Exchange Rate Forecasting with An Artificial Neural Network Model: Can We Beat a Random Walk Model?

A thesis submitted in partial fulfilment of the requirements for the degree of Master of Commerce and Management (M.C.M.)

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Developing an understanding of exchange rate movements has long been an extremely important task because an ability to produce accurate forecasts of exchange rates has practical as well as theoretical value. The practical value lies in the ability of good forecasts to provide useful information for investors in asset allocation, business firms in risk hedging, and governments in policy making. On the theoretical side, whether a currency price is predictable or not has important implications for the efficient market hypothesis in the foreign exchange market and for theoretical modelling in international finance.

Owing to the importance of the movements of exchange rates in our real life, such as financial hedges and investment abroad, this research investigates the possibility of an accurate pattern of the exchange rate movement. The purpose of this research is to carry out an empirical investigation into the extent to which *nonlinear* econometric models can improve upon the predictability of foreign exchange rates compared to a standard regression model. We will use the artificial neural network approach and employ macroeconomic fundamental variables, including relative money supply, relative income, interest rate differential and inflation rate differential to examine whether or not the artificial neural network model could significantly improve the accuracy of describing the movement of exchange rates and the predictability of exchange rates, especially out-of-sample. The empirical research will focus on the New Zealand exchange rate with the currencies of its major trading partners (Australia and the United States).

Key Words: exchange rate, macroeconomic fundamentals, artificial neural network, random walk model, forecasting, nonlinearity.

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Chapter 1 Introduction

1.1 Introduction

An exchange rate is the price of one currency indicated by another currency, which widely influences the country's international economic circumstances. Therefore, it is very important to understand the continuous movement of exchange rates because nowadays financial connections, both among industrialised countries and between developed countries and developing countries, have grown increasingly close and intense.

In fact, exchange rates tend to be very volatile in the short run, causing theory based models (PPP: Purchasing Power Parity, CIP: Covered Interest Rate Parity, UIP: Uncovered Interest Rate Parity etc) to empirically fail over short periods. Hence this research is focused on evaluating the ability of theory-based econometric models to forecast exchange rates over a relatively long horizon.

1.2 Study Rationale

Meese and Rogoff (1983) found that *a simple random walk model performed no worse than a range of competing representative time-series and structural exchange rate models*. Especially, these competing models have little out-of-sample forecasting power over various short term forecasting horizons (1-, 6- and 12-months). Since the publication of the seminal paper (Meese and Rogoff, 1983), researchers have been formulating all kinds of theoretical models and developing many powerful forecasting techniques in order to gain a better understanding of exchange rate movements, and to attempt to beat the naïve random walk model.

Among a wide range of competitive models, the forward model might be the simplest one. Also, for ordinary people, the forward model is used most frequently because the forward exchange rate is a simple and easy acquired (minimum search cost) indicator of spot exchange rate in a future period. People, even academic staff often view the forward exchange rate as an expected spot exchange rate value in the future time. In the forward market, "pure" speculation, which can be expressed as $F_t = S_{t+1}^e$ (where S_{t+1}^e is the log expected spot exchange rate for the time at $t+1$, and F_t is the log forward rate at the time t), is a special speculation in foreign exchange. In this situation, it suggests that a foreign currency does not require to be bought or held in the forward market. "Pure" speculation could happen when the majority of market players are risk neutral.

On the other hand, the monetary model is based on solid economic theory. This model, which was originally developed by Dornbusch (1976) and Frankel (1979), can be expressed as in equation (1.1):

$$s_t = \beta_0 + \beta_1 m_t + \beta_2 y_t + \beta_3 i_t + \beta_4 \pi_t + \varepsilon_t \quad (1.1)$$

where m = log relative money,

y = log relative real GDP,

i = interest rate differential,

π = inflation rate differential.

