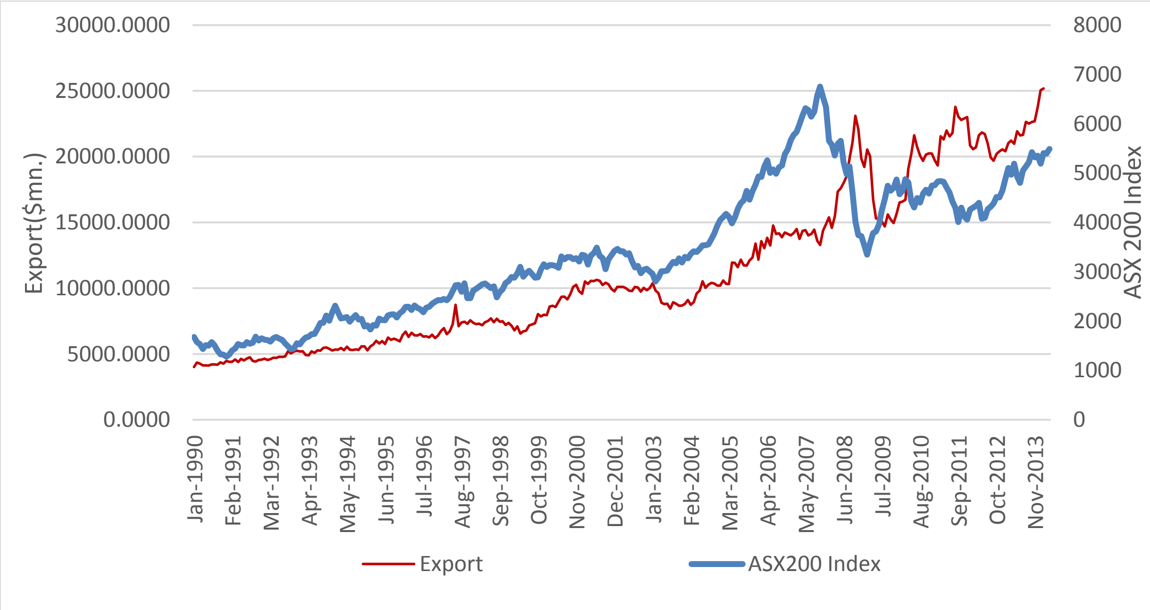

Figure 3.4: Australian Monthly NEs and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

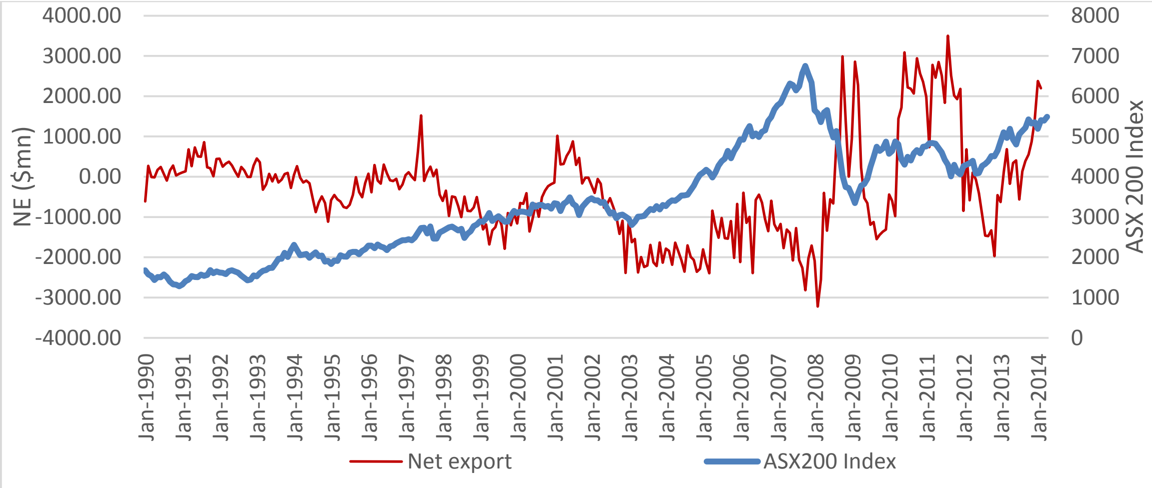

Figure 3.5: Australian Monthly NEs and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic .

3.2.4 Money Supply

Extra money entering the economy pressures stock prices upwards, with increasing demand for investments. Therefore, money supply and stock prices could have a positive relationship. However, money supply and inflation also have very close relationship and, if money supply causes inflationary effects, this could offset the positive association between money supply and stock prices. In previous studies, Pesaran and Timmermann (1995) identified money supply as a predictor variable of US stock returns. Liljeblom and Stenius (1997) also identified a significant relationship between money supply and Finland stock volatility. Kearney and Daly (1998) explained that money supply is indirectly associated with Australian stock market volatility. The current study considered monthly money supply (M3) as a predictive variable of excess stock return signs. The money supply measurement (M3) consists of currency, currency deposits with banks, certificates of deposits issued by banks, term deposits with banks and deposits with non-banks. Figure 3.6 demonstrates a speedy growth in money supply from 1990 to 2014, and is also display a positive relationship with ASX 200 index movements.

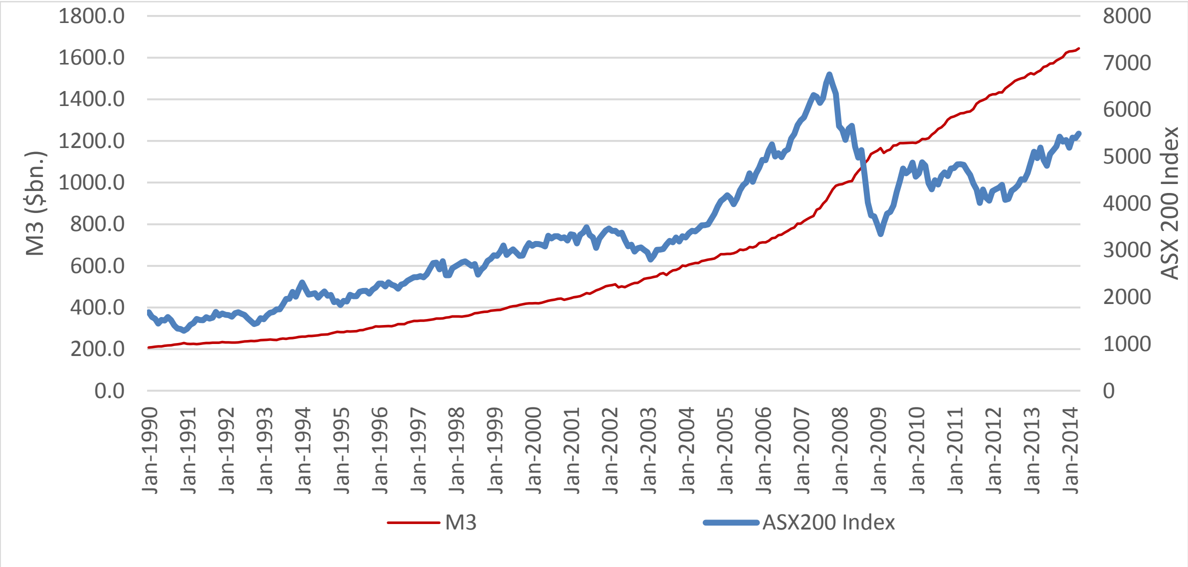

Figure 3.6: Australian Monthly Money Supply (M3) and ASX 200, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic

3.2.5 Retail Spending

Retail spending is a key indicator in measuring the business growth of an economy, and can be used as a proxy indicator of economic growth. However, consumer spending is also considered a pre-inflationary indicator. In 2015, Australian retail spending was recorded as AUD$292bn, which was 18 per cent of the GDP. The retail sector is a major provider of employment for the Australian labour force. Investors devote attention to monthly changes in retail spending, since consumer spending gives some idea of expansions and contractions in the country's business activity. Fisher and Statman (2003) reported a positive correlation between measures of consumer confidence and direct measures of investor sentiments, while Lemmon and Portniaguina (2006) found that consumer confidence displays forecasting power for returns on small stocks. Thus, the current study considered Australian monthly retail spending an explanatory variable of all predictive models to test significance for predicting excess stock return signs.

Figure 3.7 compares Australian monthly retail spending and the ASX 200 index. It displays that retail spending has improved over time, and that there have been no notable fluctuations, other than a progressive trend over this period.

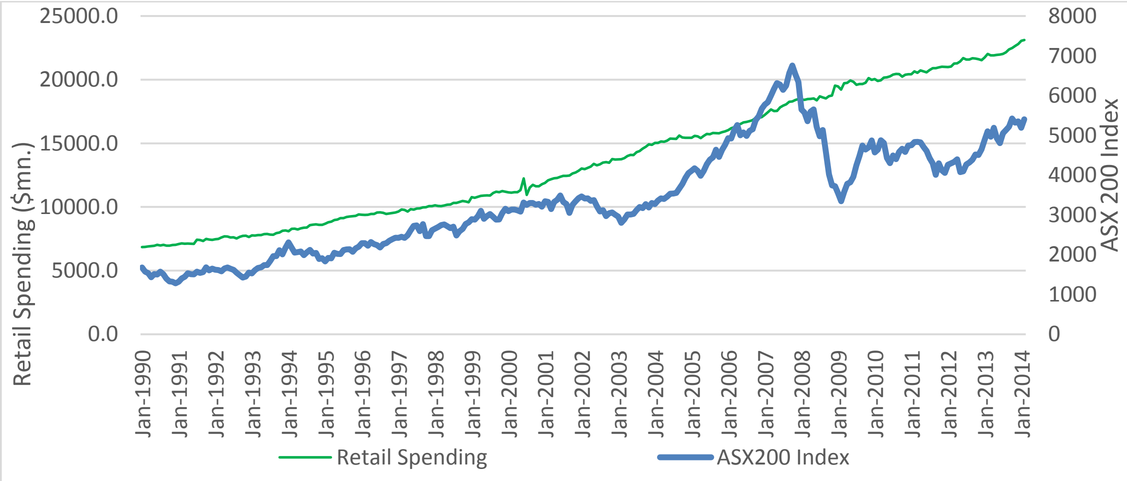

Figure 3.7: Australian Monthly Retail Spending and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.6 Private Dwelling Approvals

The number of new private house constructed is another variable that indicates that residents are confident of future economic growth. A low level of private dwelling approvals indicates negative expectations regarding the economic activity of residents. Stock and Watson (1989) identified that changes in housing authorisation can signal changes in the future activity of the construction sector and the economy. Although private building is not a major aspect of the economy, it is important to test whether stock returns are sensitive to the number of private dwelling approvals as a proxy variable of economic growth. Thus, this study used monthly private dwelling approvals as an explanatory variable of binary predictive models.

Figure 3.8 compares the monthly private dwelling approvals and ASX 200 index. There was no clear relationship between the two until 2007; however, the ASX 200 followed a similar trend between 2007 and 2014.

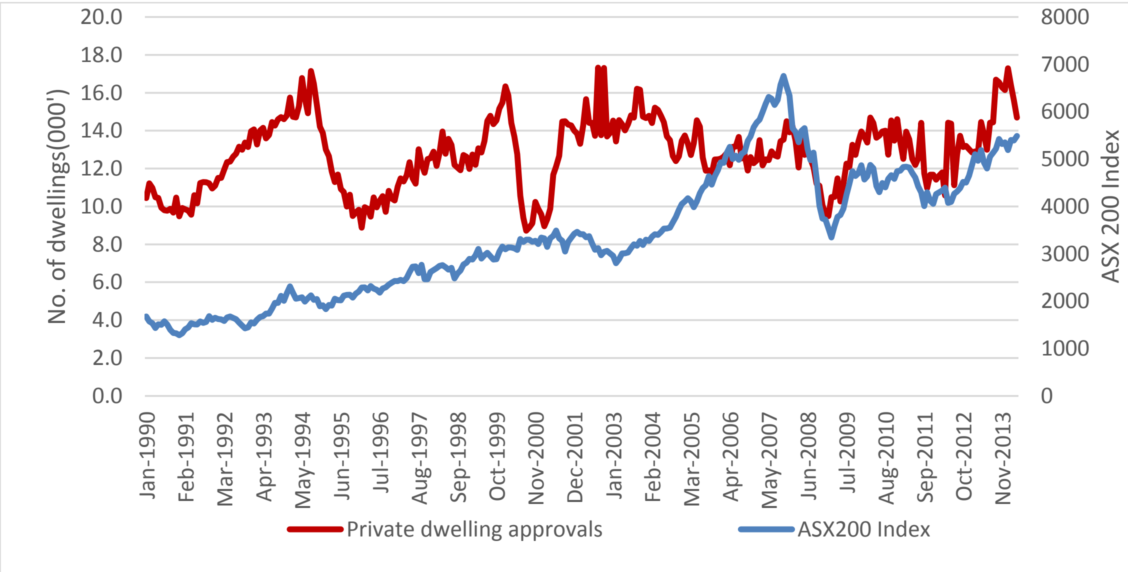

Figure 3.8: Australian Monthly Private Dwelling Approvals and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.7 Unemployment Rate

The labour market and stock price movements have a positive relationship, and the employment level signals future business growth. When the economy grows employment level improves and less is the number of people seeking for job opportunities who are willing to work. Conversely, when the economy contrast companies are not willing to hire staff due to drop in their business activities and unemployment rate increase. McQueen and Roley (1993) found a strong relationship between the unemployment rate and economic changes, based on their definition of business condition. Boyd et al. (2005) found that rising unemployment is bad news for stock investors during economic contractions and good news for stocks during economic expansions. The current study tested the monthly unemployment rate in Australia alongside other economic variables in all binary models to determine its effects on signs of ASX 200 excess returns.

Figure 3.9 illustrates the relationship between the unemployment rate and ASX stock index. An inverse relationship can be clearly identified from 1999 to 2012; however, after 2013, this relationship is not evident.

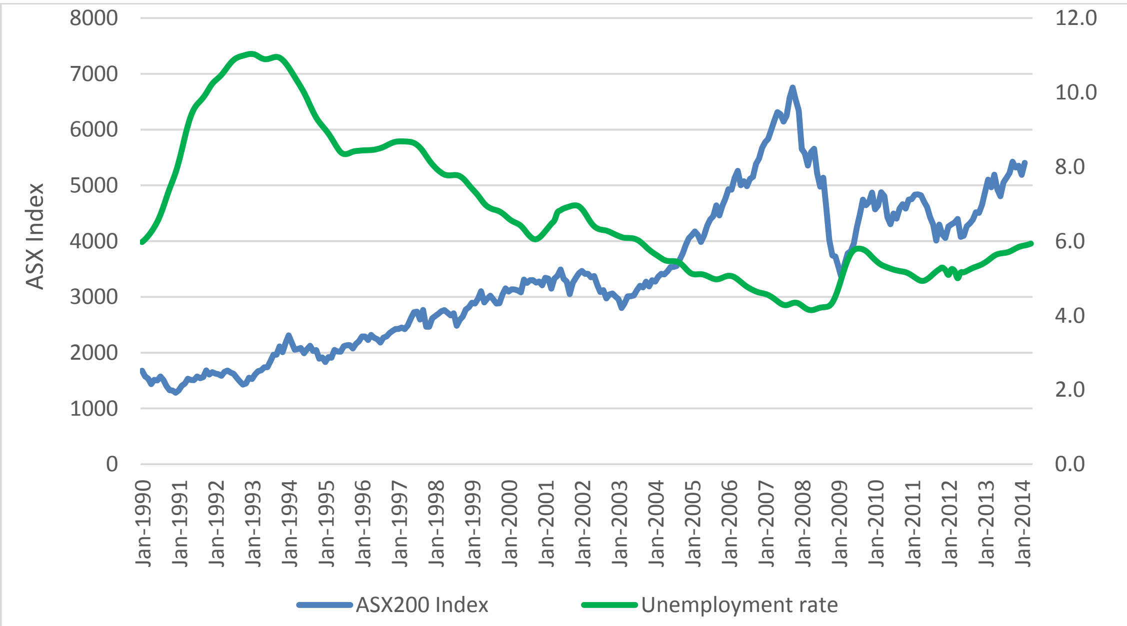

Figure 3.9: Australian Monthly Unemployment Rate and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.8 Inflation

Inflation is an increase in the general price level of goods and services in the economy over a period. The inflation level can be an important indicator for predicting stock returns. Businesses experience decreased profit margins during periods of inflation. This occurs with higher operational costs, which can result in higher prices and a subsequent drop in sales volumes. Inflation can also cause an increased interest rate, which adversely affects stock market excess returns. Geske and Roll (1983) studied the fiscal and monetary linkage between stock returns and inflation, and revealed that common stock returns are negatively related to both expected and unexpected components of the inflation rate. Boyd et al. (2001) found a significant and economically important negative relationship between inflation and equity market activity. They also highlighted that a negative relationship between inflation and equity market movements are strong for economies with higher inflation rates.

The Australian CPI and monthly commodity price index can be used to measure the country's level of inflation. In this study, monthly changes in the index were considered an explanatory variable due to the unavailability of CPI monthly data. Figure 3.10 shows an inverse relationship between inflation and ASX 200 that follow the opposite directions.

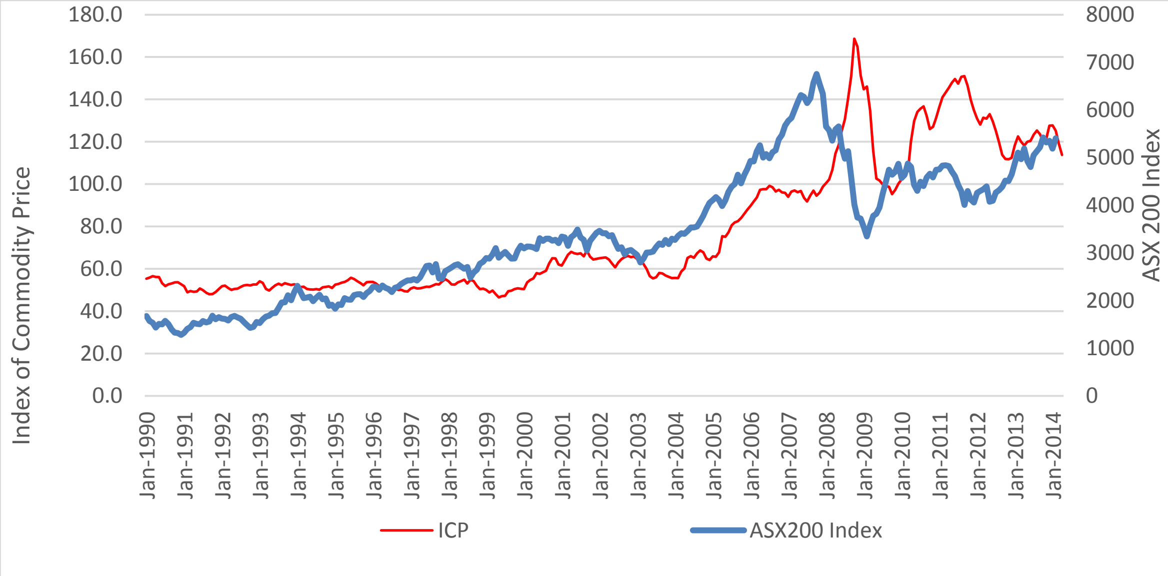

Figure 3.10: Australian Monthly Index of Commodity Price and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.9 Oil Price

Oil prices and oil-related products are the main source of revenue for the limited number of companies who operate in the energy industry. These companies can benefit from higher oil prices if there is no shortage of supply. However, energy cost accounts for a relatively large portion of expenses in many industries due to the cost of production, transportation and other operational expenses.

Australia is involved with both the import and export of petroleum products, and is one of the leading economies to engage in trading petroleum and petroleum-related products. Therefore, it is important to identify the sensitivity of the Australian share market as a whole to changes in the global oil price market. Faff and Brailsford (1999) found that the sensitivity of Australian stock returns to oil price factor differs among industries. They found that certain industries, such as oil, gas and diversified resource industries, have positive sensitivity, while industries such as paper and packaging, transport and banking have negative sensitivity. McSweeney and Worthington (2008) revealed that oil prices are an important determinant of forecasting the returns of Australian stock returns, especially in the banking, energy, material, retailing and transportation industries. Figure 3.11 shows mixed results of the relationship between oil price and the ASX index, with a positive relationship prevailing from 1990 to 2011, and the opposite occurring from 2011 to 2014.

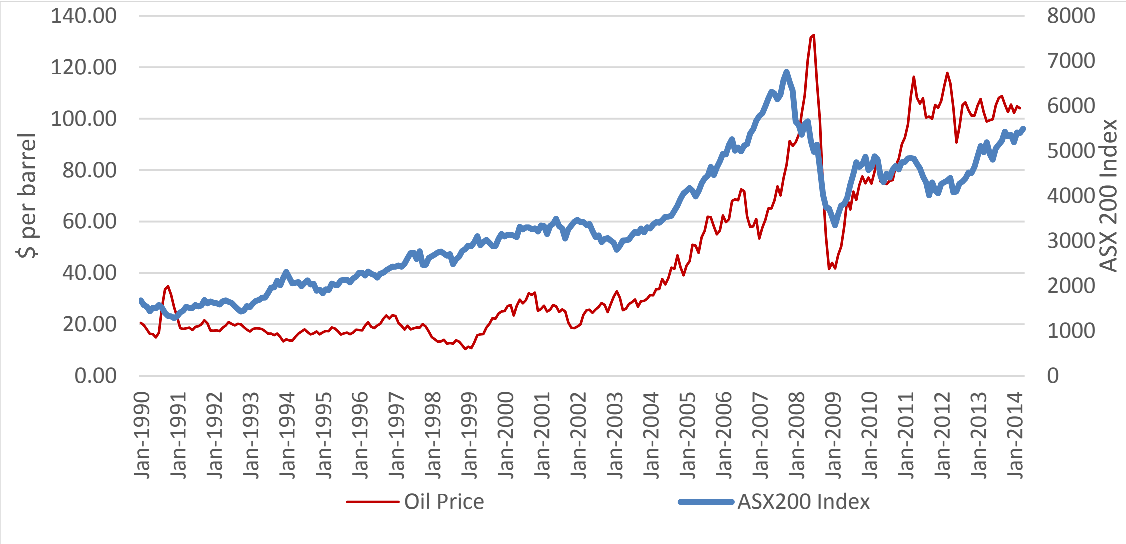

Figure 3.11: World Oil Price Monthly Changes and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.10 PER

The PER is the current market price of a stock (investment) compared to the per-share earnings of a particular stock. The PER is a financial fundamental that investors use to measure the value of equity investments. The PER of stock indices reflects the financial outlook of the overall equity market.

Generally, low PERs mean higher company earnings compared to its market price. If the PER of an equity investment is low compared to peer markets and own past, there can be potential improvement in price, and those investments are attractive to investors. However, the future financial outlook of the equity market also contributes to price movements. Thus, even if the PER is relatively low, it does not guarantee favourable price movement. If future earnings are likely to be uncertain or drop, then spot PER is misleading. Generally, a higher PER indicates overvalued stock prices, which could lead to a drop in prices unless there is a high potential of increased future earnings.

Basu (1977) confirmed that low PER portfolios earned superior returns on a risk-adjusted basis and the relationship between investment performance of equity and PER is valid. Basu (1983) also studied companies listed on the New York Stock Exchange, and confirmed that common stock that has a high Earning/Price(E/P)—which is the inverse of PER (low PER)—earns higher risk-adjusted returns than the common stock of low E/P firms, irrespective of firm size.

The current study used the ASX 200 index monthly PER as a predictor variable of binary models. Figure 3.12 indicates that the PER and ASX 200 index followed an opposite trend overall.

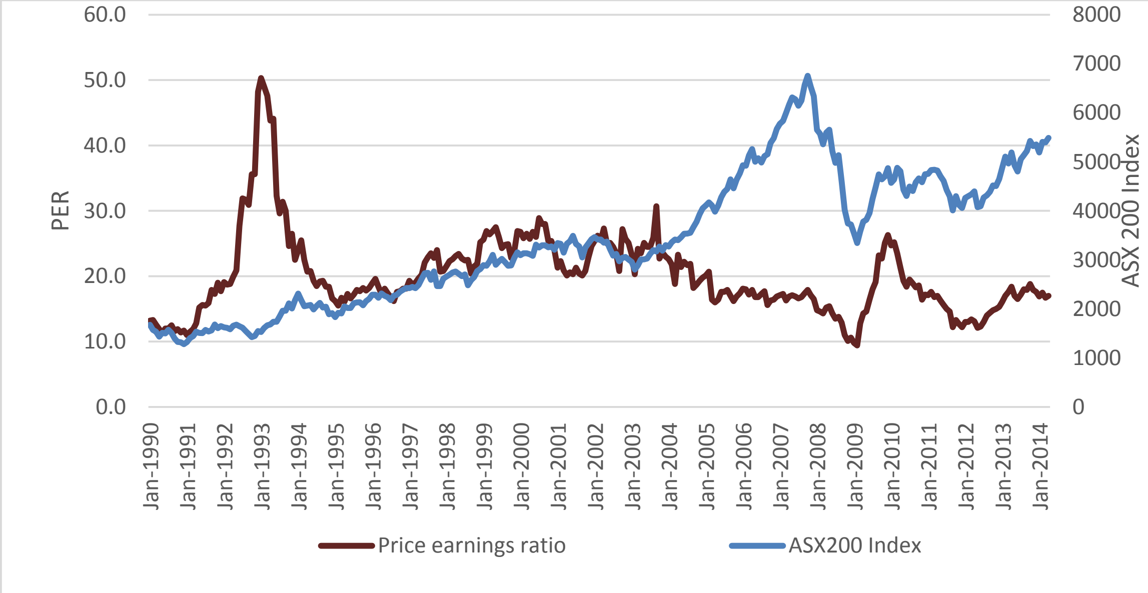

Figure 3.12: ASX Monthly PER and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.11 Dividend Yield

Dividend yield is another fundamental measurement used by investors to value stock prices. The term indicates how much a company pays out in dividends during a financial period, relative to its share price. Dividend is the money paid to share owners by companies from profit made during the financial year. The ASX 200 dividend yield is calculated based on the total dividends of all companies included in the index, as a percentage of the market capitalisation of those companies. A high dividend yield indicates higher returns compared to market price, which could attract investors to the stock. Similarly, a lower dividend yield indicates overpriced investments. Generally, when valuing investments, dividend yields are compared with risk-free interest rates, peer company/market dividend yields and historical dividend yields. However, the future earnings outlook of stocks is key before comparing the dividend yield of the investment with alternative investment options. Fama and French (1988) found that dividend yield can explain stock returns and forecasting power improves for long horizon returns when dividend yield used as the predictor variable. Lamont (1998) found that the dividend payout ratio contributes substantial forecasting power of excess stock returns at the short horizons.

The current study tested the monthly ASX 200 dividend yield ratio as a predictor variable in binary models to determine its significance in predicting stock return signs. Figure 3.13 illustrates the ASX dividend yield and ASX 200 index. It appears to indicate a clear negative relationship between the two variables over this period.

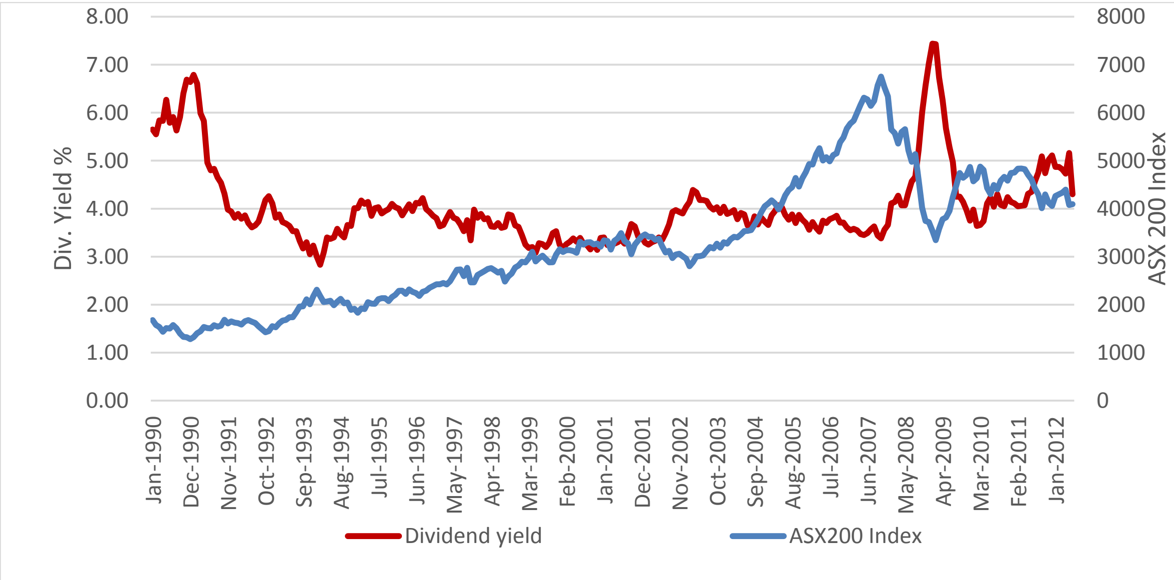

Figure 3.13: ASX Monthly Dividend Yield and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.12 MSCI World Index

The MSCI index was formed and operated by Morgan Stanley and capital. It is a global equity index that is treated as one of the best benchmark indices to represent changes in large companies around the world. The MSCI index is a representation of 23 developed international markets, including Australia. The index began in 1969 and included 1,612 securities. When predicting Australian excess stock return signs, it is important to determine how global stock index directions affect the directions of ASX returns.

In previous studies, Hilliard (1979), Jaffe and Westerfield (1985) and Eun and Shim (1989) studied the correlation between stock price returns and major stock markets, and all reported positive correlations in returns across individual stock markets. The current study tested monthly lag returns of the MSCI index as an explanatory variable. Figure 3.14 depicts a strong positive relationship between the MSCI world index and ASX 200 index.

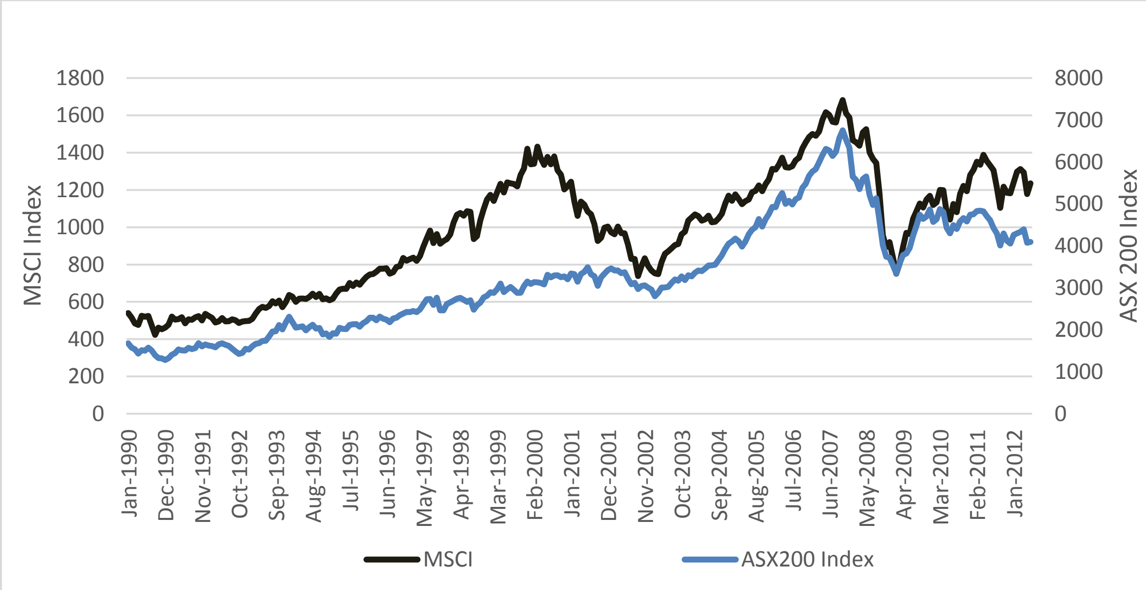

Figure 3.14: Monthly MSCI World Index and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.13 Effect of US Economy

The US has the world's largest economy and, for a long period, has been one of Australia's top-three trading partners, alongside China and Japan. Thus, it is important to identify the effects of US economic activity on domestic share price directions, considering the scale of past economic downfalls of the US economy that affected regions all around the world. Consistent with many past studies, Eun and Shim (1989) and Bessler and Yang (2003) found that the US market is probably the only market with a consistently strong effect on price movements in other major stock markets.

This study considered both S&P 500 monthly stock returns and US short- and long-term interest rates to assess the effect of US economic indicators on Australian share market behaviours. These are further discussed below.

3.2.13.1 *S&P 500 Share Returns*

The S&P 500 share index represents the 500 largest companies listed on the New York Stock Exchange and NASDAQ, which are the two largest stock exchanges in the world. The S&P 500 index is considered a benchmark index to represent the US equity market, and is one of the most commonly used stock indices by researchers in the areas of business and economics. The S&P 500 index is also considered a leading indicator of US business cycles. Investors believe that global index movements, such as the S&P 500, give early signals of the future movements of domestic markets, especially when they have strong business links with large economies. Chaudhuri and Smiles (2004) specified that using other countries' stock return variations—especially US stock returns—to explain returns in the Australia stock market significantly improves predictive results.

Therefore, this study tested S&P 500 share index monthly returns (SP500R) as a predictive variable of Australian excess stock returns. Figure 3.15 illustrates the S&P 500 and ASX 200 indices' monthly changes, demonstrating that they have a very close positive relationship and that both indices moved in the same direction during this period.

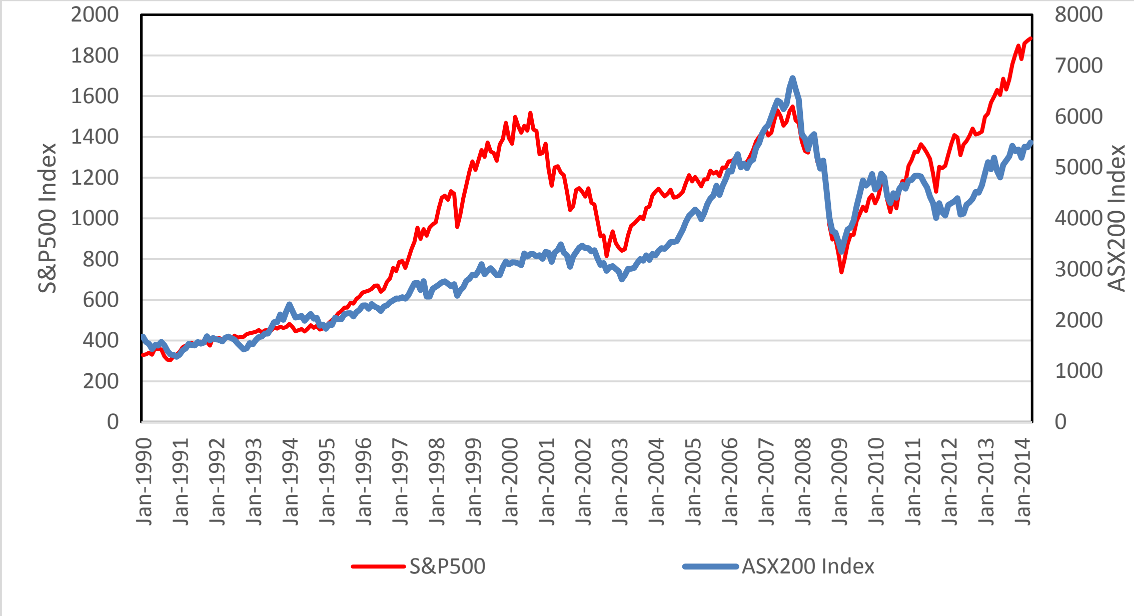

Figure 3.15: Monthly Movements of S&P 500 and ASX 200 Indices, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.13.2 *US Interest Rate*

The US interest rate is a key indicator of global economic activity. Changes in the US interest rate affect international equity investors' decisions. Higher interest rates in the US and low interest rates in foreign countries motivate international equity investors to invest more funds in non-US markets, since low interest rates are favourable for business profitability in non-US markets.

Due to the high influence of the US economy on other countries, US economic indicators are considered a benchmark or early signal for countries such as Australia. Kim (2001) identified that US monetary expansions lead to booms in non-US G6 countries, while Schmitt-Grohe (1998) discussed the identified effects of US business cycles on the Canadian economy. Thus, it is important to study how US interest rate changes affect Australian stock market excess returns. This study tested the following as explanatory variables of binary models:

- US short-term interest rate (yield on 90-day bills in the US)
- first difference between US short-term interest rate ($US3MB_t - US3MB_{t-1}$) and long-term interest rate (yield on 10-year bonds in the US)
- first difference between US long-term interest rate ($US10YB_t - US10YB_{t-1}$) and term spread (difference between 10-year yield and 90-day bill rate).

Figure 3.16 indicates an inverse relationship between US major interest rates and the Australian stock index, except for the 2005 to 2007 period (the pre-recession period), where a positive relationship appeared.

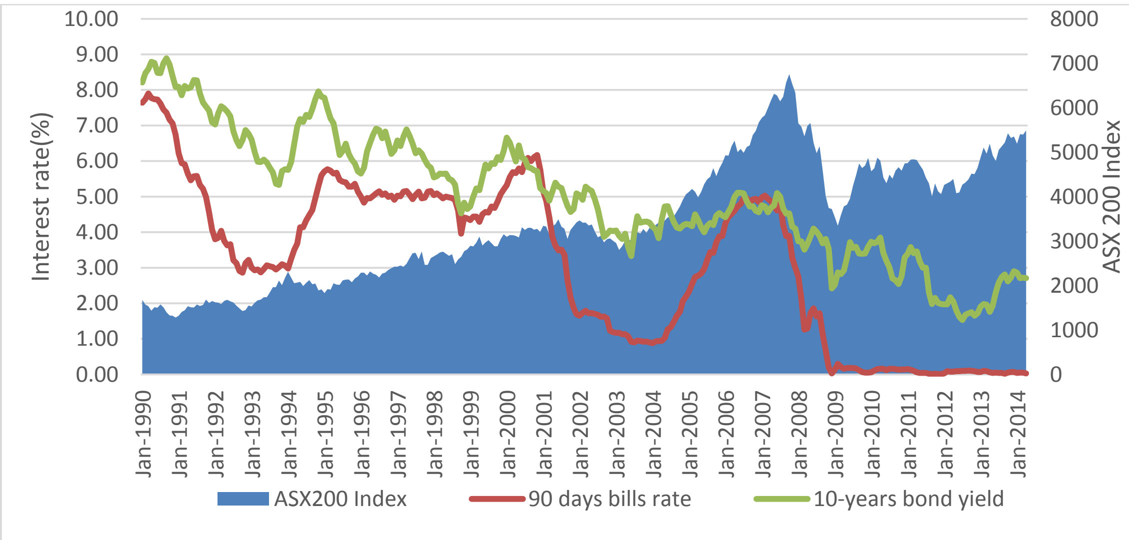

Figure 3.16: Monthly Movements of US 10-year Bond Yield, US 90-day Bill Rate and ASX 200 Index, January 1990 to April 2014

Data source: DX Database & www.rba.gov.au/statistic.

3.2.14 Leading Indicators

Based on the strong relationship between economic activity and stock returns, this study considered two leading indicators to assess the predictive power of Australian stock return directions. The Australian OECD indicator was used to represent Australian economic swings, and the US recession binary indicator was used to represent global economic swings. Several previous studies have discussed the importance of using leading indicators to predict turning points in economic activity. Smirnov (2011) analysed the performance of an existing composite index of leading indicators to predict major swings in economic activity, and stressed that the composite indicator performed reasonably well at recognised turning points. Chauvet and Potter (1998) confirmed the forecasting ability of leading indicators to predict stock market excess returns. Their study attempted to provide a fairly complete analysis of the performance of an existing composite index of leading indicators to predict major swings in economic activity in the period since World War II.

3.2.14.1 *OECD Composite Leading Indicator*

The OECD designed composite leading indicators for countries to measure economic activity and identify early signals of economic activity turning points. The Australian OECD indicator provides business cycle patterns for the economy; thus, this study used the lagged values of the OECD composite leading indicator as an independent variable to predict directional changes in the ASX 200 excess returns. Components of the Australian OECD composite leading indicator include the number of dwelling permits issued, order inflows of the manufacturing industry, production in the manufacturing industry, employment in the manufacturing industry, the S&P/ASX 200 share price index, and the terms of trade and yield on 10-year government bonds. Figure 3.17 compares the Australian OECD leading index and ASX 200 index, and confirms that these follow a similar trend over time.