This specification reflects the traditional sticky-price monetary approach[1] to exchange rate modelling. However, recent studies (Conway and Franulovich, 2002) have indicated that the traditional monetary model should be modified to include the Current Account Balance (CA)[2]. Based on this statement, we modify Dornbusch-Frankel's model as equation (1.2).

$$s_t = \beta_0 + \beta_1 m_t + \beta_2 y_t + \beta_3 i_t + \beta_4 \pi_t + \beta_5 ca_t + \varepsilon_t \quad (1.2)$$

where ca is the current account balance differential.

[1] It is the basic Dornbusch (1976) and Frankel (1979) model.

[2] Conway and Franulovich (2002) argue that the current account should be included in the monetary model because that current account indicates a country's relative wealth level.

However, the monetary model is a simple linear model which entirely ignores non-linear factors. There are three methods which can possibly catch the non-linearity factors.

1. Markov switching models can catch the non-linearity in both parameters and regimes.
2. Threshold autoregressive models (TAR: threshold autoregressive models, STAR: smooth transition autoregressive models, and SETAR: self-exciting threshold autoregressive models) can catch the nonlinearities in the data sets especially financial time-series data.
3. Artificial Neural Network (ANN) procedure is a general class of non-linear method which can capture any universal non-linearity element.

We propose to carry out an empirical investigation by using the ANN approach into the extent to which a *nonlinear* econometric model can improve upon the predictability of foreign exchange rates (especially in the long run) compared to the random walk model and a standard regression model.

1.3 Research Objectives

Owing to the importance of exchange rate movements in the international economy, such as financial hedge and investment abroad, this research investigates the possibility of developing empirical models capable of describing and forecasting the exchange rate movements. We use the artificial neural network approach and employ macroeconomic fundamental variables, including relative money supply, relative real GDP, interest rate differential, inflation rate differential, and current account balance differential to examine whether or not the artificial neural network could significantly improve the accuracy of describing the movement of exchange rates and the predictability of exchange rates, especially out-of-sample predictability. The empirical research will focus on the New Zealand exchange rate with the currencies of its major trading partners – Australia, and USA (New Zealand statistical data[3]).

In more detail, this research has the following specific objectives.

1. To test whether the Random Walk model can well describe the movement of exchange rates in-sample and out-of-sample; and further examine whether a pure Random Walk model can also well mimic the pattern of exchange rate movements
2. To empirically analyse exchange rate movements using a Monetary model (a linear regression) in-sample and out-of-sample; and further employ the Artificial Neural Network (ANN) approach to repeat the test and compare the results using several criteria to see whether this approach can significantly improve the ability of capturing short-run fluctuation or long-run trend in exchange rate forecasting
3. To measure the accuracy of predicted exchange rate movement direction (turning-point) by using the ANN approach to compare the change in actual values and change in predicted values
4. To compare the forecasting accuracy of different models (especially by examining whether the RW model can provide better forecasts than the ANN model) by using the Diebold-Mariano (DM) test

This research uses the New Zealand dollar vs. the Australian dollar and the US dollar, because Australia and the US are the main commercial partners of New Zealand, and because the US economy always influences the rest of the world. Also this research employs a long horizon period from 1990:01 to 2003:12 over 14 years to mitigate extreme exchange rate volatility in the short term.

[3] During the year from June, 2003 to June, 2004, total New Zealand's total imports and exports were 63.3 billion. Australia and USA, the two biggest trading partners occupied 21.7% and 13.0%, respectively.

1.4 Data and Software

This research considers the NZ exchange rate (NZ dollar vs. Australian dollar, and NZ dollar vs. American dollar) movement for the period from 1990 to 2003. Explanatory variables considered now are relative money supply, relative real GDP, interest rate differential, inflation rate differential, and current account balance differential. These time series data can be found in the International Finance Statistics (IFS) on a monthly or a quarterly base (which will be converted into a monthly base before starting the empirical analysis).

The software of EViews 5.1 is employed to run the standard regression model. This software does not require writing a programme, what is needed is to accurately put data into this software, run the regression, obtain the results, and carry out some diagnostic tests as well.