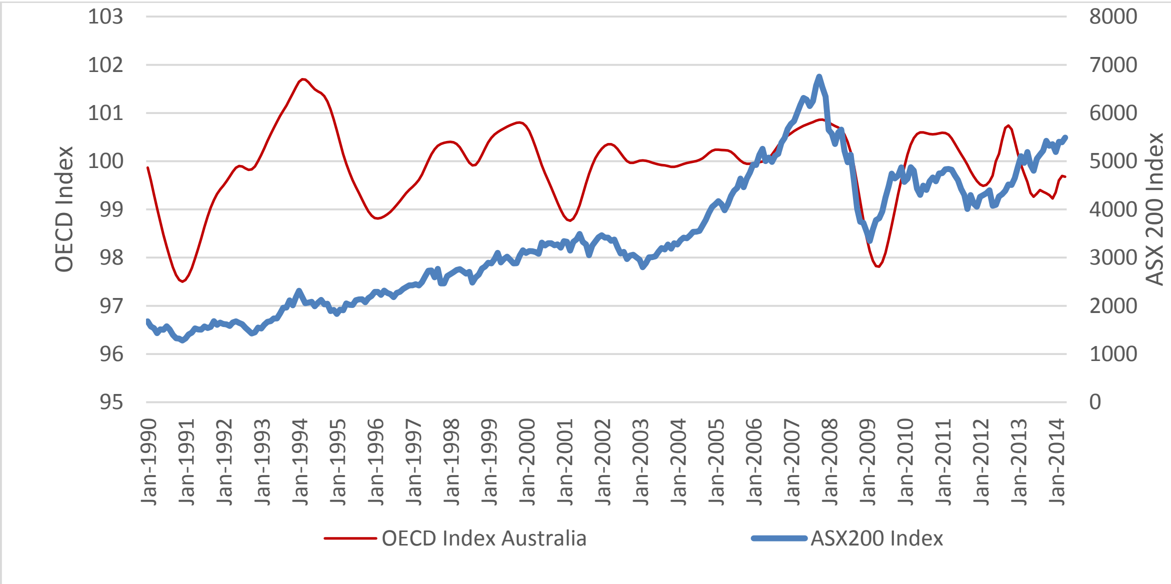

Figure 3.17: Monthly Movements of OECD Leading Indicator and ASX 200 Index, January 1990 to April 2014

Data source: DX Database and OECD Website (https://data.oecd.org/)

3.2.14.2 *US Recession Indicator*

The US recession that began in late 2007 affected many economies around the globe, causing significant distraction in the US stock market and non-US financial markets, including the Australian share market. Therefore, it is important to examine whether the US recession forecast, as a global economic indicator, is a significant explanatory variable in predicting Australian share return directions. Nyberg (2008) was the first to use a binary recession indicator as a predictor variable to forecast US stock signs, and concluded that a binary recession indicator can be successfully used to predict US stock directions.

This study used recession dates defined by the US NBER as a binary independent variable (REC), where $REC_t = 0$ if the US economy is in recession, as defined by NBER at month t, and $REC_t = 1$ if the US economy is in expansion, as defined by NBER at month t. Figure 3.18 shows the binary recession indicator (0 or 1) and ASX 200 movements. It clearly indicates that the ASX 200 index dropped during US recession periods, as defined by the NBER (1991, 2001/2002 and 2008/2009).

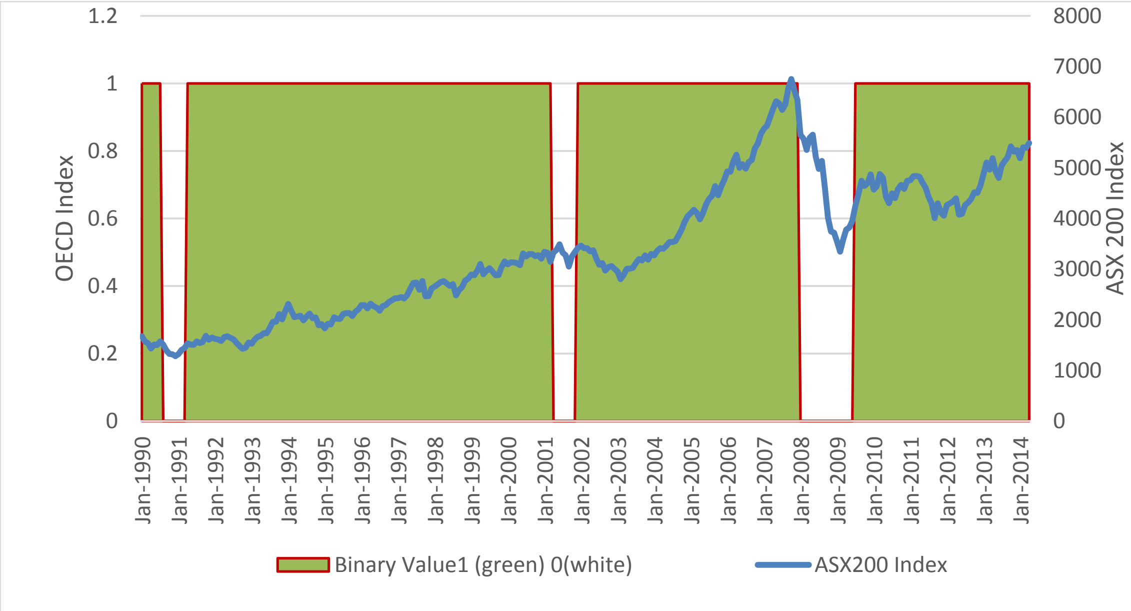

Figure 3.18: Binary Recession Indicator and ASX 200 Monthly Movements, January 1990 to April 2014

Data source: NBER website (http://www.nber.org/cycles/cyclesmain.html) and DX Database.

3.2.15 Volatility Measurements

Christoffersen and Diebold (2006) studied the strength of stock return sign predictability when using volatility dynamics. They showed that S&P 500 stock sign forecasts are significantly sensitive to changes in volatility. The current study also considered the volatility of the ASX 200 index and selected independent variables (S&P 500 index returns, MSCI world index returns, exchange rates between the AUD and USD, and exchange rates between the AUD and Chinese renminbi) to assess the forecasting ability of Australian stock monthly signs. Three volatility measurements that are SD, MAD and U^{2}' applied in all predictive models to determine the significance of the volatility of above predictor variables in predicting return signs. Both SD and MAD was calculated based on the previous four months' excess stock returns in this study.

3.3 Chapter Summary

This chapter studied the relationship between selected predictor variables and the Australian stock market. It discussed the various economic, financial, international variables and past volatility of variables that are likely to be determinants of monthly stock market movements. It also selected independent variables based on their relationship with Australian economic activity, previous studies, related theories and real-world knowledge. The next chapter examines the research process and methodology employed in this study.

Chapter 4: Research Process and Methodology

4.1 Introduction

This chapter discusses the research process and methodology used in this study to predict the directions of excess stock returns in the Australian share market. This chapter comprises four sections. The first section explains the sample and data sources. The second section discusses the binary models, diagnosis tests and evaluation methods of model performance. The third section presents the explanatory variables used to predict excess stock returns. The final section summarises this chapter.

4.2 Study Sample and Data Sources

This study considered monthly data for a total period of 312 months from January 1990 to December 2015. Predictive models were estimated using monthly data from January 1990 to May 2012 (the in-sample period). The out-of-sample period considered to evaluate the forecasting accuracy of binary models was from June 2012 to December 2015 (43 months). All historical data used in the statistical models were collected from sources such as the DX Database, DataStream and Reserve Bank of Australia website. Data series were crosschecked when they were available in more than one source in order to ensure the correct data were used in the study.

4.3 Binary Predictive Models

This study used three binary models—discriminant, logistic and probit models—to predict the monthly directions of Australian excess returns. The dependent variables of these models were binary signs, where the dependent variables had two outcomes. The binary variable was categorical and could be labelled as ‘negative’ or ‘positive’ or ‘yes’ or ‘no’, depending on the nature of the dependent variable.

The monthly excess returns of the Australian stock market were calculated using ASX 200 index. The excess stock returns were estimated using the formula $R_t = \text{Ln}\ (P_t/P_{t-1}) - rf_t$, where the monthly risk-free interest rate (rf_t) was approximated by the three-month bank-accepted bill rate in Australia. After calculating the monthly excess stock returns (R_t), the results were converted to binary values to be applied in predictive models, where positive returns had a value = 1 and negative returns had a value = 0.

$$I_t = \left\{ \begin{matrix} 1 \\ \\ 0 \end{matrix} \right\} \quad \begin{matrix} r_t > 0 \\ \\ r_t \leq 0 \end{matrix}$$

where I_t is the positive or negative sign/probability of stock return.

The three binary models and diagnostic tests used in this study are further discussed in the following sections.

4.3.1 Linear Discriminant Models

This study used the discriminant model to predict monthly excess stock return signs, with all possible variables (as previously discussed) tested as predictors.

Discriminant analysis is a classic method of classification developed by Fisher (1936). This model has been successfully tested by researchers to predict binary outcomes, with better outcomes than other classification techniques. For example, Leung et al. (2000) and Ou and Wang (2009) demonstrated that the discriminant model has stronger predictive power for stock market returns than level estimation and alternative classification models. The discriminant model is more similar to both logistic regression and probit regression as the models explain the categorical variable by the values of continuous independent variables. Discriminant model look for linear combination of variables, where the model can be expressed as follows:

$$V_{it} = \beta_0 + \sum_{j=1}^{m} \beta_j X_{t-k} + \varepsilon_t \qquad (4.1)$$

where V_{it} is the discriminant score that can be assigned to positive or negative signs of returns, β_0 is the intercept, β_j is the coefficient of the explanatory variables, and x_{t-k} (see Table 4.1) are the explanatory variables.

4.3.2 Diagnostic Tests for Discriminant Models

To test the statistical significance of discriminant models, this study performed several tests. These statistical tests were conducted to identify important predictors, the goodness-of-fit of discriminant models, the relative importance of predictor variables and the forecasting accuracy of predictive models.

4.3.2.1 *Identify Important Predictors*

Group mean statistics can be used in discriminant analysis to select useful predictor variables, and the analysis of variance (ANOVA) test can be used to verify the significant of the predictors. A correlation matrix is used to ensure that no highly correlated independent variables are employed in predictive models.

4.3.2.1.1 Checking Group Mean Statistics

It is important to identify whether selected independent variables are useful to distinguish the two categorical outcomes of the models. Mean statistics between two groups can be used to identify which variables are useful predictors. Individual variables can only be used in discriminant analysis when the means between the two groups are different. If the means between the two groups are similar for any independent variable, those variables must be avoided in discriminant analysis and will not be useful predictors to forecast the signs of Australian excess stock returns.

4.3.2.1.2 Wilks Lambda and Univariate ANOVA

The ANOVA test can also be used to test the differences in the group means of each individual predictor. The null hypothesis (H_0) indicates that the means are equal between two groups. If the p-value is less than 0.05 (at a five per cent significance level), the means of each group are significantly different and the variable can be used as a predictor. The Wilks lambda value of each variable can also be used to identify which variables contribute more to differentiating two groups. The lambda value varies from zero to one, whereby the smaller the number(close to zero), the greater the particular variable differentiates the two groups.

4.3.2.1.3 Correlation Matrix

The bivariate correlations between all independent variables need to be considered when selecting predictive variables for discriminate models. Even if means between two groups are significantly different, multicollinearity can still mislead the model's significance. Therefore, any two variables with absolute correlations over 40 per cent need to be dropped from the model or used as factors to avoid misleading results.

4.3.2.1.4 Tests of Significance (Goodness-of-fit Test)

This study used the Wilks lambda test to check the overall model significance. It also used a canonical correlation square value as a goodness-of-fit measure and relative measurement to check the strength of the discriminant models.

4.3.2.1.5 Wilks Lambda Test

The Wilks lambda test is used in discriminant analysis to determine the significance of the discriminant function as a whole. In Wilks lambda test for model significant, the null hypothesis (H_0) is the discriminant function is not significant. The significance value (p-value) less than 0.05 indicates the significance of the model for identifying two groups which is positive returns and negative returns in this study.

4.3.2.1.6 Canonical Correlation

Squared canonical correlation (CC^2) is similar to the coefficient of determination (R^2), which is used to evaluate the goodness-of-fit of ordinary least squares (OLS) regression. In the discriminant model, CC^2 measures the percentage of variation in the dependent outcome that can be explained by the set of the independent variables used. A higher CC^2 indicates better predictive discriminant models.

4.3.2.2 *Relative Importance of Independent Variables*

After identifying the key determinants of Australian monthly stock returns, predictor variables can be ranked based on their importance using both standardised canonical discriminant function coefficients and structure matrix function coefficients.

4.3.2.2.1 Standardised Canonical Discriminant Function Coefficients

Standardised canonical discriminant function coefficients indicate the contribution of each variable to the discriminant function. The absolute size of the coefficients can be used to measure the relative importance of the predictor variables, whereby larger means indicate a more important predictor.

4.3.2.2.2 Structure Matrix Function Coefficients

The structure matrix shows the absolute correlation between each independent variable and the discriminant function. If the correlation is high, the variable is a strong predictor. In the structure matrix table, independent variables are ranked from the most important to least important variable.

4.3.2.3 *Model Clasification Results (Hit Ratio)*

The classification table can be used to measure the forecasting performance of the discriminant model. This table compares the observed and predicted categories of the dependent variables—also called the ‘hit ratio’ of the discriminant model. If the percentage correctly classified is over 50 per cent, this indicates a good predictive model and the hit ratio can be estimated for both the in-sample and out-of-sample predictions.

4.3.3 Logistic Model

The logistic model can be used to predict the probability of positive or negative excess market returns by fitting data to a logistic function curve. In this model, the dependent variable is the logarithm of the ratio of the probability that a particular event (negative/positive return signs) will occur to the probability that particular event will not occur. The binary logistic model is based on the cumulative distribution function, where the error term is logit.

Therefore, the logistic function can be written as:

$$P_{it} = \Lambda(.) = \Lambda\,(\beta_0 + \sum_{j=1}^{m} \beta_j\, X_{t-k} + \varepsilon_t) \qquad (4.2)$$

or

$$Ln\left(\frac{P_{it}}{1 - P_{it}}\right) = \pi_t = \beta_0 + \sum_{j=1}^{m} \beta_j\, X_{t-k} + \varepsilon_t \qquad (4.2.1)$$

where Λ denotes the values of the logistic cumulative distribution, P_{it} is the probability that the particular outcome of positive returns (1) will occur in time t, $1 - P_{it}$ is the probability that the particular outcome of negative returns (0) will occur in time t, β_0 is the intercept, β_j is the coefficient of the explanatory variables, and x_{t-k} (see Table 4.1) are the explanatory variables.

4.3.4 Probit Regression Model

The probit regression model also estimates by using the maximum likelihood method, where the model is based on the cumulative distribution function. The probit model is similar to the logistic regression model, where the difference is the specification of the error term in the model. The distribution of the error term of the probit model is a normal distribution, where the error term distribution in the logistic model is a logit distribution.

The equation can be written as:

$$P_{it} = \phi(.) = \phi(\beta_0 + \sum_{j=1}^{m} \beta_j X_{t-k} + \varepsilon_t) \tag{4.3}$$

or

$$Ln\left(\frac{P_{it}}{1 - P_{it}}\right) = \pi_t = \beta_0 + \sum_{j=1}^{m} \beta_j X_{t-k} + \varepsilon_t \tag{4.3.1}$$

where ϕ denotes the values of the cumulative standard normal distribution, P_{it} is the probability that the particular outcome of positive returns (1) will occur in time t, $1 - P_{it}$ is the probability that the particular outcome of negative returns (0) will occur in time t, β_0 is the intercept, β_j is the coefficient of the explanatory variables, and x_{t-k} (see Table 4.1) are the explanatory variables.

4.3.5 Static, Dynamic, Autoregressive and Dynamic Autoregressive Logistic/Probit Models

This study tested benchmark (static) logit/probit models at the first stage for sign forecasting, and then compared them with the developed logit/probit models, including dynamic, autoregressive and dynamic autoregressive logistic/probit models. The static logit/probit model is:

$$\pi_t = \beta_0 + \beta_j x_{t-k} \tag{4.4}$$

where π_t is the probability of a binary outcome of the logit/probit model and x_{t-k} are the explanatory variables.

The basic static model (4.4) can be extended to dynamic probit/logit models (4.5) by adding the lagged return indicator (I_{t-1}) to the equation:

$$\pi_t = \beta_0 + \delta_1 I_{t-1} + \beta_j x_{t-k} \tag{4.5}$$

This dynamic probit model was successfully tested by Valckx et al. (2002), Moneta (2005) and Dueker (1997) in recession forecasting and by Nyberg (2008) in predicting the excess return of US stocks.

Kauppi and Saikkonen (2008) expanded the static model (4.4) and dynamic probit model (4.5) by incorporating the lagged values of the binary response variable (π_{t-1}). The new models became the autoregressive probit model (4.6) and dynamic autoregressive probit model (4.7):

$$\pi_t = \beta_0 + \propto_1 \pi_{t-1} + \beta_j x_{t-k} \tag{4.6}$$

$$\pi_t = \beta_0 + \propto_1 \pi_{t-1} + \delta_1 I_{t-1} + \beta_j x_{t-k} \tag{4.7}$$

4.3.6 Diagnostic Test for Logistic and Probit Models

To test the statistical significance of the logit and probit models, this study performed the following common tests, which are further discussed below:

- test for multicollinearity

- probability values of the independent variables (p-values)
- likelihood ratio (LR) statistic
- probability of LR statistic
- McFadden R-squared (R^2_{Mcf})/Cox and Snell R-squared, and Nagelkerke R-squared
- hit ratio (correct foresting ratio).

4.3.6.1 *Multicollinearity*

When two or more independent variables in predictive models are highly correlated, the models tend to provide biased results of individual predictors. A simple cross-correlation test can measure this multicollinearity problem. Generally, a negative or positive correlation coefficient over 0.4 (absolute value) is considered the multicollinearity. Factor analysis (grouped into one variable or factor), considering more sample data, or dropping one of the variables are some techniques used by previous studies to avoid the multicollinearity problem. The current study dropped one of the highly correlated predictors from the model when the multicollinearity problem arose.

4.3.6.2 *Probability/Significant Values of Independent Variables (P-values)*

The probability value (or p-value) of independent variables measures the significance of each variable for predicting the binary outcome. The null hypothesis (H_0) indicates that the coefficients are not significantly different from zero. If the null hypothesis can be rejected, then the predicting variable is statistically significant to forecast stock returns. The traditional approach is considered at the five per cent significance level, where 10 per cent significance level also in use for testing the significance. At a five per cent significance level, if the p-value is less than 0.05, the null hypothesis can be rejected and the explanatory variable is significant in predicting the dependent variable.

4.3.6.3 *LR Statistic and Probability of LR Statistic*

LR measures the goodness-of-fit of two models by evaluating how many times more likely to data are under one model compared to other model. The LR statistic tests the null hypothesis (H_0) that all slope coefficients (except constant) are equal to zero. The probability (p) value of the LR statistic can be used to measure the significance of the model. The probability (LR statistic) determines the validity of the model, where a significance value of less than 0.05 indicates the significance of the logistic/probit model for predicting binary outcomes.

4.3.6.4 *The McFadden R-squared Value (R^2_{Mcf})*

The McFadden R-squared measures how successful the logistic/probit models are for predictions. This is similar to the goodness-of-fit measurement coefficient of determination (R^2), which is generally used to evaluate the goodness-of-fit of OLS regression. However, a satisfactory level of the two measurements are not the same, with an R^2_{Mcf} value over 0.20 generally considered a high level of goodness-of-fit, compared to the R^2 level of 0.50 used in linear regression models.

4.3.6.5 *Cox and Snell R-squared and Nagelkerke R-squared*

The Cox and Snell R^2 value also indicates the strength of association of the model, as do other R^2 values. The value of this test lies between zero and one, where a value close to one indicates a strong relationship between dependent and independent variables of the logistic model. Nagelkerke R^2 is a modified form of the Cox and Snell R^2 value.

4.3.6.6 *Classification Results (Hit Ratio)*

Logistic/probit analysis allows examination of both observed and predicted model results. This is also called the 'hit/miss ratio'. After estimating predictive models, the models can be used to classify each data record using the computed probability given by the models. The hit ratio can be estimated for both in-sample and out-of-sample predictions, where a hit ratio over 50 per cent indicates a good predictive model.