The software of NeuroShell 2 is employed to run the artificial neural networks model. The first step is to enter data into a spreadsheet, and define inputs and actual output(s) to form a data file. The second is to set the minimum and maximum values tightly around the actual input and output data since neural networks require variables to be scaled into the range 0 to 1 (a logistic function[4]) or -1 to 1 (a hyperbolic tangent function[5]), hence the network needs to know the variable's real value range. The third step is to do some preparatory work such as specifying the level of the problem complexity, selecting the training pattern, setting the number of hidden neurons, and choosing an appropriate method to extract a validation set and a test set from the whole data set. After that, a suitable architecture of the network for solving the problem should be chosen and training criteria set accordingly. Then we can start training until the minimum average error in the validation set is unlikely to be any lower. Finally, the results can be obtained once the training process stops.

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[4] Logistic function: $f(x) = \dfrac{1}{1+e^{-x}}$

[5] Hyperbolic tangent function : $f(x) = \dfrac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$

1.5 Chapter Outline of This Thesis

The remainder of this thesis is presented as follows. Chapter 2 gives a review of the literature on exchange rate determination and forecasting, provides a summary of existing empirical tests results of exchange rate models to date, and identifies the gaps and limitations in these previous studies. Chapter 3 discusses the methods which are used in this research including a simple linear regression model, but with a focus on the artificial neural network model, introduces forecasting measurements and followed by the report format outlined, provides the explanation of the economic theory supporting the selection of the explanatory variables considered for the forecasting models, and describes the data to be used in this research. Chapter 4 presents, interprets and discusses the empirical results obtained. Finally, Chapter 5 points out the limitations of this research, and makes suggestions for further studies in this area.

Chapter 2 Literature Review

2.1 Introduction

Forecasting exchange rates is an extremely difficult task and has long posed a challenge to academicians (Qi and Wu, 2003, pp637). This chapter provides a literature review of the relevant aspects of exchange rate determination and forecasting in two major perspectives --- the theoretical development of models and the empirical findings of models. Also, this chapter identifies the gaps and limitations in these previous studies, and outlines the basic framework of this research.

2.2 The Background of the Exchange Rate

2.2.1 Purchasing Power Parity

Purchasing power parity (PPP) is a simple theory which consists of 'Absolute PPP' and 'Relative PPP'. 'Absolute PPP' means that the exchange rate between two nations is equal to the ratio of the two nations' aggregate price levels which are expressed in the same currency. The concept of 'Relative PPP' is that if one currency depreciates relative to another, then the aggregate price level in the nation the currency of which has been experiencing depreciation will be higher than before, and the degree of depreciation just matches the aggregate price inflation differential (Sarno and Taylor, 2002).

However, PPP theory does not always hold in the real world (Sarno and Taylor, 2002) mainly for a basket of reasons --- non-tradable goods/service, trade barriers, actual or threatened trade protection, transportation costs, information costs, limited international labour mobility, and imperfect competition markets and so on (Salvatore, 2001). The most serious reason causing deviation from PPP theory is the non-tradable goods/service. That is, not all products and service are tradable, but a nation's aggregate price level is determined by both tradable and non-tradable products and service (Salvatore, 2001). Actually, the non-tradable products and service often have unequal prices in different areas/nations largely due to productivity level differential (Hallwood and MacDonald, 2000).

Because of the existence of factors which lead to deviation from PPP, the consequence of various adjustment costs makes exchange rates move a great deal in order to gradually respond to the relative domestic prices (Salvatore, 2001). Therefore, deviations from purchasing power parity die out very slowly (Frankel, 1986 and 1990), and hence PPP theory fails in the short run, but it is theoretically retained in the long run which is evidenced by the fact that national price levels (consumer price indices and produce price indices) of the two nations (US and UK), expressed in the same currency (US dollar), did tend to move together over long periods (1820-2001 and 1971-2001 respectively) (Taylor and Taylor, 2004).

However quite a few of the empirically tested results of PPP in the long run are also not very supportive. This is the result of shocks especially the real shocks (Salvatore, 2001), such as the change of taste and technology development, and the application of non-suitable methodology of investigating the PPP theory (Taylor and Taylor, 2004). The latter factor means that many previous studies built a linear framework which caused the adjustment speed of PPP deviations to be the same at all times (Taylor and Taylor, 2004); but in practice, the process of adjustment itself might not be linear (Heckscher, 1916).

2.2.2 Non-Linearity

Adopting nonlinear dynamics in real exchange rate adjustment is a good way to solve the PPP puzzles (Taylor and Taylor, 2004). That is, transactions costs exist in international arbitrage (Heckscher, 1916); hence the adjustment speed of PPP deviations from parity is no longer uniform as in the linear framework (Taylor and Taylor, 2004).

Moreover, it is suggested (Gradojevic and Yang, 2000) that exchange rate changes are strongly *non*-linearly dependent (Hsieh, 1989), and hence exchange rates could *not* be linearly predicted (Bailie and McMahon, 1989). Therefore, many elegant models and sophisticated forecasting techniques, which are based on a linear framework, have lacked the capability to beat the naïve random walk model since the publication of the seminal paper of Meese and Rogoff (1983) (Preminger and Franck, 2005; Qi and Wu, 2003).

From the point of view of an asset price, exchange rates are likely to contain significant nonlinearities (Pippenger and Goering, 1998) as well as other economic and financial time-series data; and the nonlinearity has been found by a SETAR (self-exciting threshold autoregressive) model rather than a standard non-linear ARCH (autoregressive conditional heteroskedasticity) model[6]. As a result of the SETAR model capturing the nonlinearity occurring in economic data, this model is superior to the naïve random walk model in terms of accuracy of forecasting changes in the exchange rate for both in-sample forecasts and one-step-ahead out-of-sample forecasts (forecast horizon is 1 month), and it further provides more accurate predictions of the *direction*[7] of change in the exchange rate (Pippenger and Goering, 1998)[8].

More recently, many empirical studies (Taylor, Peel and Sarno, 2001; Sarno, Taylor and Chowdhury, 2004) have discovered that the exchange rate deviation from PPP follows a nonlinear process in nature, and it is increasingly mean reverting[9] with the size of the deviation from the equilibrium level (Sarno and Taylor, 2002). In order to deal with the neglected non-linearity[10], which cannot be detected by a traditional linear regression, we can therefore build an estimation model by allowing the

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[6] The threshold autoregressive (TAR) model can be described as additive nonlinear dependence while the autoregressive conditional heteroskedasticity (ARCH) model can be described as multiplicative nonlinear dependence (Hsieh, 1989).

[7] Not only the SETAR model, but also the Markov switching model appears to predict a more accurately directional change in the exchange rates (Engel, 1994).

[8] This paper uses monthly observations of the Austrian schilling, Belgian franc, Danish krone, French franc, German mark, Irish punt, Italian lira, Netherlands guilder, Norwegian krone, Swiss franc, UK pound and US dollar.

[9] This new finding implies that the prevalent null hypothesis of unit root behaviour in exchange rate series is not true which is opposite to Bailie and Bollerslev (1989, 1994).

[10] The nonlinear nature in the exchange rate may arise from the heterogeneity of opinion in the foreign exchange market (Kilian and Taylor, 2003) or from the intervention operations of central banks (Taylor, 2004).

parameter(s) to vary[11] (Taylor and Taylor, 2004) or leaving the parameter(s) to be unspecified (Sharma, Tarboton and Lall, 1997). The latter of non-parametric models no longer hold the prevalent linear and/or distributional assumptions about the parametric form of the functional relationship between the variables in the regression models (Fernandes and Gramming, 2005). Therefore, non-parametric models are more easily applicable and can further capture both linear and nonlinear relations because of computational advances and increased computational power (Medeiros, Terasvirta and Rech, 2002; Sharma, Tarboton and Lall, 1997).