4.4 Explanatory Variables to Predict Directions of Australian Stock Market Excess Return

One of the main objectives of this study was to identify the key determinants of the directional changes in monthly excess stock returns in the Australian share market. To achieve this objective, this study considered a number of possible variables and their lag values under three main categories: economic variables, financial variables and international variables. In addition, this study also tested the predictive power of different volatility measures (SD, MAD and U^2) of several independent variables, including past volatility of ASX 200 lag returns. The variables listed in Table 4.1 were tested as explanatory variables (x_{t-k}) in this study.

Table 4.1: Explanatory Variables of Binary Models

Explanatory Variables (X_{t-k})	Abbreviations
Yield on 90-day bills in Australia	AU3MB
Yield on 10-year bonds in Australia	AU10YB
Term structure of interest rates (difference between 10-year bond yields and 90-day bill yields)	AUTS
Yield on 90-day bills in the US	US3MB
Yield on 10-year bonds in the US	US10YB
Term structure of interest rates (difference between 10-year bond yields and 90-day bill yields in the US)	USTS
First difference of yield on 90-day bills in Australia (FDAU3MB), and first difference of yield on 10-year bonds in Australia	FDAU10YB
First difference of yield on 90-day bills in the US (FDUS3MB), and first difference of yield on 10-year bonds in the US	FDUS10YB
S&P 500 monthly returns	SP500R
Money supply	M3
Private dwelling approvals	PDWE
Retail spending	RS
MSCI world index	MSCIR
Employment rate	EMP
RBA index of commodity prices	CP
USD exchange rate	US$
Chinese Renminbi exchange rate	CREN
Net export	NE
Oil price	OIL
Dividend yields	DIV
PER	PER
OECD composite leading indicator for Australia	OECD
Recession dates defined by NBER (D = 1 if contraction period, D = 0 if expansion period)	REC
MAD ASX 200 index lag returns	MADASXLR
SD ASX 200 index lag returns	SDASXLR
U2 ASX 200 index lag returns	ASXLR2
MAD SP500 index returns	MADSP500R
SD SP500 index returns	SDSP500R
U2 SP500 index returns	SP500R2
MAD MSCI index lag returns	MADMSCILR
SD MSCI index lag returns	SDMSCILR
U2 MSCI index lag returns	MSCILR2
MAD USD exchange rates	MAD$AUD

SD USD exchange rates	SD$AUD
MAD Chinese Renminbi exchange rates	MADRENAUD
SD Chinese Renminbi exchange rates	SDRENAUD

4.5 Chapter Summary

This chapter described the research process and methodology used to predict the monthly signs of Australian excess stock returns, and the methodology used to identify the determinants. This chapter discussed the three types of binary models—discriminant, probit and logistic models. In addition to the static logistic/probit models, further developed dynamic, autoregressive and dynamic autoregressive logistic/probit models were used to predict excess stock return signs. This chapter presented the various economic, financial and international variables considered as possible determinants of stock directions. This chapter also discussed the use of volatility measures—such as the SD, MAD and U^2 of several independent variables—to predict stock directions. This chapter proposed various diagnostic tests to test the significance of the estimated models, and to identify the determinants of stock returns. The next chapter analyses the estimated predictive models and presents the results based on the methodology employed.

Chapter 5: Model Estimation and Discussion of Results

5.1 Introduction

Following Chapter 4, which discussed the methodology employed in the study, this chapter mainly presents the findings of the study. This chapter contains four sections. The first section discusses the discriminant models to predict monthly excess stock return signs, and identifies the key determinants based on discriminant analysis. The second section discusses the estimated logistic and probit models to forecast excess stock return signs, and identifies the key determinants based on logistic and probit regression analysis. The third section compares the best logistic and discriminant models to forecast monthly excess stock return signs based on diagnostic testing and forecasting results. The final section summarises the chapter.

5.2 Discriminant Models to Predict Monthly Excess Stock Return Signs

This study used SPSS statistical software (version 22) to estimate the discriminant models. In discriminant models, the binary dependent variable is identified either as a negative (0) or positive (1) sign of monthly Australian excess stock returns, using various economic, financial and international factors as explanatory variables. The discriminant model used in this study was explained in Section 4.3.1 and Equation 4.1.

At the first stage of the discriminant analysis, models were estimated with different combinations of possible predictor variables of monthly excess stock return signs. The mean statistical differences between two groups (negative and positive signs) were tested for each predictor variable to identify the usefulness of the variables for sign predictions. The variables with very close mean values were dropped from the estimated models. Further, a hypothesis test was conducted to confirm the significance of predictor variables, where the null hypothesis is group means are the same for each predictor variables. This was conducted by performing an ANOVA test, whereby the variables with a p-value of less than a 0.05 significance level were considered the important variables that had different mean values.

A multicollinearity test was also conducted to identify the highly correlated variables. If the correlation coefficient was over 40 per cent, those variables were dropped or not included in the same model. Explanatory variables were tested in different combinations to avoid the multicollinearity effect. In the modelling process, if the coefficient signs of the estimated models were not matched with the expected signs (priori signs), those models were not considered for predictions. The Wilks lambda discriminant function significant test was conducted to verify the significance of discriminant models, where the null hypothesis (H_0) was: discriminant function is not significant. The models with a p-value of less than 0.05 significance were considered valid discriminant models for sign predictions.

5.2.1 Estimated Discriminant Models

Table 5.1 shows the estimated discriminant models' chi-square, significance (p) and CC^2 values, which were used to measure the models' goodness-of-fit. The models were estimated using 269 months of data from January 1990 to May 2012.

Table 5.1: Estimated Discriminant Models, January 1990 to May 2012

	Estimated Discriminant Models	n	Chi	p	CC^2	Rank
DM1	-0.130+26.626 SP500R	269	87.848	0.000	0.281	11
DM2	-0.258+25.327 SP500R-3.377 NE	269	96.269	0.000	0.304	7
DM3	0.958+26.137 SP500R-0.610 $AU3MB_{t-2}$	269	90.540	0.000	0.288	8
DM4	1.796+26.28 SP500R-1.017 $AU10YB_{t-2}$	269	94.359	0.000	0.298	8
DM5	-0.039+26.359 SP500R-4.643 MADAUD$	269	87.960	0.000	0.282	10
DM6	1.232+25.316 SP500R-2.799 NE-0.776 $AU10YB_{t-2}$	269	99.940	0.000	0.314	2
DM7	0.484+25.118 SP500R-3.101 NE-0.410 $AU3MB_{t-2}$	269	97.412	0.000	0.307	5
DM8	1.462+25.945 SP500R-1.829 NE_{t-1}-0.879 $AU10YB_{t-2}$	269	96.642	0.000	0.305	6
DM9	0.685+25.762 SP500R -2.145NE_{t-1}-0.504 $AU3MB_{t-2}$	269	93.740	0.000	0.297	9
DM10	-0.215+25.217SP500R -3.348NE_{t-1}.-2.129MADAUD$	269	96.152	0.000	0.304	7
DM11	-0.176+25.973SP500R -2.36NE-2.380MADAUD$	269	91.850	0.000	0.293	9
DM12	1.722+24.836 SP500R- 2.555NE-0.934 $AU10YB_{t-2}$-9.286 MADAUD$	269	100.846	0.000	0.317	1
DM13	0.669+24.845 SP500R- 3.002NE-0.460 $AU3MB_{t-2}$-4.787 MADAUD$	269	97.530	0.000	0.308	4
DM14	2.020+25.352 SP500R- 1.5NE_{t-1}-1.058 $AU10YB_{t-2}$-10.611 MADAUD$	269	97.831	0.000	0.309	3
DM15	0.902+25.423 SP500R- 2.018NE_{t-1}-0.561 $AU3MB_{t-2}$-5.638 MADAUD$	269	93.970	0.000	0.298	8

Note: n = number of periods; chi = chi-square statistic; p = probability value (Wilks lambda) and rank is based on CC^2.

In this process, 15 discriminant models were identified as significant models for predicting Australian monthly excess stock return signs. The Wilks lambda test confirmed the overall significance of each model. Of all 15 estimated models, the discriminant model 12 (DM12) measured as the best significant model based on the CC^2 value, which recorded 31.7 per cent. DM12 included four predictive variables: SP500R, NE, $AU10YB_{t-2}$ (lag value by two periods) and MADAUD$. DM6 was the second-strongest discriminant model, with a reported CC^2 value of 31.4 per cent, which was just behind the best predictive model, DM12. DM6 included variables SP500R, NE and $AU10YB_{t-2}$, which was the same as DM12, except for MADAUD$. This indicated that including MADAUD$ (in DM12) improved the goodness-of-fit measures.

DM14 was the third-best model based on the CC^2 value of 30.9 per cent. Both models DM14 and DM12 (the best model in terms of CC^2) had NEs; however, DM14's NE was lagged by one period (NE_{t-1}), which indicated a higher predictive power of NE compared to the lagged value. Model DM13 (ranked fourth) also recorded a higher CC^2 value of 30.8 per cent, which was slightly lower than the best model (DM12). Models DM13 and DM12 only differed with one variable, where $AU10YB_{t-2}$ in D13 was replaced by $AU3MB_{t-2}$ (a lag value by two periods) in DM12.

DM15 included the predictor variables SP500R, NE_{t-1}, $AU3MB_{t-2}$ and MADAUD$, with a recorded CC^2 value of 29.8 per cent. DM15 was also a close model to the best model DM12, where NE was replaced by NE_{t-1} and $AU10YB_{t-2}$ was replaced by $AU3MB_{t-2}$ in DM12. DM1 included only one predictor variable, SP500R, and recorded a higher CC^2 value of 28.1 per cent, which was still a higher goodness-of-fit compared to the other models with multiple explanatory variables. This indicated a strong relationship between the SP500 share index returns and Australian excess stock return directions.

5.2.2 Identifying Key Determinants of ASX Monthly Excess Stock Return Signs Based on Discriminant Analysis

While many economic, financial and international factors were tested as determinants of Australian monthly excess stock return directions, only a few variables were identified as key contributory factors, based on discriminant analysis. SP500R was significant in all 15 estimated models and identified as the best predictor variable among all other significant predictors. This finding is consistent with previous studies in Australia by Kazi (2009) and Chaudhuri and Smiles (2004), who found a strong influence of US stock movements on Australian stock returns.

Based on the group mean statistic test and ANOVA test conducted on each valid discriminant model, SP500R, NE, NE_{t-1} $AU10YB_{t-2}$, $AU3MB_{t-2}$ and MADAUD$ were identified as the significant determinants of excess stock return signs. However, the goodness-of-fit measures of the estimated discriminant models slightly changed with different combinations of the variables included in the models. Due to a high correlation between $AU10YB_{t-2}$ and $AU3MBt_{-2}$, the two variables were tested separately in discriminant models to avoid the multicollinearity problem. Table 5.2 presents the correlation matrix of the significant variables.

Table 5.2: Correlation Matrix

	SP500R	AU3MB$_{t-2}$	AU10YB$_{t-2}$	MADAUD$	NE	Ne$_{t-1}$
SP500R	1.00					
AU3MB$_{t-2}$	-0.05	1.00				
AU10YB$_{t-2}$	0.04	**0.81***	1.00			
MADAUD$	-0.20	-0.19	-0.32	1.00		
NE	-0.09	0.29	0.36	0.10	1.00	
Ne$_{t-1}$	-0.04	0.23	0.34	0.12	0.83	1.00

Note: * over 40 per cent correlation.

Table 5.3 presents the statistically significant predictor variables identified in the discriminant models.

Table 5.3: Statistically Significant Explanatory Variables in Discriminant Analysis

Explanatory Variables	Statistical Significance	Explanatory Variables	Statistical Significance
AU3MB	*Significant*	NE	*Significant*
AU3MB$_{t-1}$	*Significant*	Ne$_{t-1}$	*Significant*
AU3MB$_{t-2}$	*Significant*	OIL & Lags	Insignificant
AU10YB	*Significant*	DIV & Lags	Insignificant
AU10YB$_{t-1}$	*Significant*	PE & Lags	Insignificant
AU10YB$_{t-2}$	*Significant*	OECD & Lags	Insignificant
AUTS & Lags	Insignificant	REC & Lags	Insignificant
US3MB & Lags	Insignificant	MADASXLR & Lags	Insignificant
US10YB & Lags	Insignificant	SDASXLR & Lags	Insignificant
USTS & Lags	Insignificant	ASXLR^2 & Lags	Insignificant
FDAU10YB & Lags	Insignificant	MADSP500R & Lags	Insignificant
FDUS10YB & Lags	Insignificant	SDSP500R & Lags	Insignificant
SP500R	*Significant*	SP500R^2 & Lags	Insignificant
M3 & Lags	Insignificant	MADMSCIRL & Lags	Insignificant
PDWE & Lags	Insignificant	SDMSCIRL & Lags	Insignificant
RS & Lag values	Insignificant	MSCIRL^2 & Lags	Insignificant
MSCIR & Lags	Insignificant	MAD$AUD	*Significant*
EMP & Lags	Insignificant	SD$AUD & Lags	Insignificant
CP & Lags	Insignificant	MADRENAUD & Lags	Insignificant
US$ & Lags	Insignificant	SDRENAUD & Lags	Insignificant

Note: significance at five per cent level.

5.2.2.1 *Ranking Most Important and Strong Predictors Based on Discriminant Analysis*

This study considered three measurements—standardised canonical discriminant function coefficients, structure matrix function coefficients and Wilks lambda values—to measure the relative importance and strength of explanatory variables to predict monthly excess stock returns. The best five discriminant models selected based on CC^2 values—DM6, DM7, DM12, DM13 and DM14—were considered to rank predictor variables. Table 5.4 shows each variable's ranking in the models, based on the three above measures.

Table 5.4: Most Important and Strong Predictors Based on Discriminant Analysis

Discriminant Model	Explanatory Variables	Standardised Canonical Discriminant Function Coefficients	Rank	Structure Matrix Function Coefficients	Rank	Wilks Lambda	Rank
DM6	SP500R	0.951	1	0.924	1	0.719	1
	NE	-0.268	2	-0.302	2	0.960	2
	$AU10YB_{t-2}$	-0.221	3	-0.183	3	0.985	3
DM7	SP500R	0.943	1	0.939	1	0.719	1
	NE	-0.297	2	-0.306	2	0.960	2
	$AU3MB_{t-2}$	-0.120	3	-0.182	3	0.985	3
DM12	SP500R	0.933	1	0.918	1	0.719	1
	NE	-0.245	3	-0.3	2	0.960	2
	$AU10YB_{t-2}$	-0.266	2	-0.181	3	0.985	3
	MADAUD$	-0.124	4	-0.176	4	0.986	4
DM13	SP500R	0.933	1	0.937	1	0.985	1
	NE_{t-1}	-0.288	2	-0.288	2	0.960	2
	$AU3MB_{t-2}$	-0.145	3	-0.182	3	0.985	3
	MADAUD$	-0.064	4	-0.18	4	0.986	4
DM14	SP500R	0.952	1	0.935	1	0.719	1
	NE_{t-1}	-0.148	3	-0.193	2	0.984	2
	$AU10YB_{t-2}$	-0.301	2	-0.185	3	0.985	3
	MADAUD$	-0.142	4	-0.18	4	0.986	4

SP500R was identified as the most important and strong independent variable for predicting stock signs, based on the three ranking measures in the selected models. NE or NE_{t-1} was ranked as the second-most important predictor, based on the structure matrix scores and Wilks lambda values, even though the standardised canonical discriminant function coefficients showed some mixed results. Based on all ranking scores, $AU10YBt_{-2}$ and $AU3MB_{t-2}$ ranked as the third-most important predictor after SP500R and NE or NE_{t-1}. Among the statistically significant variables identified from the discriminant analysis, MADAUD$ was recorded as the least important predictor, based on the statistical scores considered.

5.2.3 Forecasting Accuracy of Discriminant Models

Table 5.5 shows both the in-sample and out-of-sample forecasting accuracy of the estimated discriminant models. The classification results' hit ratio (percentage correct) was used to measure the predictive performance of the 15 estimated discriminant models. The in-sample period consisted of 269 months from January 1990 to May 2012, while the out-of-sample period consisted of 43 months from June 2012 to December 2015.

Table 5.5: Classification Results of Discriminant Models

Estimated Discriminant Models	In-sample Hit Ratio	Out-of-sample Hit Ratio	Average Hit Ratio	Rank
DM 1) -0.130+26.626 SP500R	77.300	60.500	68.900	10
DM 2) -0.258+25.327 SP500R-3.377 NE	78.400	51.100	64.750	1
DM 3) 0.958+26.137 SP500R-0.610 $AU3MB_{t-2}$	78.100	62.800*1	70.450	3
DM 4) 1.796+26.28 SP500R-1.017 $AU10YB_{t-2}$	79.200	53.500	66.350	9
DM 5) -0.039+26.359 SP500R-4.643 MADAUD$	78.800	60.500	69.650	6
DM 6) 1.232+25.316 SP500R-2.799 NE-0.776 $AU10YB_{t-2}$	80.300*1	55.800	68.050	12
DM 7) 0.484+25.118 SP500R-3.101 NE-0.410 $AU3MB_{t-2}$	78.400	60.500	69.450	7
DM 8) 1.462+25.945 SP500R-1.829 NE_{t-1}-0.879 $AU10YB_{t-2}$	78.400	53.500	65.950	4
DM 9) 0.685+25.762 SP500R -2.145NE_{t-1}-0.504 $AU3MB_{t-2}$	79.200	60.500	69.850	5
DM 10) -0.215+25.217SP500R -3.348NE. -2.129MADAUD$	78.400	58.100	68.250	11
DM 11) -0.176+25.973SP500R -2.36NE_{t-1}-2.380MADAUD$	79.200	60.500	69.850	5
DM 12) 1.722+24.836 SP500R- 2.555NE-0.934 $AU10YB_{t-2}$-9.286 MADAUD$	79.900*2	58.100	69.000	8
DM 13) 0.669+24.845 SP500R- 3.002NE-0.460 $AU3MB_{t-2}$-4.787 MADAUD$	78.800	62.800*1	70.800*	2
DM 14) 2.020+25.352 SP500R- 1.5NE_{t-1}-1.058 $AU10YB_{t-2}$-10.611 MADAUD$	78.400	58.100	68.250	9
DM 15) 0.902+25.423 SP500R- 2.018NE_{t-1}-0.561 $AU3MB_{t-2}$-5.638 MADAUD$	79.900*2	62.800*1	71.350*	1

Note: *rank; Rank = based on average hit ratio.

All 15 estimated discriminant models that had different combinations of independent variables reported an impressive in-sample forecasting accuracy of binary stock return signs of over 75 per cent. DM6 included independent variables SP500R, NE and $AU10YB_{t-2}$, and recorded the highest in-sample predictive performance of 80.30 per cent. DM12 and DM15 recorded the second-highest in-sample hit ratio of 79.90 per cent. DM12 included predictive variables SP500R, NE, $AU10YB_{t-2}$ and MADAUD$, while DM15 included predictor variables SP500R, $NEt_{-1,}$ $AU3MBt_{-2}$ and MADAUD$. The hit ratios between the two models indicated that there was no real effect on in-sample forecasting accuracy when $AU10YB_{t-2}$ and NE in model D12 were replaced by $AU3MB_{t-2}$ and NE_{t-1}, respectively.

Models DM13 and DM15 recorded the highest out-of-sample hit ratio, which was reported as 62.8 per cent. Both DM13 and DM15 included SP500R, NE, $AU3MB_{t-2}$ and MADAUD$ as explanatory variables. The only difference was that variable NE in DM13 was replaced by the lag value (NE_{t-1}) in DM15. All discriminant models except DM2 (51.1 per cent hit ratio), DM4 (53.5 per cent) and DM8 (53.5 per cent) recorded over 55 per cent for their out-of-sample hit ratios.

Based on the average hit ratio, DM15 (which included SP500R, NE_{t-1}, $AU3MB_{t-2}$ and MADAUD$) outperformed the other 15 estimated models, with the highest average hit ratio of 71.35 per cent. The lowest average hit ratio was recorded as 64.7 per cent for DM2, which included two variables—SP500 and NE. The high in-sample and out-of-sample hit ratios of all predictor models indicated that Australian monthly excess stock signs can be successfully predicted using discriminant models. This finding aligns with Leung et al. (2000) and Ou and Wang (2009), who that found discriminant models are strong in predicting the directions of stock markets.

5.3 Logistic/Probit Regression Models for Predicting Monthly Excess Stock Return Signs

This study estimated both logistic and probit models using EViews and SPSS statistical software. These models explained the probability outcome of excess stock return signs by using explanatory variables, which were various economic, financial and international factors. Static binary logistic/probit models were estimated first, and then developed models (such as dynamic, autoregressive and dynamic autoregressive models) were tested for sign forecasting. All tested logistic and probit models were explained in Section 4.3. and Equations 4.2 to 4.7.

Before the models were estimated, highly correlated predictor variables were tested in separate models to avoid the multicollinearity effect. Validity tests for the estimated logistic/probit models were conducted using the LR statistic and probability of LR statistic (p-value). The p-value of the LR statistic measured the overall significance of the models, where the null hypotheses (H_0) = that all coefficients of the explanatory variables were equal to zero.

5.3.1 Estimated Logistic Models

Table 5.6 presents the 19 logistic models identified as statistically significant models for predicting Australian monthly excess stock return signs. The McFadden R-squared value (R^2_{Mcf}) displays the models' goodness-of-fit, whereby the LR statistic and p-value of the LR statistic indicate the validity of the estimated models. The logistic models were estimated using 269 months of data from January 1990 to May 2012.

Table 5.6: Estimated Logistic Models, January 1990 to May 2012

Logistic Models	n	LR Statistic	Prob.	R^2_{Mcf}	Rank
LM1) -0.005+37.386SP500R	269	92.802	0.000	0.250	16
LM 2) -0.224+38.400 SP500R- 4.848 NE	269	102.491	0.000	0.277	8
LM 3) -0.150+37.795SP500R-3.118NE_{t-1}	269	96.937	0.000	0.262	15
LM 4) 2.324+38.34 5SP500R-1.229AU10YB	269	98.111	0.000	0.264	14
LM 5) 2.303+38.42SP500R-1.215$AU10YB_{t-1}$	269	97.999	0.000	0.264	14
LM 6) 2.605+38.610SP500R-1.372 $AU10YB_{t-2}$	269	99.536	0.000	0.269	12
LM 7) 2.414+38.610SP500R-1.271$AU10YB_{t-3}$	269	98.768	0.000	0.266	13
LM 8) 3.931+39.282SP500R-1.728AUD10YB-37.544MADAUD$	269	104.119	0.000	0.281	7
LM 9)3.89+39.40SP500R-1.707$AU10YB_{t-1}$-37.49MADAUD$	269	103.949	0.000	0.281	7
LM 10) 4.231+39.640SP500R-1.867$AU10YB_{t-2}$-38.991MADAUD	269	105.921	0.000	0.285	5
LM 11)3.925+39.605SP500R-1.725$AU10YB_{t-3}$-37.329MADAUD$	269	104.684	0.000	0.282	6
LM 12)2.916+38.563SP500R-1.319AU3MB-32.423MADAUD$	269	100.947	0.000	0.272	9
LM 13) 2.689+38.500SP500R-1.119$AU3MB_{t-1}$-31.685MADAUD$	269	100.237	0.000	0.270	11
LM 14)2.699+38.525SP500R-1.206$AU3MB_{t-2}$-31.377MADAUD$	269	100.560	0.000	0.271	10
LM 15)2.697+38.585SP500R-1.205$AU3MB_{t-3}$-31.157MADAUD$	269	100.934	0.000	0.272	9
LM 16)2.993+39.885SP500R-1.341AU10YB-3.900NE-36.012MADAUD$	269	109.876	0.000	0.296	3
LM 17)2.884+39.946SP500R-1.283$AU10YB_{t-1}$-3.848NE-35.644MADAUD$	269	109.458	0.000	0.295	4
LM 18) 3.264+40.179SP500R-1.462$AU10YB_{t-2}$-3.673NE-37.332MADAUD$	269	110.893	0.000	0.299	1
LM 19)2.931+40.184SP500R-1.305$AU10YB_{t-3}$-3.762NE-35.604MADAUD$	269	109.885	0.000	0.297	2

Note: n = number of periods; Rank = rank based on R^2_{Mcf}.

Logistic models with R^2_{Mcf} values over 0.20 (20 per cent) are generally considered strong models for forecasting binary outcomes. Logistic model LM18, which included explanatory variables SP500R, NE, MADAUD$ and $AU10YB_{t-2}$, reported the highest R^2_{Mcf} value of 29.9 per cent. LM16, LM17 and

LM19—all similar models to LM18—demonstrated over 29 per cent of R^2_{Mcf}. All four models included SP500R, NE and MADAUD$ as predictor variables, with only one different variable—AU10YB. LM16 included AU10YB as a predictor, while this was replaced by the lagged value of AU10YB ($AU10YB_{t-1}$, $AU10YB_{t-2}$ and $AU10YB_{t-3}$) in LM17, LM18 and LM19, respectively.

LM10 included SP500R, $AU10YB_{t-2}$ and MADAUD$ as predictor variables, and also recorded a high R^2_{Mcf} value of 28.5 per cent. LM10 included the same variables in the best model (LM18), except MADAUD$. LM12, LM13, LM14 and LM15—all close models to LM10—still demonstrated a strong goodness-of-fit measure, with an R^2_{Mcf} value higher than 27.0 per cent. The variable AU10YB in LM10 was replaced by AU3MB or lag values of AU3MB in LM12, LM13, LM14 and LM115. LM1 which only included SP500R as a predictor variable also indicated strong goodness-of-fit, with a 25.0 per cent R^2_{Mcf} value.

5.3.2 Estimated Probit Models

Table 5.7 presents the 19 probit models identified as statistically significant models for predicting signs. The same diagnostic measures used in the logistical analysis—the McFadden R-squared value (R^2_{Mcf}), LR statistic and p-value of the LR statistic—were used to display the goodness-of-fit and validity of the probit models. The probit models were estimated using 269 months of data from January 1990 to May 2012.

Table 5.7: Estimated Probit Models, January 1990 to May 2012

Probit Models	n	LR Statistic	Prob.	R^2_{Mcf}	Rank
PM1) -0.003+21.068SP500R	269	90.835	0.000	0.250	16
PM 2) -0.129+21.357 SP500R- 2.836 NE	269	100.254	0.000	0.277	8
PM 3) -0.083+21.211SP500R-1.776NE_{t-1}	269	94.889	0.000	0.262	15
PM 4) 1.282+21.341SP500R-0.675AU10YB	269	95.653	0.000	0.264	14
PM 5) 1.280+21.394SP500R-0.672$AU10YB_{t-1}$	269	95.624	0.000	0.264	14
PM 6) 1.452+21.445SP500R-0.761 $AU10YB_{t-2}$	269	97.096	0.000	0.269	12
PM 7) 1.330+21.422SP500R-0.697$AU10YB_{t-3}$	269	96.263	0.000	0.266	13
PM 8) 2.198+21.597SP500R-0.959AUD10YB-20.994MADAUD$	269	101.251	0.000	0.281	7
PM 9)2.183+21.672P500R-0.949$AU10YB_{t-1}$-20.986MADAUD$	269	101.149	0.000	0.281	7
PM 10) 2.377+21.741SP500R-1.040$AU10YB_{t-2}$-21.927MADAUD	269	103.053	0.000	0.285	5
PM 11)2.187+21.710SP500R-0.949$AU10YB_{t-3}$-20.961MADAUD$	269	101.748	0.000	0.282	6
PM 12)1.477+21.077SP500R-0.651AU3MB-17.552MADAUD$	269	97.526	0.000	0.272	9
PM 13) 1.364+21.083SP500R-0.590$AU3MB_{t-1}$-17.173MADAUD$	269	96.945	0.000	0.270	11
PM 14)1.3778+21.091SP500R-0.598$AU3MB_{t-2}$-17.092MADAUD$	269	97.285	0.000	0.271	10
PM 15)1.394+21.130SP500R-0.606$AU3MB_{t-3}$-17.062MADAUD$	269	97.651	0.000	0.272	9
PM 16)1.681+21.793SP500R-0.752AU10YB-2.302NE-19.744MADAUD$	269	107.052	0.000	0.296	3
PM 17)1.627+21.852SP500R-0.724$AU10YB_{t-1}$-2.275NE-19.576MADAUD$	269	106.728	0.000	0.295	4
PM 18) 1.840+21.927SP500R-0.822$AU10YB_{t-2}$-2.175NE-20.599MADAUD$	269	108.111	0.000	0.299	1
PM 19)1.631+21.921SP500R-0.723$AU10YB_{t-3}$-2.225NE-19.566MADAUD$	269	107.021	0.000	0.297	2

Note: n = number of periods; Rank = rank based on R^2_{Mcf}.

Similar to logistic models, probit models with R^2_{Mcf} values over 0.20 (20 per cent) are generally considered strong models for forecasting binary outcomes. The estimated logistic models demonstrated very similar diagnostic measurements to the probit models when the same variables were used. The logistic and probit models reported only small differences in intercepts and coefficient values, as reported in Tables 5.6 and 5.7. The probit model PM18 recorded the highest R^2_{Mcf} of 29.9 per cent. PM18 included the explanatory variables SP500R, NE, $AU10YB_{t-2}$ and MADAUD$, which were the same variables in the best logistic model LM18. PM16, PM17 and PM19 included variables SP500R, NE, MADAUD$ and AU10YB or lag values of AU10YB (AU10YB, $AU10YB_{t-1}$ and $AU10YB_{t-3}$, respectively), and demonstrated a high level of goodness-of-fit (R^2_{Mcf} > 28.5 per cent) that was very similar to the goodness-of-fit levels in logistic models LM16, LM17 and LM19, with the same predictive variables. The lowest R^2_{Mcf} reported was 24.5 per cent, which was still well over the 20 per cent mark. This result was from PM1, which only included SP500R as the predictor variable.

5.3.3 Dynamic, Autoregressive and Dynamic Autoregressive Models

After the static models were identified, the dynamic models that included the lagged value of the return indicator (I_{t-1}) as a predictor variable were tested for sign predictability. However, none of the dynamic models showed any statistical significance for predicting ASX monthly signs. The results were the same for the autoregressive models that included the lagged value of the binary response model (π_{t-1}) as a predictor variable. Moreover, the dynamic autoregressive model that included both I_{t-1} and π_{t-1} as predictor variables was tested, and did not indicate any significance for sign prediction.

5.3.4 Identifying Key Determinants of ASX Monthly Excess Stock Returns Based on Logistic and Probit Analysis

Both the logistic and probit models indicated predictive powers of several explanatory variables selected as determinants in this study. SP500R, NE, AU10YB and the lagged values of AU10YB ($AU10YB_{t-1}$, $AU10YB_{t-2}$ and $AU10YB_{t-3}$) were identified as significant predictors. AU3MB and its lagged values ($AU3MB_{t-1}$, $AU3MBt_{-2}$ and $AU3MB_{t-3}$) were also significant in predicting signs. Due to a high correlation between AU10YB and AU3MBt, the two variables were tested separately in logistic/probit models as well. MADAUD$ was also identified as a predictor variable of ASX monthly excess stock return signs.

However, the forecasting accuracy of the models varied with a different combination of these variables used in the binary logistic and probit models. SP500R was highlighted as the most powerful predictor, which was proven by the higher R^2_{Mcf} values in both the logistic model LM1 (25 per cent) and probit model PM1 (24.5 per cent), which used only SP500R as the predictor variable. SP500R was also significant in all tested logistic and probit models, along with other significant variables.

Above discussed findings of the current study are consistent with previous studies in Australia (Di Lorio & Faff 2000; Jain et al. 2011; Kazi 2009; Kearney & Daly 1998), which found significant effects of macroeconomic variables on Australian stock market returns. Table 5.8 reports the statistical significance of the predictor variables considered in the probit and logistic analyses.

Table 5.8: Statistical Significance of Explanatory Variables in Probit and Logistic Analysis

Explanatory Variables	Statistical Significance	Explanatory Variables	Statistical Significance
AU3MB	*Significant*	NE	*Significant*
$AU3MB_{t-1}$	*Significant*	Ne_{t-1}	*Significant*
$AU3MB_{t-2}$	*Significant*	OIL & Lags	Insignificant
$AU3MB_{t-3}$	*Significant*	DIV & Lags	Insignificant
AU10YB	*Significant*	PE & Lags	Insignificant
$AU10YB_{t-1}$	*Significant*	OECD & Lags	Insignificant
$AU10YB_{t-2}$	*Significant*	AUTS & Lags	Insignificant
$AU10YB_{t-3}$	*Significant*	REC & Lags	Insignificant
US3MB & Lags	Insignificant	MADASXLR & Lags	Insignificant
US10YB & Lags	Insignificant	SDASXLR & Lags	Insignificant
USTS & Lags	Insignificant	$ASXLR^2$ & Lags	Insignificant
FDAU10YB & Lags	Insignificant	MADSP500R & Lags	Insignificant
FDUS10YB & Lags	Insignificant	SDSP500R & Lags	Insignificant
SP500R	*Significant*	$SP500R^2$ & Lags	Insignificant
M3 & Lags	Insignificant	MADMSCIRL & Lags	Insignificant
PDWE & Lags	Insignificant	SDMSCIRL & Lags	Insignificant
RS & Lag values	Insignificant	$MSCIRL^2$ & Lags	Insignificant
MSCIR & Lags	Insignificant	MAD$AUD	Significant
EMP & Lags	Insignificant	SD$AUD & Lags	Insignificant
CP & Lags	Insignificant	MADRENAUD & Lags	Insignificant
US$ & Lags	Insignificant	SDRENAUD & Lags	Insignificant
CREN & Lags	Insignificant		

5.3.5 Forecasting Accuracy of Logistic/Probit Models Based on Classification Results

Table 5.9 shows both the in-sample and out-of-sample classification results of the estimated logistic models. The classification results could not be generated for the probit models due to the unavailability of a method or tool to generate results in SPSS and EViews. However, considering the similar diagnostic measurements of both the logistic and probit models, it could be reasonably assumed that forecasting accuracy would be the same when the explanatory variables were the same. This also aligns with a previous study in which Hagle and Mitchell (1992) identified a very similar goodness-of-fit measure in both logistic and probit models.

The in-sample period for the estimated models consisted of 269 months from January 1990 to May 2012, and the out-of-sample period was 232 months from June 2012 to December 2015. Table 5.9 shows the classification results obtained for each logistic model.

Table 5.9: Classification Results of Logistic Models

Logistic Models	R^2	In Sample	Out of Sample	Average	Rank
LM1) -0.005+37.386SP500R	0.390	77.700	58.100	67.900	5
LM 2) -0.224+38.400 SP500R- 4.848 NE	0.424	78.100	58.100	68.100	4
LM 3) -0.150+37.795SP500R-3.118NE_{t-1}	0.405	78.400	60.500	69.450	2
LM 4) 2.324+38.34 5SP500R-1.229AU10YB	0.409	79.600*[1]	53.500	66.550	6
LM 5) 2.303+38.42SP500R-1.215$AU10YB_{t-1}$	0.414	78.400	53.500	65.950	8
LM 6) 2.605+38.610SP500R-1.372 $AU10YB_{t-2}$	0.414	78.800	53.500	66.150	7
LM 7) 2.414+38.610SP500R-1.271$AU10YB_{t-3}$	0.411	79.200	55.800	67.500	6
LM 8) 3.931+39.282SP500R-1.728AUD10YB-37.544MADAUD$	0.429	79.600*[1]	58.100	68.850	3
LM 9)3.89+39.40SP500R-1.707$AU10YB_{t-1}$-37.49MADAUD$	0.429	79.200	58.100	68.650	3
LM 10) 4.231+39.640SP500R-1.867$AU10YB_{t-2}$-38.991MADAUD	0.435	79.200	58.100	68.650	3
LM 11)3.925+39.605SP500R-1.725$AU10YB_{t-3}$-37.329MADAUD$	0.431	79.200	60.500	68.850	3
LM 12)2.916+38.563SP500R-1.319AU3MB-32.423MADAUD$	0.418	78.400	60.500	69.450	2
LM 13) 2.689+38.500SP500R-1.119$AU3MB_{t-1}$-31.685MADAUD$	0.416	78.800	60.500	69.650	2
LM 14)2.699+38.525SP500R-1.206$AU3MB_{t-2}$-31.377MADAUD$	0.417	78.800	60.500	69.650	2
LM 15)2.697+38.585SP500R-1.205$AU3MB_{t-3}$-31.157MADAUD$	0.418	78.800	60.500	69.650	2

LM 16)2.993+39.885SP500R-1.341AU10YB-3.900NE-36.012MADAUD$	0.448	79.200	62.800*1	71.000	1
LM 17)2.884+39.946SP500R-1.283AU10YB$_{t-1}$-3.848NE-35.644MADAUD$	0.447	79.200	62.800*1	71.000	1
LM 18) 3.264+40.179SP500R-1.462AU10YB$_{t-2}$-3.673NE-37.332MADAUD$	0.452	79.200	62.800*1	71.000	1
LM 19)2.931+40.184SP500R-1.305AU10YB$_{t-3}$-3.762NE-35.604MADAUD$	0.448	79.200	62.800*1	71.000	1

Note: * rank; R^2 = Nagelkerke R^2; Rank = rank based on average hit ratio.

The selected 19 logistic models reported impressive in-sample performance, where the lowest reported in-sample hit ratio was 77.7 per cent for logistic model LM1, which only included SP500R as the explanatory variable. Based on the in-sample predictive performances, LM4 and LM8 recorded the highest forecasting accuracy of 79.6 per cent. Logistic model LM4 included two explanatory variables (SP500R and AU10YB), whereas LM8 included SP500R, AU10YB and MADAUD$, which was an extended model of LM4.

Based on the out-of-sample forecasting accuracy, 10 logistic models recorded a hit ratio of over 60 per cent.LM16, LM17, LM18 and LM19 included SP500R, NE, MADAUD$ and AU10YB or the lagged values of AU10YB (AU10YB$_{t-1}$, AU10YB$_{t-2}$ and AU10YB$_{t-3}$), and demonstrated a high out-of-sample forecasting ratio of 62.8 per cent and outperformed the other models. The minimum recorded hit ratio was 53.5 per cent by LM4.

In terms of the average forecasting accuracy (both in-sample and out-of-sample), logistic models LM16, LM17, LM18 and LM19 recorded the same highest average hit ratio of 71.0 per cent. LM12, LM13, LM14 and LM15 showed the same second-highest average hit ratio of 69.7 per cent. LM12, LM13, LM14 and LM15 included independent variables SP500R, MADAUD$ and AU3MB or lagged values of AU3MB (AU3MB$_{t-1}$, AU3MB$_{t-2}$ and AU3MB$_{t-3}$).

All logistic models recorded over a 65 per cent average forecasting accuracy. The minimum recorded was 65.9 per cent by LM5, which had only SP500R and AU10YBt_{-1} as predictor variables. This indicated that the logistic models can be successfully used to predict Australian stock returns. This finding supports the findings of Leung et al. (2000) and Hong and Chung (2003) that logistic models have strong predictive power for stock return signs.

5.4 Comparison of Binary Models

Upon identifying the binary models based on the analysis explained above, it was interesting to compare the estimated binary regression models and see which models gave the best results for forecasting Australian monthly excess stock return signs. However, due to the limitations of producing the classification results of probit models using SPSS and EViews, this study did not compare the forecasting results of probit models with logistic or discriminant models. It could be reasonably assumed that the forecasting results comparison for the probit models would be very similar to the logistic and discriminant models' comparison, as the goodness-of-fitness measures of the logistic and probit models were very similar.

For the comparison, the best predictive models were selected based on the CC^2 values of the discriminant models and McFadden R-squared values of the logistic models. DM1 and LM1 which only have predictor variable S&P500R also considered for the comparison in addition to the best models selected based goodness of fit measures. Table 5.10 and Table 5.11 presents the best estimated models and their in-sample and out-of-sample forecasting results.