Since the early 1990s, a number of researchers have been building all kinds of nonlinear models to explain the movements of exchange rates (Qi and Wu, 2003). A powerful nonparametric prediction technique --- locally weighted regression (Diebold and Nason, 1990)[12] --- only occasionally provides a lower mean squared prediction error (MSPE) and/or a lower mean absolute prediction error (MAPE) for one-step-ahead out-of-sample prediction (forecast horizon is 1 week) relative to a random walk model with weekly data. A multivariate model with nearest-neighbour non-parametric technique[13] (Mizrach, 1992)[14] improves upon the random walk model for only one of three exchange rates (Italian lira vs. US dollar) explored for out-of-sample forecasts in a 3-year horizon with daily data, and the improvement is limited. These unsatisfactory results could be caused by the fact that '*the high frequency data may contain more than one type of nonlinearity thus decreasing the explanatory power of the non-parametric model*' (Pippenger and Goering, 1998, pp166).

By using a non-parametric estimator[15] to handle non-linearity, all five estimated structural models[16] (Meese and Rose, 1991)[17], with locally weighted regression technique, cannot significantly out-predict the random walk model for one-step-ahead

[11] One of these kinds of models is well known as the "threshold autoregressive" model.
[12] This paper uses weekly observations of the Belgian franc, Canadian dollar, Danish krone, Dutch guilder, French franc, German mark, Italian lira, Japanese yen, Swiss franc, UK pound and US dollar.
[13] This is a special case of locally weighted regression (Meese and Rose, 1991).
[14] This paper uses daily observations of the French franc, German mark, Italian lira and US dollar.
[15] An estimator has no assumption about the parametric form because the error distribution is unknown due to lack of *a priori* information (Levy, 2000).
[16] The five structural models are the flexible-price monetary model, the stick-price monetary model with trade-balance, the stick-price monetary model without trade-balance, the Lucas model and the quadratic flexible-price (Hodrick) model.
[17] This paper uses monthly observations (seasonally adjusted) of the Canadian dollar, German mark, Japanese yen, UK pound and US dollar.

out-of-sample prediction (forecast horizon is 1 month). The results from Meese and Rose (1991), which supplement those of Diebold and Nason (1990) and Mizrach (1992), suggest that even sophisticated non-linear models have great difficulties in beating the random walk model for out-of-sample forecasting. However, we cannot simply infer that the poor explanatory power is *not* mainly contributed by non-linearity; in fact, a specific non-linear model cannot capture too many possible non-linear patterns in a given data set, and some extremely complicated forms of nonlinearities may be far beyond the ability of these nonlinear models to detect (Zhang, Patuwo and Hu, 1998).

2.2.3 Macroeconomic and Microeconomic Foundations

2.2.3.1 Macroeconomic Items

Recent research (Taylor, Peel and Sarno, 2001) does provide convincing evidence in favour of long-run purchasing power parity (PPP) holding when exchange rates are applied among major industrialised countries, and nonlinearity in the exchange rates is apparent (Clarida, Sarno, Taylor and Valente, 2003).

On the other hand, monetary models also behave as a long-run equilibrium relationship in the determination and forecasting of exchange rates (MacDonald and Taylor, 1993). This finding supports the existence of long-run correlation between the exchange rate and the relative macroeconomic fundamentals[18].

A nonlinear adjustment of the exchange rates is necessary in the way of the exchange rates getting towards the long-run monetary fundamentals and towards the long-run PPP equilibrium. The empirical findings on the nonlinear nature of exchange rates are consistent (Sarno and Taylor, 2002). Hence we can use monetary fundamentals in a nonlinear form as a base to improve the predictability of exchange rates.

[18] Basically, they are relative money supply, relative income level, interest rate differential and inflation rate differential.

2.2.3.2 Microeconomic Items

There is little evidence that macroeconomic fundamentals can provide a high level of satisfaction in explaining exchange rate determination (Frankel and Rose, 1995), and hence the negative findings lead to a more updated branch (microeconomic approach) to attempt to understand the deviations from macroeconomic fundamentals.