Table 5.10: Best Discriminant Models

Estimated Discriminant Models	CC^2	In-sample Hit Ratio	Out-of-sample Hit Ratio	Average Hit Ratio
DM1) -0.130+26.626 SP500R	0.281	77.3	60.5	68.90
DM6) 1.232+25.316 SP500R-2.799 NE-0.776 $AU10YB_{t-2}$	0.314	80.3	55.8	68.05
DM7) 0.484+25.118 SP500R-3.101 NE-0.410 $AU3MB_{t-2}$	0.307	78.4	60.5	69.45
DM12) 1.722+24.836 SP500R- 2.555NE-0.934 $AU10YB_{t-2}$-9.286 MADAUD$	0.317	79.9	58.1	69.00
DM13) 0.669+24.845 SP500R- 3.002NE-0.460 $AU3MB_{t-2}$-4.787 MADAUD$	0.308	78.8	62.8	70.80
DM14) 2.020+25.352 SP500R- 1.5NE_{t-1}-1.058 $AU10YB_{t-2}$-10.611 MADAUD$	0.309	78.4	58.1	68.25
DM15) 0.902+25.423 SP500R- 2.018NE_{t-1}-0.561 $AU3MB_{t-2}$-5.638 MADAUD$	0.298	79.90	62.8	71.35

Table 5.11 presents the best estimated logistic models and their in-sample and out-of-sample forecasting results.

Table 5.11: Best Logistic Models

Logistic Models	R^2Mcf	In-sample Hit Ratio	Out-of-sample Hit Ratio	Average Hit Ratio
LM1) -0.005+37.386SP500R	0.250	77.7	58.1	67.9
LM10) 4.231+39.640SP500R-1.867$AU10YB_{t-2}$-38.991MADAUD	0.285	79.2	58.1	68.65
LM16)2.993+39.885SP500R-1.341AU10YB-3.900NE-36.012MADAUD$	0.296	79.2	62.8	71.00
LM17)2.884+39.946SP500R-1.283$AU10YB_{t-1}$-3.848NE-35.644MADAUD$	0.295	79.2	62.8	71.00
LM18) 3.264+40.179SP500R-1.462$AU10YB_{t-2}$-3.673NE-37.332MADAUD$	0.299	79.2	62.8	71.00
LM19)2.931+40.184SP500R-1.305$AU10YB_{t-3}$-3.762NE-35.604MADAUD$	0.297	79.2	62.8	71.00

Model LM18 was recorded as the best logistic model for sign predictions based on the highest R^2Mcf value and average forecasting accuracy. Model DM12 was the best discriminant model based on CC^2. Both LM18 and DM12 had the same explanatory variables of SP500R, NE, $AU10YB_{t-2}$ and MADAUD$, which indicated that these four explanatory variables had the best forecasting power for monthly Australian excess stock return signs. LM18 and DM12 recorded very close forecasting performance, with the in-sample accuracy recorded as 79.2 per cent for LM18 and 79.9 per cent for DM12. LM18 recorded an out-of-sample hit ratio of 62.8 per cent, while DM12 had an out-of-sample hit ratio of 58.1 per cent.

In discriminant analysis, $AU3MB_{t-2}$ could be used to replace $AU10YB_{t-2}$ when three other significant variables—SP500R, NE, and MADAUD—were included in the model ($AU10YB_{t-2}$ in DM14 replaced by $AU3MB_{t-2}$ in DM15). When long-term interest rates were replaced by short-term interest rates in DM15, the forecasting performance only changed slightly compared to DM14, with the in-sample hit ratio changing to 78.9 per cent from 78.40 per cent, and the out-of-sample changing to 62.8 per cent from 58.1 per cent. However, AU3MB or lags did not indicate statistical significance in the logistic regression analysis if combined with all three other explanatory variables—SP500R, NE and MADAUD.

In the discriminant analysis, the lag value of NE ($NE_{(t-1)}$) could be used to replace NE when the other three variables—SP500R, MADAUD$ and (AU10YB)/(AU3MB)—remained the same. DM12 had explanatory variables SP500R, MADAUD$, $AU10YB_{t-2}$ and NE, where NE was replaced by $NE_{(t-1)}$ in model DM14. Between these two models, only a slight difference was identified in forecasting accuracy, with the in-sample hit ratio recorded as 78.4 per cent in DM14 and 79.9 per cent in the best model DM12, and the out-of-sample forecasting accuracy recorded as 58.1 per cent in both models. However, the lag values of NE were not statistically significant when used with the three other explanatory variables—SP500R, MADAUD and AU10YB/AU3MB—in the logistic models. Both the discriminate and logistic regression analyses indicated relatively high statistical significance and predictive power of SP500R as a single predictor, compared to the other variables. Both DM1 and LM1 only had SP500R as the explanatory variable and still reported a high average forecasting accuracy of 68.9 and 67.9 per cent, respectively.

5.5 Chapter Summary

This chapter discussed the results of the estimated binary predictive models. The best binary models for predicting Australian monthly stock returns were identified based on goodness-of-fit measures and forecasting accuracy. The determinants of the monthly direction of stock returns were also identified based on the diagnostic tests discussed in Chapter 4. After testing various combinations of predictor variables in binary models, this chapter identified and discussed significant models. Fifteen discriminant models, 19 logit models and 19 probit models were verified as statistically significant. While various dependent variables were tested as determinants of ASX sign predictions, only five variables and their lag values—SP500R, AU10YB, AU3MB, NE and MADAUD$—were identified as key determinant of monthly sign predictions. The next chapter summarises and concludes the major findings of this chapter.

Chapter 6: Summary and Conclusion

6.1 Introduction

This thesis investigated the predictability of Australian monthly excess stock return directions, and the determinants of these monthly directions. To achieve this aim, this thesis contained six chapters. Chapter 2 discussed the literature relating to stock market predictability and the factors affecting stock directional changes. Chapter 3 reviewed the possible determinants of Australian stock return directions. This was followed by Chapter 4, which presented methodology employed by the study to predict excess stock directions and identify determinants. Chapter 5 detailed the estimated models and statistical results, and this final chapter provides a summary of the study and a conclusion. This chapter contains six main sections. The first section presents an overview of the study, while the second section summarises the study findings. The third section presents the implications of the study, while the fourth section discusses the study limitations. The fifth section presents suggestions for future research, while the final section concludes this chapter.

6.2 Study Overview

The predictability of stock market returns is a focal topic discussed by many researchers. A correct prediction of stock returns or directions helps investors successfully achieve their investment goals. Breen et al. (1989), Hong and Chung (2003) and Nyberg (2008) demonstrated that, to some extent, stock returns are predictable. In the literature, researchers have used classification models—especially binary classification models—as a successful tool for predicting global stock market directions. However, little attention has been devoted in the literature to predicting Australian stock directions using binary models. Against this background, this study focused on the ability to predict Australian excess stock returns. The main objective of this study was to predict monthly excess stock return directions using binary models, and then identify the key determinants of Australian excess stock return directions. The findings of this study will contribute to the literature on stock market predictability, particularly regarding predictive models and the determinants of Australian short-term stock directions.

This study investigated Australian monthly excess stock returns from January 1990 to December 2015. Three binary models—discriminant, logistic and probit models—were considered to forecast monthly excess stock return signs and identify the determinants. In addition to benchmark static models, developed binary models—such as dynamic logit/probit, autoregressive and dynamic autoregressive models—were also tested for sign prediction. In the logistic and probit analyses, various diagnostic tests were performed to identify predictability. This study undertook tests for multicollinearity, p-values of the explanatory variables, LR statistics, p-values of the LR statistics and McFadden R-squared values to test the model significance and identify key determinants. In the discriminant analysis, the multicollinearity test, ANOVA, Wilks lambda test and squared canonical correlation values were used to measure the models' goodness-of-fit. A hit ratio was used to assess the forecasting accuracy of statistically significant binary models for both the in-sample and out-of-sample.

This study considered the past volatility of stock returns, economic variables, financial variables and international factors as explanatory variables to predict Australian excess stock return signs. These variables were selected based on their relationship with Australian stock returns, which were identified through a review of past studies and theories.

6.3 Summary of Findings

The major and specific aims of the study stated in Chapter 1 (Section 1.3) have been accomplished, and the results presented in Chapter 5. This section summarise the study findings under two main areas: (1) use of binary models to predict Australian monthly excess stock return directions and (2) determinants of Australian monthly excess stock return directions.

6.3.1 Use of Binary Models to Predict Australian Monthly Excess Stock Return Directions

The statistical results of the estimated logistic, probit and discriminant models showed that Australian monthly excess stock return signs can be successfully predicted using all three binary models. In addition, this study found that the dynamic logistic/probit, autoregressive and dynamic autoregressive models were not effective in predicting Australian excess stock return signs, yet only the benchmark static models were statistically significant. In terms of forecasting accuracy, both the logistic and discriminant models recorded impressive accuracy. The hit ratio (classification results) of the best logistic model slightly outperformed the best discriminant model, with a recorded average hit ratio of 69.0 per cent and 71.0 per cent, respectively. The results also confirmed that all three types of binary models explored in the study have similar predictive power and identified the same predictor variables as the determinants of Australian stock return signs.

6.3.2 Determinants of Australian Monthly Excess Stock Return Directions

This study found that S&P500 monthly returns (SP500R) were the most important determinant of Australian excess stock return monthly directions, based on the results of all estimated models. In addition, this study found that both monthly Australian long-term interest rates (AU10YB) and short-term interest rates (AU3MB) were key determinants, while the lagged values of interest rates ($AU10YB_{t-1}$, $AU10YB_{t-2}$, $AU10YB_{t-3}$, $AU3MB_{t-1}$, $AU3MB_{t-2}$ and $AU3MB_{t-3}$) also indicated predictive power for Australian share returns. Further, the monthly NE and first period lag value (NE_{t-1}) were significant in predicting Australian stock return signs. The exchange rate volatility between Australia and the US, measured by MAD (MADAUD$), was also identified as a determinant of ASX monthly signs.

The predictive models that included the explanatory variables of SP500R alongside NE, $AU10YB_{t-2}$ and MADAUD$ showed the best goodness-of-fit measures and forecasting results. This indicated that these four explanatory variables together had the best forecasting power for monthly Australian excess stock return signs. Further, the results of this study confirmed that various other economic, financial and international variables tested using three different binary models (except SP500R, AU10YB, AU3MB, NE and MADAUD$) did not have statistical significance in predicting Australian monthly excess stock return signs. In addition, three volatility measures—SD, MAD and U^2—of lagged values of ASX200 were not significant as predictive variables. Also, the statistical results confirmed that the US binary recession indicator and OECD composite leading indicator were not useful in predicting Australian monthly excess stock return signs.

6.4 Study Implications

The findings of this study could be useful for various stakeholders, including investors, fund managers, security analysts, economists, security exchanges, researchers and academics. The benefits of the study for different groups are further discussed below.

First, this study confirmed that Australian monthly excess stock return signs are predictable using binary models. Therefore, this study is useful to examine the timing of investments in the Australian stock market in the short term. The ability to predict monthly excess stock return signs means that investors can make more effective equity investment decisions to achieve their investment goals.

Second, the statistical results of the logistic, probit and discriminant models demonstrated very similar diagnostic measurements and classification results. In addition, all three models identified the same key determinants of monthly stock return signs. This indicates that security analysts and researchers can successfully use any of these three binary models to predict monthly excess stock return signs. However, the dynamic, autoregressive and dynamic autoregressive models did not show significant sign prediction power. This means that developed binary models are not very effective in predicting Australian monthly stock signs.

Third, this study found a clear relationship between US stock market monthly return changes (S&P 500) and Australian excess stock return signs. This means that investors and fund managers can attain an indication of Australian short-term excess stock return directions by studying US monthly stock return movements. Further, this finding indicates both short- and long-term interest rates as key factors affecting Australian monthly excess stock return signs. This shows that investors and fund managers should focus on the country's interest rate movements, alongside other determinants, when formulating short-term investment strategies.

Fourth, the results indicated that monthly NE (difference between exports and imports) and exchange rate volatility between the USD and AUD (measured by MAD) are key indicators that can be used to understand the Australian monthly directional changes of excess stock returns. Therefore, investors and fund managers can emphasise changes in the NE and exchange rate volatility between the USD and AUD as indicators of short-term stock movements.

Fifth, this study suggests that the leading economic indicators used to measure overall economic activity (such as the OECD indicator and US recession indicator) do not have predictive power for Australian monthly stock market directions. This also supports present study's finding that only a few macroeconomic variables significantly influence Australian stock returns, and not many macroeconomic factors or the overall economic activity.

Finally, the study findings also indicate that fundamental variables are more effective for predicting Australian monthly excess stock return signs than using the past volatility of ASX returns as a predictor variable. Therefore, fundamental analysis of excess stock returns is more useful than technical analysis for investors and other stakeholders to forecast directional changes in Australian share returns.

6.5 Study Limitations

One study limitation was the unavailability of monthly data for some important predictor variables. For example, GDP data were only available in quarterly intervals and subsequently could not be used to forecast monthly stock return movements. However, this study used compatible variables to represent important economic variables when monthly data were unavailable. To represent GDP, this study used monthly retail spending and private dwelling approvals as proxy variables. In addition, the bank-accepted bill rate was used as a proxy for the risk-free rate when estimating excess stock returns. This was due to the unavailability of monthly changes in treasury notes rates for the total sampling period considered. In this study, Australian stock returns were estimated based on monthly index changes, and dividends were not considered. This was mainly due to the complexity of adjusting the dividends announced by listed companies in each calendar month to stock returns. However, the share index–based return calculation has been widely used by past studies and is consistent with prior research on stock market performance.

In addition, this study used the ASX 200 share index to represent Australian stock returns and the ASX 200 may not represent total stock market activity, which is another study limitation. However, both Australian benchmark stock indices (the ASX 200 and All Ordinaries index) have very similar movements, and the ASX 200 represents a higher portion of the actual Australian stock market. This is the same for the S&P 500 index, which was used as a predictor variable and may not represent total stock market activity in the US. However, the S&P 500 index has been used by many researchers as a benchmark index of the US, and represents a significant portion of actual US stock market activity.

This study used only real historical monthly data for explanatory variables, rather than expected values. Therefore, the unavailability of expected values for explanatory variables limited the exposure of the study and limited its ability to assess the forecasting accuracy of estimated models. In addition, in the Australian stock market, separate stock indices are available for different business sectors; however, this study did not forecast monthly return signs for individual sectors. If models were estimated for each business sector, the outcomes would be different and the forecasting performance and determinants of return signs could also be different.

The unavailability of an option to estimate the classification results (hit ratio) of the probit regression models in both the SPSS and EViews statistical programs was another limitation of this study. However, it can be reasonably assumed that the hit ratios were very similar between the probit and logistic models, considering the very close statistical measurements of both estimated models. The very similar forecasting accuracy of the probit and logistic models was also consistent with prior research in this field.

6.6 Suggestions for Future Research

This study considered volatility and various macroeconomic, financial and international factors for predicting monthly Australian excess stock return signs. Future research could test how various other factors affect monthly stock returns. For example, political events, weather, natural disasters, crime or war activities, disease or new technologies could be significant factors affecting the short-term movement of Australian stocks. Therefore, these variables could be tested as explanatory variables of binary models in predicting directional changes in Australian stock returns.

Future research could also construct a composite leading indicator using various individual factors that affect stock returns to determine how successfully this indicator can be used to forecast monthly excess stock directions, compared to the significant predictors identified in this study.

In the current study, only the Australian stock market return signs were forecasted using binary models. However, other Australian investment market directions can be predicted using binary models. Therefore, future research could be conducted on other investment markets, such as the Australian Forex market, futures markets and bonds markets.

This study only focused on the monthly movements of Australian excess stock returns. However, future research could forecast excess stock returns at different time intervals, such as three-month, six-month and yearly intervals. This type of analysis would provide more information of the medium- to long-term directional changes of Australian stock returns. In addition, it will be important to determine which predictor variables are significant in each time interval to forecast return signs.

6.7 Conclusion

This study considered the predictability of Australian monthly excess stock return signs with binary models. Various diagnostic tests—included the p-values of explanatory variables, p-values of LR statistics, McFadden R-squared values and hit ratios of predictive models—confirmed that both logistic and probit models can be used successfully to predict Australian monthly stock signs. The discriminant models also demonstrated good predictive power, with hit ratios, ANOVA tests, Wilks lambda tests and CC^2 values confirming their predictive ability for stock signs. Although dynamic, autoregressive and dynamic autoregressive models were tested for sign forecasting, only static probit and logistic models were found to be useful in predicting Australian stock signs. This study also found that discriminant, logistic and probit models had very similar stock sign predictive power, with both the in-sample and out-of-sample results being very similar.

The findings confirmed that the S&P 500 index monthly returns outperformed the other explanatory variables considered in this study. The Australian long-term interest rate (10-year bond rate), Australian short-term interest rate (three-month bank-accepted bill rate), monthly NEs and volatility of the AUD and USD exchange rate (measured by MAD) were the other statistically significant variables identified as determinants of Australian monthly stock return directions. While various other economic, financial and international factors were considered as possible determinants of Australian stock signs—including a US binary recession indicator and OECD composite leading indicator—they did not show significant predictive power.

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Appendices

Appendix 1: Results Tables of Discriminant Models (DM1 to DM15)

DM1

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.390[a]	100.0	100.0	.530

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.719	87.848	1	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	1.000

Structure Matrix

	Function
	1
SP500R	1.000

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	26.626
(Constant)	-.130

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	87	35	122
			1	26	121	147
		%	0	71.3	28.7	100.0
			1	17.7	82.3	100.0
Cases Not Selected	Original	Count	0	8	11	19
			1	6	18	24
		%	0	42.1	57.9	100.0
			1	25.0	75.0	100.0

a. 77.3% of selected original grouped cases correctly classified.

b. 60.5% of unselected original grouped cases correctly classified.

DM2

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.436[a]	100.0	100.0	.551

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.696	96.269	2	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.951
NE	-.323

Structure Matrix

	Function
	1
SP500R	.946
NE	-.309

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.327
NE	-3.377
(Constant)	-.258

Classification Results[a,b]

				Predicted Group Membership		
			ASX200R	0	1	Total
Cases Selected	Original	Count	0	93	29	122
			1	29	118	147
		%	0	76.2	23.8	100.0
			1	19.7	80.3	100.0
Cases Not Selected	Original	Count	0	7	12	19
			1	6	18	24
		%	0	36.8	63.2	100.0
			1	25.0	75.0	100.0

a. 78.4% of selected original grouped cases correctly classified.

b. 58.1% of unselected original grouped cases correctly classified.

DM3

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
AU3MBt-2	.985	3.939	1	267	.048

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.405[a]	100.0	100.0	.537

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Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.712	90.539	2	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.982
AU3MBt-2	-.192

Structure Matrix

	Function
	1
SP500R	.981
AU3MBt-2	-.191

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	26.137
AU3MBt-2	-.610
(Constant)	.958

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	88	34	122
			1	25	122	147
		%	0	72.1	27.9	100.0
			1	17.0	83.0	100.0
Cases Not Selected	Original	Count	0	6	13	19
			1	3	21	24
		%	0	31.6	68.4	100.0
			1	12.5	87.5	100.0

a. 78.1% of selected original grouped cases correctly classified.

b. 62.8% of unselected original grouped cases correctly classified.

DM4

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
AU10YBt-2	.985	4.070	1	267	.045

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.426[a]	100.0	100.0	.546

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.701	94.359	2	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.987
AU10YBt-2	-.290

Structure Matrix

	Function
	1
SP500R	.958
AU10YBt-2	-.189

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	26.281
AU10YBt-2	-1.017
(Constant)	1.796

Classification Results[a,b]

				Predicted Group Membership		
			ASX200R	0	1	Total
Cases Selected	Original	Count	0	92	30	122
			1	26	121	147
		%	0	75.4	24.6	100.0
			1	17.7	82.3	100.0
Cases Not Selected	Original	Count	0	2	17	19
			1	3	21	24
		%	0	10.5	89.5	100.0
			1	12.5	87.5	100.0

a. 79.2% of selected original grouped cases correctly classified.

b. 53.5% of unselected original grouped cases correctly classified.

DM5

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.392[a]	100.0	100.0	.531

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.718	87.966	2	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.990
MADAUD$	-.062

Structure Matrix

	Function
	1
SP500R	.998
MADAUD$	-.192

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	26.359
MADAUD$	-4.643
(Constant)	-.039

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	88	34	122
			1	23	124	147
		%	0	72.1	27.9	100.0
			1	15.6	84.4	100.0
Cases Not Selected	Original	Count	0	8	11	19
			1	6	18	24
		%	0	42.1	57.9	100.0
			1	25.0	75.0	100.0

a. 78.8% of selected original grouped cases correctly classified.

b. 60.5% of unselected original grouped cases correctly classified.

DM6

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001
AU10YBt-2	.985	4.070	1	267	.045

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.457[a]	100.0	100.0	.560

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.686	99.948	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.951
NE	-.268
AU10YBt-2	-.221

Structure Matrix

	Function
	1
SP500R	.924
NE	-.302
AU10YBt-2	-.183

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.316
NE	-2.799
AU10YBt-2	-.776
(Constant)	1.232

Classification Results[a,b]

			ASX200R	Predicted Group Membership		Total
				0	1	
Cases Selected	Original	Count	0	92	30	122
			1	23	124	147
		%	0	75.4	24.6	100.0
			1	15.6	84.4	100.0
Cases Not Selected	Original	Count	0	3	16	19
			1	3	21	24
		%	0	15.8	84.2	100.0
			1	12.5	87.5	100.0

a. 80.3% of selected original grouped cases correctly classified.

b. 55.8% of unselected original grouped cases correctly classified.

DM7

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001
AU3MBt-2	.985	3.939	1	267	.048

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.443[a]	100.0	100.0	.554

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.693	97.411	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.943
NE	-.297
AU3MBt-2	-.129

Structure Matrix

	Function
	1
SP500R	.939
NE	-.306
AU3MBt-2	-.182

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.118
NE	-3.101
AU3MBt-2	-.410
(Constant)	.484

Classification Results[a,b]

			ASX200R	Predicted Group Membership		Total
				0	1	
Cases Selected	Original	Count	0	93	29	122
			1	29	118	147
		%	0	76.2	23.8	100.0
			1	19.7	80.3	100.0
Cases Not Selected	Original	Count	0	6	13	19
			1	4	20	24
		%	0	31.6	68.4	100.0
			1	16.7	83.3	100.0

a. 78.4% of selected original grouped cases correctly classified.

b. 60.5% of unselected original grouped cases correctly classified.

DM8

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NEt-1	.984	4.429	1	267	.036
AU10YBt-2	.985	4.070	1	267	.045

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.439[a]	100.0	100.0	.552

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.695	96.642	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.974
NEt-1	-.177
AU10YBt-2	-.250

Structure Matrix

	Function
	1
SP500R	.943
NEt-1	-.194
AU10YBt-2	-.186

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.945
NEt-1	-1.829
AU10YBt-2	-.879
(Constant)	1.462

Unstandardized coefficients

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	92	30	122
			1	28	119	147
		%	0	75.4	24.6	100.0
			1	19.0	81.0	100.0
Cases Not Selected	Original	Count	0	3	16	19
			1	4	20	24
		%	0	15.8	84.2	100.0
			1	16.7	83.3	100.0

a. 78.4% of selected original grouped cases correctly classified.

b. 53.5% of unselected original grouped cases correctly classified.

DM9

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NEt-1	.984	4.429	1	267	.036
AU3MBt-2	.985	3.939	1	267	.048

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.423[a]	100.0	100.0	.545

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.703	93.740	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.968
NEt-1	-.208
AU3MBt-2	-.159

Structure Matrix

	Function
	1
SP500R	.960
NEt-1	-.198
AU3MBt-2	-.187

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.762
NEt-1	-2.146
AU3MBt-2	-.504
(Constant)	.684

Classification Results[a,b]

			ASX200R	Predicted Group Membership		Total
				0	1	
Cases Selected	Original	Count	0	93	29	122
			1	27	120	147
		%	0	76.2	23.8	100.0
			1	18.4	81.6	100.0
Cases Not Selected	Original	Count	0	6	13	19
			1	4	20	24
		%	0	31.6	68.4	100.0
			1	16.7	83.3	100.0

a. 79.2% of selected original grouped cases correctly classified.

b. 60.5% of unselected original grouped cases correctly classified.

DM10

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.436[a]	100.0	100.0	.551

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.696	96.152	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.947
NE	-.321
MADAUD$	-.028

Structure Matrix

	Function
	1
SP500R	.946
NE	-.309
MADAUD$	-.182

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.217
NE	-3.348
MADAUD$	-2.129
(Constant)	-.215

Classification Results[a,b]

			ASX200R	Predicted Group Membership		Total
				0	1	
Cases Selected	Original	Count	0	93	29	122
			1	29	118	147
		%	0	76.2	23.8	100.0
			1	19.7	80.3	100.0
Cases Not Selected	Original	Count	0	7	12	19
			1	6	18	24
		%	0	36.8	63.2	100.0
			1	25.0	75.0	100.0

a. 78.4% of selected original grouped cases correctly classified.

b. 58.1% of unselected original grouped cases correctly classified.

DM11

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NEt-1	.984	4.429	1	267	.036
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.413[a]	100.0	100.0	.541

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.708	91.853	3	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.975
NEt-1	-.229
MADAUD$	-.032

Structure Matrix

	Function
	1
SP500R	.972
NEt-1	-.200
MADAUD$	-.187

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.973
NEt-1	-2.365
MADAUD$	-2.380
(Constant)	-.176

Unstandardized coefficients

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	90	32	122
			1	24	123	147
		%	0	73.8	26.2	100.0
			1	16.3	83.7	100.0
Cases Not Selected	Original	Count	0	8	11	19
			1	6	18	24
		%	0	42.1	57.9	100.0
			1	25.0	75.0	100.0

a. 79.2% of selected original grouped cases correctly classified.

b. 60.5% of unselected original grouped cases correctly classified.

DM12

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001
AU10YBt-2	.985	4.070	1	267	.045
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.463[a]	100.0	100.0	.563

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.683	100.846	4	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.933
NE	-.245
AU10YBt-2	-.266
MADAUD$	-.124

Structure Matrix

	Function
	1
SP500R	.918
NE	-.300
AU10YBt-2	-.181
MADAUD$	-.176

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	24.836
NE	-2.556
AU10YBt-2	-.934
MADAUD$	-9.286
(Constant)	1.722

Unstandardized coefficients

Classification Results[a,b]

				Predicted Group Membership		
			ASX200R	0	1	Total
Cases Selected	Original	Count	0	92	30	122
			1	24	123	147
		%	0	75.4	24.6	100.0
			1	16.3	83.7	100.0
Cases Not Selected	Original	Count	0	3	16	19
			1	2	22	24
		%	0	15.8	84.2	100.0
			1	8.3	91.7	100.0

a. 79.9% of selected original grouped cases correctly classified.

b. 58.1% of unselected original grouped cases correctly classified.

DM13

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NE	.960	11.102	1	267	.001
AU3MBt-2	.985	3.939	1	267	.048
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.445[a]	100.0	100.0	.555

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.692	97.532	4	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.933
NE	-.288
AU3MBt-2	-.145
MADAUD$	-.064

Structure Matrix

	Function
	1
SP500R	.937
NE	-.306
AU3MBt-2	-.182
MADAUD$	-.180

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	24.845
NE	-3.003
AU3MBt-2	-.459
MADAUD$	-4.786
(Constant)	.669

Unstandardized coefficients

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	94	28	122
			1	29	118	147
		%	0	77.0	23.0	100.0
			1	19.7	80.3	100.0
Cases Not Selected	Original	Count	0	6	13	19
			1	3	21	24
		%	0	31.6	68.4	100.0
			1	12.5	87.5	100.0

a. 78.8% of selected original grouped cases correctly classified.

b. 62.8% of unselected original grouped cases correctly classified.

DM14

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NEt-1	.984	4.429	1	267	.036
AU10YBt-2	.985	4.070	1	267	.045
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.447[a]	100.0	100.0	.556

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.691	97.831	4	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.952
NEt-1	-.148
AU10YBt-2	-.301
MADAUD$	-.142

Structure Matrix

	Function
	1
SP500R	.935
NEt-1	-.193
AU10YBt-2	-.185
MADAUD$	-.180

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.352
NEt-1	-1.528
AU10YBt-2	-1.058
MADAUD$	-10.611
(Constant)	2.020

Unstandardized coefficients

Classification Results[a,b]

				Predicted Group Membership		
			ASX200R	0	1	Total
Cases Selected	Original	Count	0	90	32	122
			1	26	121	147
		%	0	73.8	26.2	100.0
			1	17.7	82.3	100.0
Cases Not Selected	Original	Count	0	3	16	19
			1	2	22	24
		%	0	15.8	84.2	100.0
			1	8.3	91.7	100.0

a. 78.4% of selected original grouped cases correctly classified.

b. 58.1% of unselected original grouped cases correctly classified.

DM15

Tests of Equality of Group Means

	Wilks' Lambda	F	df1	df2	Sig.
SP500R	.719	104.254	1	267	.000
NEt-1	.984	4.429	1	267	.036
AU3MBt-2	.985	3.939	1	267	.048
MADAUD$	.986	3.851	1	267	.051

Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.426[a]	100.0	100.0	.546

a. First 1 canonical discriminant functions were used in the analysis.

Wilks' Lambda

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1	.701	93.971	4	.000

Standardized Canonical Discriminant Function Coefficients

	Function
	1
SP500R	.955
NEt-1	-.196
AU3MBt-2	-.177
MADAUD$	-.075

Structure Matrix

	Function
	1
SP500R	.958
NEt-1	-.197
AU3MBt-2	-.186
MADAUD$	-.184

Canonical Discriminant Function Coefficients

	Function
	1
SP500R	25.423
NEt-1	-2.018
AU3MBt-2	-.561
MADAUD$	-5.638
(Constant)	.902

Classification Results[a,b]

			ASX200R	Predicted Group Membership 0	1	Total
Cases Selected	Original	Count	0	93	29	122
			1	25	122	147
		%	0	76.2	23.8	100.0
			1	17.0	83.0	100.0
Cases Not Selected	Original	Count	0	6	13	19
			1	3	21	24
		%	0	31.6	68.4	100.0
			1	12.5	87.5	100.0

a. 79.9% of selected original grouped cases correctly classified.

b. 62.8% of unselected original grouped cases correctly classified.

Appendix 2: Results Tables of Logistic Models (LM1 to LM19)

<u>Results From SPSS</u>

LM1

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	277.784[a]	.292	.390

Classification Table[a]

	Observed		Predicted: Selected Cases[b] BASX 0	1	Percentage Correct	Unselected Cases[c,d] BASX 0	1	Percentage Correct
Step 1	BASX	0	83	39	68.0	2	4	33.3
		1	21	126	85.7	2	13	86.7
	Overall Percentage				77.7			71.4

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	37.386	5.097	53.802	1	.000	17243053279486780.000
	Constant	-.005	.150	.001	1	.971	.995

a. Variable(s) entered on step 1: SP500R.

LM2

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	268.096[a]	.317	.424

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	91	31	74.6	7	12	36.8
		1	28	119	81.0	6	18	75.0
	Overall Percentage				78.1			58.1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.400	5.284	52.817	1	.000	47537977330287936.000
	@NE	-4.848	1.593	9.261	1	.002	.008
	Constant	-.224	.170	1.746	1	.186	.799

a. Variable(s) entered on step 1: SP500R, @NE.

LM 3

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	273.649[a]	.303	.405

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	8	11	42.1
		1	23	124	84.4	6	18	75.0
	Overall Percentage				78.4			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	37.795	5.180	53.231	1	.000	25961909930299680.000
	NEt1	-3.118	1.551	4.040	1	.044	.044
	Constant	-.150	.168	.798	1	.372	.861

a. Variable(s) entered on step 1: SP500R, NEt1.

LM4

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	272.475[a]	.306	.409

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	89	33	73.0	2	17	10.5
		1	22	125	85.0	3	21	87.5
	Overall Percentage				79.6			53.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.345	5.203	54.303	1	.000	44971101855159568.000
	AU10YB	-1.229	.542	5.146	1	.023	.293
	Constant	2.324	1.037	5.022	1	.025	10.220

a. Variable(s) entered on step 1: SP500R, AU10YB.

LM5

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	272.587[a]	.305	.408

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	2	17	10.5
		1	23	124	84.4	3	21	87.5
	Overall Percentage				78.4			53.5

a. The cut value is .500

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.428	5.226	54.073	1	.000	48856458410769576.000
	AU10YBt1	-1.215	.541	5.044	1	.025	.297
	Constant	2.303	1.039	4.915	1	.027	10.005

a. Variable(s) entered on step 1: SP500R, AU10YBt1.

LM6

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.050[a]	.309	.414

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	88	34	72.1	2	17	10.5
		1	23	124	84.4	3	21	87.5
	Overall Percentage				78.8			53.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.610	5.259	53.907	1	.000	58611742101367024.000
	AU10YBt2	-1.372	.539	6.481	1	.011	.254
	Constant	2.605	1.036	6.317	1	.012	13.526

a. Variable(s) entered on step 1: SP500R, AU10YBt2.

LM7

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	271.818[a]	.307	.411

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	88	34	72.1	3	16	15.8
		1	22	125	85.0	3	21	87.5
	Overall Percentage				79.2			55.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.603	5.264	53.774	1	.000	58225484005114600.000
	AU10YBt3	-1.271	.529	5.782	1	.016	.281
	Constant	2.414	1.018	5.628	1	.018	11.182

a. Variable(s) entered on step 1: SP500R, AU10YBt3.

LM8

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	266.467[a]	.321	.429

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	90	32	73.8	3	16	15.8
		1	23	124	84.4	2	22	91.7
	Overall Percentage				79.6			58.1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.282	5.370	53.504	1	.000	114754246752561792.000
	AU10YB	-1.728	.591	8.546	1	.003	.178
	MADAUD$	-37.544	15.696	5.721	1	.017	.000
	Constant	3.931	1.257	9.783	1	.002	50.946

a. Variable(s) entered on step 1: SP500R, AU10YB, MADAUD$.

LM9

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	266.637[a]	.321	.429

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	90	32	73.8	3	16	15.8
		1	24	123	83.7	2	22	91.7
	Overall Percentage				79.2			58.1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.403	5.395	53.332	1	.000	129515228596018800.000
	AU10YBt1	-1.707	.588	8.413	1	.004	.181
	MADAUD$	-37.492	15.781	5.644	1	.018	.000
	Constant	3.897	1.256	9.631	1	.002	49.250

a. Variable(s) entered on step 1: SP500R, AU10YBt1, MADAUD$.

LM10

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	264.666[a]	.325	.435

Classification Table[a]

			Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
	Observed		0	1		0	1	
Step 1	ASX200R	0	89	33	73.0	3	16	15.8
		1	23	124	84.4	2	22	91.7
	Overall Percentage				79.2			58.1

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.640	5.441	53.074	1	.000	164265044841416000.000
	AU10YBt2	-1.867	.585	10.174	1	.001	.155
	MADAUD$	-38.991	15.851	6.051	1	.014	.000
	Constant	4.231	1.251	11.439	1	.001	68.808

a. Variable(s) entered on step 1: SP500R, AU10YBt2, MADAUD$.

LM11

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	265.902[a]	.322	.431

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	89	33	73.0	4	15	21.1
		1	23	124	84.4	2	22	91.7
	Overall Percentage				79.2			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.605	5.439	53.021	1	.000	158529016536995296.000
	AU10YBt3	-1.721	.570	9.109	1	.003	.179
	MADAUD$	-37.329	15.754	5.615	1	.018	.000
	Constant	3.925	1.220	10.359	1	.001	50.672

a. Variable(s) entered on step 1: SP500R, AU10YBt3, MADAUD$.

LM12

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	269.638[a]	.313	.418

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	4	15	21.1
		1	23	124	84.4	2	22	91.7
	Overall Percentage				78.4			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.562	5.315	52.639	1	.000	55906514192865008.000
	AU3MB	-1.320	.561	5.538	1	.019	.267
	MADAUD$	-32.424	15.361	4.455	1	.035	.000
	Constant	2.916	1.122	6.752	1	.009	18.466

a. Variable(s) entered on step 1: SP500R, AU3MB, MADAUD$.

LM13

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	270.350[a]	.311	.416

a. Estimation terminated at iteration number 6 because parameter estimates changed by less than .001.

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	4	15	21.1
		1	22	125	85.0	2	22	91.7
	Overall Percentage				78.8			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.500	5.315	52.477	1	.000	52508696488161376.000
	AU3MBt1	-1.199	.542	4.893	1	.027	.302
	MADAUD$	-31.685	15.368	4.251	1	.039	.000
	Constant	2.689	1.091	6.081	1	.014	14.724

a. Variable(s) entered on step 1: SP500R, AU3MBt1, MADAUD$.

LM14

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	269.988[a]	.312	.417

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	4	15	21.1
		1	22	125	85.0	2	22	91.7
	Overall Percentage				78.8			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.523	5.314	52.550	1	.000	53764968543105640.000
	AU3MBt2	-1.205	.528	5.221	1	.022	.300
	MADAUD$	-31.376	15.372	4.166	1	.041	.000
	Constant	2.699	1.063	6.444	1	.011	14.861

a. Variable(s) entered on step 1: SP500R, AU3MBt2, MADAUD$.

LM15

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	269.652[a]	.313	.418

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	87	35	71.3	4	15	21.1
		1	22	125	85.0	2	22	91.7
	Overall Percentage				78.8			60.5

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	38.580	5.315	52.693	1	.000	56894759574726032.000
	AU3MBt3	-1.205	.513	5.517	1	.019	.300
	MADAUD$	-31.157	15.383	4.103	1	.043	.000
	Constant	2.697	1.037	6.764	1	.009	14.842

a. Variable(s) entered on step 1: SP500R, AU3MBt3, MADAUD$.

LM16

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	260.710[a]	.335	.448

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	91	31	74.6	5	14	26.3
		1	25	122	83.0	2	22	91.7
	Overall Percentage				79.2			62.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.885	5.496	52.660	1	.000	209813573026724384.000
	AU10YB	-1.341	.618	4.706	1	.030	.262
	@NE	-3.900	1.649	5.591	1	.018	.020
	MADAUD$	-36.012	16.109	4.997	1	.025	.000
	Constant	2.993	1.331	5.056	1	.025	19.949

a. Variable(s) entered on step 1: SP500R, AU10YB, @NE, MADAUD$.

LM17

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	262.867[a]	.330	.441

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	93	29	76.2	5	14	26.3
		1	27	120	81.6	2	22	91.7
	Overall Percentage				79.2			62.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	39.492	5.475	52.029	1	.000	141678084309309504.000
	AU3MBt1	-.892	.556	2.576	1	.109	.410
	@NE	-4.368	1.627	7.208	1	.007	.013
	MADAUD$	-31.368	15.834	3.925	1	.048	.000
	Constant	1.937	1.135	2.915	1	.088	6.940

a. Variable(s) entered on step 1: SP500R, AU3MBt1, @NE, MADAUD$.

LM18

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	259.693[a]	.338	.452

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	91	31	74.6	5	14	26.3
		1	25	122	83.0	2	22	91.7
	Overall Percentage				79.2			62.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	40.179	5.551	52.385	1	.000	281495259026185984.000
	AU10YBt2	-1.462	.614	5.664	1	.017	.232
	@NE	-3.673	1.667	4.854	1	.028	.025
	MADAUD$	-37.332	16.230	5.291	1	.021	.000
	Constant	3.264	1.331	6.014	1	.014	26.147

a. Variable(s) entered on step 1: SP500R, AU10YBt2, @NE, MADAUD$.