The microstructure information is also called technical information (Rubio, 2004), and it competes with fundamental information in terms of the ability to forecast foreign exchange rates. The microstructure literature is concerned with a wide range of issues including the transmission of information between market participants, the behaviour of market agents, the relationship between information flows, the importance of order flow and the heterogeneity of agents' expectations (Sarno and Taylor, 2002). The new studies of the microstructure of the foreign exchange market seem to be able to supply more positive empirical results on foreign exchange rates determination and forecasting (Frankel and Rose, 1995).

Because the microeconomic variables are hardly available to the public, and hence are extremely difficult to gather because of time and resource restrictions, this research focuses only on macroeconomic fundamentals models.

2.3 The Theoretical Models and the Empirical Findings of the Exchange Rate

2.3.1 Random Walk Model

The random walk model, which was first presented in the foreign exchange field by the seminal paper --- Meese and Rogoff (1983), provides a forecast of *no* change in the level of the exchange rate. That is, the observed spot exchange rate at time t is exactly same as the expected value of the spot exchange rate in the next period $t+1$. Empirically, *the simple random walk model performs no worse than a range of competing representative time-series and structural exchange rate models*

(Gradojevic and Yang, 2000, pp1) in terms of out-of-sample forecast accuracy for various short term forecasting horizons (1-, 6-, and 12-months) based on the work of Meese and Rogoff (1983)[19].

One of the competing models --- the Markov-Switching model[20], generally does not produce superior out-of-sample forecasts to the random walk model with drift over short horizons within one year (1-, 2-, 3-, and 4- quarters) (Engel and Hamilton, 1990; Engel, 1994)[21]. However, there is more positive evidence supporting regression-based models for out-of-sample forecasting in the longer horizon. For example, the out-of-sample forecasts from the flexible-price monetary model which contains "fundamental"[22] information do outperform those of the driftless random walk model in longer horizons (12- and 16-quarters) (Mark, 1995)[23].

2.3.2 Forward Model

In the foreign exchange market, in any time *t* the spot exchange rate is observed, and the forward rate is also observed and it further releases the market's expectation of the spot rate in the next period at *t+1*, and hence the forward rate is often interpreted as the expected value of the spot rate in the future (Hallwood and MacDonald, 2000). On the other hand, the hypothesis that the forward rate is an unbiased predictor of the future spot rate has been rejected by many empirical researches (Bilson, 1981; Chiang and Chiang, 1987; Fama, 1984; Giddy and Dufey, 1975; Hansen and Hodrick, 1980 and 1983; Hsieh, 1984 and Levich, 1979). The reasons for rejecting this hypothesis

[19] This paper uses monthly (seasonally unadjusted) observations of the US dollar, UK pound, German mark, Japanese yen and the trade-weighted dollar (which consists of ten countries' currencies, and the weight is measured by the share of the total trade in the period 1972 through 1976).
[20] Basically, Markov switching models assume that there is more than one 'state' (For example, a medium or long term GDP includes both contraction and expansion phases) in the long horizontal time series data, and also assume that the first difference of a time series follows a *nonlinear* stationary process rather than a linear stationary process; therefore, this allows the Markov switching models to capture the non-linearity in both parameters and regimes (Hamilton, 1989).
[21] These two papers use quarterly observations of the German mark, French franc, UK pound and US dollar.
[22] This fundamental value is defined as a linear combination of log relative money stocks and log relative real incomes (Mark, 1995).
[23] This paper uses quarterly observations of the US dollar, Canadian dollar, German mark, Japanese yen and Swiss franc.

are that market behaviour is inconsistent with rational-expectations[24] (Lewis, 1989) and/or there exists a time-varying risk premium[25] (Domowitz and Hakkio, 1985). In other words, if the conditions of rational expectations and risk neutrality hold, then a one-to-one relationship, which is between the forward rate and its corresponding future spot rate, should exist in reality (Delcoure, Barkoulas, Baum and Chakraborty, 2003). Therefore, the forward rate can be viewed as a reasonably good (even though not optimal) predictor (with a low search cost) of the spot exchange rate in the (near) future, at least in the sense that the term of the forward premium/discount does contain valuable information in forecasting spot exchange rate appreciation/depreciation (Hallwood and MacDonald, 2000).