LM19

Model Summary

Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	260.701[a]	.335	.448

Classification Table[a]

	Observed		Predicted					
			Selected Cases[b]			Unselected Cases[c]		
			ASX200R		Percentage Correct	ASX200R		Percentage Correct
			0	1		0	1	
Step 1	ASX200R	0	91	31	74.6	5	14	26.3
		1	25	122	83.0	2	22	91.7
	Overall Percentage				79.2			62.8

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	SP500R	40.184	5.549	52.434	1	.000	282806116107090208.000
	AU10YBt3	-1.305	.600	4.724	1	.030	.271
	@NE	-3.762	1.670	5.072	1	.024	.023
	MADAUD$	-35.604	16.132	4.871	1	.027	.000
	Constant	2.931	1.302	5.067	1	.024	18.738

Logistic Models Results from Eview

LM1

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.005486	0.149774	-0.036626	0.9708
SP500R	37.38619	5.096954	7.335006	0.0000

McFadden R-squared	0.250421	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.411202
Akaike info criterion	1.047524	Sum squared resid	45.14626
Schwarz criterion	1.074250	Log likelihood	-138.8919
Hannan-Quinn criter.	1.058257	Deviance	277.7839
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	92.80253	Avg. log likelihood	-0.516327
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.224021	0.169550	-1.321268	0.1864
SP500R	38.40031	5.283791	7.267566	0.0000
NE	-4.847987	1.593088	-3.043137	0.0023

McFadden R-squared	0.276564	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.402657
Akaike info criterion	1.018943	Sum squared resid	43.12720
Schwarz criterion	1.059033	Log likelihood	-134.0479
Hannan-Quinn criter.	1.035043	Deviance	268.0957
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	102.4907	Avg. log likelihood	-0.498319
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM3

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.150211	0.168157	-0.893274	0.3717
SP500R	37.79541	5.180333	7.295942	0.0000
NE(-1)	-3.117653	1.551047	-2.010031	0.0444

McFadden R-squared	0.261577	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.408071
Akaike info criterion	1.039589	Sum squared resid	44.29475
Schwarz criterion	1.079679	Log likelihood	-136.8247
Hannan-Quinn criter.	1.055689	Deviance	273.6494
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	96.93701	Avg. log likelihood	-0.508642
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM4

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.324343	1.037242	2.240888	0.0250
SP500R	38.34480	5.203495	7.369046	0.0000
AU10YB	-1.228912	0.541707	-2.268590	0.0233

McFadden R-squared	0.264746	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.406336
Akaike info criterion	1.035224	Sum squared resid	43.91898
Schwarz criterion	1.075313	Log likelihood	-136.2376
Hannan-Quinn criter.	1.051324	Deviance	272.4751
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	98.11126	Avg. log likelihood	-0.506459
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM5

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.303036	1.038826	2.216961	0.0266
SP500R	38.42766	5.225799	7.353452	0.0000
AU10YB(-1)	-1.214714	0.540851	-2.245930	0.0247

McFadden R-squared	0.264445	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.406746
Akaike info criterion	1.035638	Sum squared resid	44.00768
Schwarz criterion	1.075728	Log likelihood	-136.2933
Hannan-Quinn criter.	1.051738	Deviance	272.5867
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	97.99973	Avg. log likelihood	-0.506667
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.604650	1.036348	2.513297	0.0120
SP500R	38.60971	5.258624	7.342169	0.0000
AU10YB(-2)	-1.371769	0.538833	-2.545813	0.0109

McFadden R-squared	0.268591	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.405211
Akaike info criterion	1.029926	Sum squared resid	43.67616
Schwarz criterion	1.070016	Log likelihood	-135.5251
Hannan-Quinn criter.	1.046026	Deviance	271.0502
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	99.53624	Avg. log likelihood	-0.503811
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM7

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.414346	1.017666	2.372435	0.0177
SP500R	38.60310	5.264237	7.333086	0.0000
AU10YB(-3)	-1.271138	0.528640	-2.404546	0.0162

McFadden R-squared	0.266519	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.405792
Akaike info criterion	1.032781	Sum squared resid	43.80140
Schwarz criterion	1.072871	Log likelihood	-135.9090
Hannan-Quinn criter.	1.048881	Deviance	271.8180
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	98.76836	Avg. log likelihood	-0.505238
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM8

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.930766	1.256701	3.127844	0.0018
SP500R	39.28157	5.370262	7.314646	0.0000
AU10YB	-1.728085	0.591134	-2.923341	0.0035
MADAUD$	-37.54449	15.69624	-2.391942	0.0168

McFadden R-squared	0.280959	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.400831
Akaike info criterion	1.020323	Sum squared resid	42.57633
Schwarz criterion	1.073776	Log likelihood	-133.2335
Hannan-Quinn criter.	1.041790	Deviance	266.4669
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	104.1195	Avg. log likelihood	-0.495292
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM9

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.896900	1.255690	3.103394	0.0019
SP500R	39.40258	5.395477	7.302890	0.0000
AU10YB(-1)	-1.706653	0.588410	-2.900450	0.0037
MADAUD$	-37.49164	15.78097	-2.375749	0.0175

McFadden R-squared	0.280500	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.401353
Akaike info criterion	1.020955	Sum squared resid	42.68742
Schwarz criterion	1.074408	Log likelihood	-133.3184
Hannan-Quinn criter.	1.042421	Deviance	266.6368
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	103.9496	Avg. log likelihood	-0.495607
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM10

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.231322	1.251058	3.382195	0.0007
SP500R	39.64026	5.441185	7.285225	0.0000
AU10YB(-2)	-1.867155	0.585378	-3.189656	0.0014
MADAUD$	-38.99060	15.85087	-2.459840	0.0139

McFadden R-squared	0.285819	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.399446
Akaike info criterion	1.013627	Sum squared resid	42.28272
Schwarz criterion	1.067080	Log likelihood	-132.3328
Hannan-Quinn criter.	1.035094	Deviance	264.6656
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	105.9208	Avg. log likelihood	-0.491943
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM11

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.925380	1.219611	3.218551	0.0013
SP500R	39.60471	5.439067	7.281527	0.0000
AU10YB(-3)	-1.720921	0.570198	-3.018109	0.0025
MADAUD$	-37.32945	15.75396	-2.369529	0.0178

McFadden R-squared	0.282482	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.400470
Akaike info criterion	1.018224	Sum squared resid	42.49969
Schwarz criterion	1.071677	Log likelihood	-132.9512
Hannan-Quinn criter.	1.039691	Deviance	265.9024
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	104.6840	Avg. log likelihood	-0.494242
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM12

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.915951	1.122218	2.598381	0.0094
SP500R	38.56246	5.315093	7.255275	0.0000
AU3MB	-1.319557	0.560726	-2.353303	0.0186
MADAUD$	-32.42350	15.36104	-2.110763	0.0348

McFadden R-squared	0.272401	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.402298
Akaike info criterion	1.032112	Sum squared resid	42.88851
Schwarz criterion	1.085565	Log likelihood	-134.8191
Hannan-Quinn criter.	1.053579	Deviance	269.6381
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	100.9483	Avg. log likelihood	-0.501186
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM13

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.689461	1.090643	2.465942	0.0137
SP500R	38.49976	5.314629	7.244110	0.0000
AU3MB(-1)	-1.198602	0.541860	-2.212014	0.0270
MADAUD$	-31.68549	15.36771	-2.061822	0.0392

McFadden R-squared	0.270482	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.403362
Akaike info criterion	1.034757	Sum squared resid	43.11572
Schwarz criterion	1.088210	Log likelihood	-135.1748
Hannan-Quinn criter.	1.056224	Deviance	270.3496
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	100.2368	Avg. log likelihood	-0.502509
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM14

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.698718	1.063152	2.538411	0.0111
SP500R	38.52340	5.314221	7.249115	0.0000
AU3MB(-2)	-1.205426	0.527542	-2.284985	0.0223
MADAUD$	-31.37559	15.37192	-2.041097	0.0412

McFadden R-squared	0.271456	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.403005
Akaike info criterion	1.033414	Sum squared resid	43.03941
Schwarz criterion	1.086867	Log likelihood	-134.9942
Hannan-Quinn criter.	1.054881	Deviance	269.9884
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	100.5980	Avg. log likelihood	-0.501837
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM15

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.697457	1.037142	2.600856	0.0093
SP500R	38.57998	5.314800	7.258971	0.0000
AU3MB(-3)	-1.204975	0.513032	-2.348732	0.0188
MADAUD$	-31.15734	15.38267	-2.025483	0.0428

McFadden R-squared	0.272364	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.402827
Akaike info criterion	1.032163	Sum squared resid	43.00140
Schwarz criterion	1.085616	Log likelihood	-134.8259
Hannan-Quinn criter.	1.053630	Deviance	269.6518
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	100.9346	Avg. log likelihood	-0.501212
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM16

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.993203	1.331124	2.248629	0.0245
SP500R	39.88500	5.496303	7.256696	0.0000
AU10YB	-1.340888	0.618140	-2.169229	0.0301
NE	-3.899647	1.649180	-2.364597	0.0180
MADAUD$	-36.01177	16.10900	-2.235506	0.0254

McFadden R-squared	0.296494	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.396496
Akaike info criterion	1.006356	Sum squared resid	41.50325
Schwarz criterion	1.073173	Log likelihood	-130.3549
Hannan-Quinn criter.	1.033190	Deviance	260.7099
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	109.8765	Avg. log likelihood	-0.484591
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM17

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.883831	1.337509	2.156121	0.0311
SP500R	39.94588	5.510240	7.249389	0.0000
AU10YB(-1)	-1.282919	0.618130	-2.075484	0.0379
NE	-3.847826	1.662314	-2.314741	0.0206
MADAUD$	-35.64423	16.19070	-2.201525	0.0277

McFadden R-squared	0.295364	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.397281
Akaike info criterion	1.007912	Sum squared resid	41.66768
Schwarz criterion	1.074728	Log likelihood	-130.5642
Hannan-Quinn criter.	1.034746	Deviance	261.1284
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	109.4580	Avg. log likelihood	-0.485369
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM18

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.263739	1.330832	2.452404	0.0142
SP500R	40.17889	5.551321	7.237717	0.0000
AU10YB(-2)	-1.462154	0.614394	-2.379834	0.0173
NE	-3.672964	1.667049	-2.203273	0.0276
MADAUD$	-37.33214	16.23017	-2.300168	0.0214

McFadden R-squared	0.299237	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.395883
Akaike info criterion	1.002577	Sum squared resid	41.37498
Schwarz criterion	1.069393	Log likelihood	-129.8465
Hannan-Quinn criter.	1.029410	Deviance	259.6931
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	110.8933	Avg. log likelihood	-0.482701
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

LM19

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.930554	1.301845	2.251077	0.0244
SP500R	40.18354	5.549370	7.241100	0.0000
AU10YB(-3)	-1.304854	0.600357	-2.173463	0.0297
NE	-3.762122	1.670467	-2.252137	0.0243
MADAUD$	-35.60420	16.13152	-2.207119	0.0273

McFadden R-squared	0.296518	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.396685
Akaike info criterion	1.006323	Sum squared resid	41.54281
Schwarz criterion	1.073139	Log likelihood	-130.3505
Hannan-Quinn criter.	1.033157	Deviance	260.7010
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	109.8854	Avg. log likelihood	-0.484574
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

Appendix 3: Results Tables of Probit Models (PM1 to PM19)

PM1

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.003015	0.088440	-0.034094	0.9728
SP500R	21.06840	2.599727	8.104084	0.0000

McFadden R-squared	0.245112	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.412855
Akaike info criterion	1.054837	Sum squared resid	45.50998
Schwarz criterion	1.081563	Log likelihood	-139.8755
Hannan-Quinn criter.	1.065570	Deviance	279.7511
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	90.83531	Avg. log likelihood	-0.519983
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM2

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.129088	0.099703	-1.294723	0.1954
SP500R	21.35782	2.658915	8.032534	0.0000
NE	-2.836828	0.937220	-3.026855	0.0025

McFadden R-squared	0.270530	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.404627
Akaike info criterion	1.027255	Sum squared resid	43.55043
Schwarz criterion	1.067345	Log likelihood	-135.1658
Hannan-Quinn criter.	1.043355	Deviance	270.3317
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	100.2547	Avg. log likelihood	-0.502475
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM3

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.083354	0.098134	-0.849395	0.3957
SP500R	21.21146	2.631224	8.061440	0.0000
NE(-1)	-1.776011	0.885791	-2.005001	0.0450

McFadden R-squared	0.256053	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.409817
Akaike info criterion	1.047200	Sum squared resid	44.67458
Schwarz criterion	1.087290	Log likelihood	-137.8484
Hannan-Quinn criter.	1.063300	Deviance	275.6968
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	94.88966	Avg. log likelihood	-0.512447
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM4

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.282008	0.595488	2.152872	0.0313
SP500R	21.34158	2.607724	8.183986	0.0000
AU10YB	-0.675645	0.309978	-2.179654	0.0293

McFadden R-squared	0.258114	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.408213
Akaike info criterion	1.044360	Sum squared resid	44.32572
Schwarz criterion	1.084450	Log likelihood	-137.4665
Hannan-Quinn criter.	1.060460	Deviance	274.9329
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	95.65350	Avg. log likelihood	-0.511028
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM4

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.279953	0.597155	2.143419	0.0321
SP500R	21.39399	2.617060	8.174819	0.0000
AU10YB(-1)	-0.672386	0.309656	-2.171392	0.0299

McFadden R-squared	0.258036	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.408572
Akaike info criterion	1.044468	Sum squared resid	44.40363
Schwarz criterion	1.084558	Log likelihood	-137.4810
Hannan-Quinn criter.	1.060568	Deviance	274.9619
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	95.62446	Avg. log likelihood	-0.511082
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM6

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.452204	0.594094	2.444401	0.0145
SP500R	21.44691	2.626457	8.165720	0.0000
AU10YB(-2)	-0.761383	0.307454	-2.476417	0.0133

McFadden R-squared	0.262006	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.407103
Akaike info criterion	1.038999	Sum squared resid	44.08499
Schwarz criterion	1.079088	Log likelihood	-136.7453
Hannan-Quinn criter.	1.055099	Deviance	273.4907
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	97.09574	Avg. log likelihood	-0.508347
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM7

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.330099	0.583389	2.279952	0.0226
SP500R	21.42196	2.626962	8.154652	0.0000
AU10YB(-3)	-0.696870	0.301461	-2.311641	0.0208

McFadden R-squared	0.259759	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.407738
Akaike info criterion	1.042094	Sum squared resid	44.22266
Schwarz criterion	1.082184	Log likelihood	-137.1616
Hannan-Quinn criter.	1.058194	Deviance	274.3232
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	96.26316	Avg. log likelihood	-0.509895
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM8

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.197836	0.721272	3.047167	0.0023
SP500R	21.59731	2.654737	8.135383	0.0000
AU10YB	-0.959287	0.337367	-2.843449	0.0045
MADAUD$	-20.99351	9.000326	-2.332527	0.0197

McFadden R-squared	0.273218	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.402963
Akaike info criterion	1.030987	Sum squared resid	43.03058
Schwarz criterion	1.084440	Log likelihood	-134.6678
Hannan-Quinn criter.	1.052454	Deviance	269.3355
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	101.2509	Avg. log likelihood	-0.500624
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM 9

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.182703	0.721025	3.027222	0.0025
SP500R	21.67161	2.666713	8.126711	0.0000
AU10YB(-1)	-0.948741	0.335805	-2.825276	0.0047
MADAUD$	-20.98606	9.066680	-2.314636	0.0206

McFadden R-squared	0.272943	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.403410
Akaike info criterion	1.031366	Sum squared resid	43.12590
Schwarz criterion	1.084819	Log likelihood	-134.7187
Hannan-Quinn criter.	1.052833	Deviance	269.4375
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	101.1489	Avg. log likelihood	-0.500813
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM10

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.376768	0.716728	3.316137	0.0009
SP500R	21.74107	2.679610	8.113519	0.0000
AU10YB(-2)	-1.040249	0.332829	-3.125479	0.0018
MADAUD$	-21.92742	9.121968	-2.403804	0.0162

McFadden R-squared	0.278080	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.401557
Akaike info criterion	1.024289	Sum squared resid	42.73075
Schwarz criterion	1.077742	Log likelihood	-133.7669
Hannan-Quinn criter.	1.045756	Deviance	267.5338
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	103.0526	Avg. log likelihood	-0.497275
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM11

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.186861	0.699209	3.127620	0.0018
SP500R	21.71002	2.678692	8.104710	0.0000
AU10YB(-3)	-0.949218	0.324120	-2.928601	0.0034
MADAUD$	-20.96054	9.087693	-2.306475	0.0211

McFadden R-squared	0.274559	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.402614
Akaike info criterion	1.029140	Sum squared resid	42.95592
Schwarz criterion	1.082593	Log likelihood	-134.4193
Hannan-Quinn criter.	1.050607	Deviance	268.8386
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	101.7478	Avg. log likelihood	-0.499700
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM12

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.477217	0.622707	2.372249	0.0177
SP500R	21.07674	2.629918	8.014219	0.0000
AU3MB	-0.650797	0.306865	-2.120797	0.0339
MADAUD$	-17.55223	8.876527	-1.977375	0.0480

McFadden R-squared	0.263169	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.405219
Akaike info criterion	1.044832	Sum squared resid	43.51375
Schwarz criterion	1.098285	Log likelihood	-136.5299
Hannan-Quinn criter.	1.066298	Deviance	273.0597
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	97.52669	Avg. log likelihood	-0.507546
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM13

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.363494	0.607843	2.243169	0.0249
SP500R	21.08341	2.635491	7.999804	0.0000
AU3MB(-1)	-0.590199	0.297725	-1.982362	0.0474
MADAUD$	-17.17328	8.882357	-1.933415	0.0532

McFadden R-squared	0.261599	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.406128
Akaike info criterion	1.046994	Sum squared resid	43.70918
Schwarz criterion	1.100447	Log likelihood	-136.8207
Hannan-Quinn criter.	1.068461	Deviance	273.6413
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	96.94509	Avg. log likelihood	-0.508627
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM14

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.377609	0.593185	2.322393	0.0202
SP500R	21.09144	2.635675	8.002294	0.0000
AU3MB(-2)	-0.597897	0.289955	-2.062037	0.0392
MADAUD$	-17.09156	8.874290	-1.925964	0.0541

McFadden R-squared	0.262513	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.405749
Akaike info criterion	1.045734	Sum squared resid	43.62757
Schwarz criterion	1.099187	Log likelihood	-136.6513
Hannan-Quinn criter.	1.067201	Deviance	273.3025
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	97.28389	Avg. log likelihood	-0.507997
Prob(LR statistic)	0.000000		
Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM15

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.394115	0.580152	2.403016	0.0163
SP500R	21.12965	2.636334	8.014786	0.0000
AU3MB(-3)	-0.606296	0.282740	-2.144361	0.0320
MADAUD$	-17.06269	8.864760	-1.924778	0.0543

McFadden R-squared	0.263504	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.405459
Akaike info criterion	1.044369	Sum squared resid	43.56526
Schwarz criterion	1.097822	Log likelihood	-136.4676
Hannan-Quinn criter.	1.065836	Deviance	272.9353
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	97.65115	Avg. log likelihood	-0.507315
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM16

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.680764	0.766083	2.193971	0.0282
SP500R	21.79335	2.700892	8.068947	0.0000
AU10YB	-0.752493	0.353303	-2.129878	0.0332
NE	-2.302151	0.966695	-2.381465	0.0172
MADAUD$	-19.74442	9.169873	-2.153184	0.0313

McFadden R-squared	0.288873	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.398750
Akaike info criterion	1.016855	Sum squared resid	41.97638
Schwarz criterion	1.083671	Log likelihood	-131.7670
Hannan-Quinn criter.	1.043689	Deviance	263.5341
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	107.0523	Avg. log likelihood	-0.489840
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM17

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.627278	0.768726	2.116850	0.0343
SP500R	21.85244	2.710514	8.062103	0.0000
AU10YB(-1)	-0.723583	0.352637	-2.051923	0.0402
NE	-2.274778	0.973740	-2.336124	0.0195
MADAUD$	-19.57559	9.229117	-2.121069	0.0339

McFadden R-squared	0.287998	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.399439
Akaike info criterion	1.018060	Sum squared resid	42.12159
Schwarz criterion	1.084876	Log likelihood	-131.9291
Hannan-Quinn criter.	1.044894	Deviance	263.8582
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	106.7282	Avg. log likelihood	-0.490443
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM18

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.839813	0.763235	2.410545	0.0159
SP500R	21.92678	2.721169	8.057854	0.0000
AU10YB(-2)	-0.822073	0.349121	-2.354697	0.0185
NE	-2.174828	0.976570	-2.227006	0.0259
MADAUD$	-20.59827	9.268292	-2.222445	0.0263

McFadden R-squared	0.291731	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.398097
Akaike info criterion	1.012917	Sum squared resid	41.83906
Schwarz criterion	1.079733	Log likelihood	-131.2373
Hannan-Quinn criter.	1.039751	Deviance	262.4747
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	108.1117	Avg. log likelihood	-0.487871
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		

PM19

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.631274	0.747333	2.182795	0.0291
SP500R	21.92050	2.720722	8.056869	0.0000
AU10YB(-3)	-0.723507	0.341054	-2.121388	0.0339
NE	-2.224692	0.978925	-2.272587	0.0231
MADAUD$	-19.56593	9.232213	-2.119311	0.0341

McFadden R-squared	0.288788	Mean dependent var	0.546468
S.D. dependent var	0.498764	S.E. of regression	0.398916
Akaike info criterion	1.016972	Sum squared resid	42.01145
Schwarz criterion	1.083788	Log likelihood	-131.7827
Hannan-Quinn criter.	1.043805	Deviance	263.5654
Restr. deviance	370.5864	Restr. log likelihood	-185.2932
LR statistic	107.0210	Avg. log likelihood	-0.489898
Prob(LR statistic)	0.000000		

Obs with Dep=0	122	Total obs	269
Obs with Dep=1	147		