Empirical findings of a simple forward rate model are very similar to those of the random walk model. That is, the forward rate model also can not be beaten by structural exchange rate models, at least in the short run. For example, the simple forward rate model is superior to the Markov switching model regarding the accuracy of out-of-sample forecasts at short horizons within one year (1-, 2-, and 4- quarters) (Engel, 1994).

2.3.3 Monetary Models[26]

The early explanation of exchange rate determination and movements from long-run monetary models is within the scope of the Keynesian approach[27], which mainly relies on the elasticities of demand for, and supply of exports and imports[28], and the demand for and supply of foreign currency (Lerner, 1936; Metzler, 1942a and 1942b

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[24] Systematic forecast errors will be induced when market behaviour is in the process of rationally learning a new exchange rate regime or a new monetary policy, instead of immediately believing that the change would persist (Lewis, 1989).

[25] Risk premium implies that market participants set the forward rate above their expectation of the future spot rate to require compensation for taking a forward position. Moreover, the risk premium is not constant over time (Domowitz and Hakkio, 1995).

[26] The theory of this section is mainly based on Hallwood and MacDonald (2000), Sarno and Taylor (2002), Mark (2001), Salvatore (2001), Shapiro (1999), Mankiw (2002) and Frankel (1979).

[27] Keynesian theory is a very broad area. The greatest contribution of Keynes to the development of exchange rate modelling is that he asserted the importance of the aggregate demand because he strongly believed that the aggregate demand or effective demand (rather than adjustments in prices) determines the level of output and employment in the economy (Sarno and Taylor, 2002).

[28] The sufficient condition for a devaluation of the exchange rate to improve the balance of trade – that the sum of the demand elasticities of imports and exports should be greater than unity in absolute value (Marshall-Lerner-Harberger condition).

and Harberger, 1950). However, the simple Keynesian approach can only capture short-term fluctuations in exchange rate movements. Therefore, Meade (1951) developed the theory of the simple Keynesian approach to provide the Keynesian income-expenditure model, which was able to explain the exchange rate movements in the medium term through "*multiplier*". Later, this model was further extended by Mundell (1961, 1962 and 1963) and Fleming (1962) introduced capital flows into the analysis.

The major advance in exchange rate modelling took place after 1973 because the Bretton Woods system[29] broke down and many exchange rates started to emerge into a floating system.

We now have a few of the monetary-based exchange rate models on hand: the stick-price monetary model (Dornbush-Frankel), the flexible-price monetary model (Frenkel-Bilson) and the general equilibrium model.

2.3.3.1 Stick-Price Monetary (Dornbush-Frankel) Model (SPMM)

The stick-price monetary model was originally developed by Dornbusch and Frankel in late 1970s. This model assumes that prices are rigid, at least in the short run. Therefore, if the nominal domestic money supply is reduced, then in this model, the real domestic money supply will follow since the prices cannot immediately respond to the change but remain the same in the short run. However, the domestic money demand remains unchanged compared to a contraction of real domestic money supply due to the same reason of rigid prices in the short run. In order to release the pressure of the shortage of real domestic money supply, nominal domestic interest rates will rise to hold back domestic residents' consumption. The rise of nominal domestic interest rates will then lead to a capital inflow, and consequently an appreciation of domestic currency and a depreciation of the nominal exchange rate[30] (defined as the price of foreign currency, that is, direct quotation: Home Currency/Foreign Currency).

[29] The International Monetary Fund was established at the Bretton Woods Conference in 1944. And this conference introduced a system of fixed exchange rates, to which most major exchange rates had been officially pegged. Later, this monetary system became known as the Bretton Woods system (Sarno and Taylor, 2002).

[30] The exchange rate is defined as direct quotation (Home Currency/Foreign Currency) through the whole thesis.

Rational foreign investors are likely to be aware that the value of domestic currency is artificially forced up and that they might suffer a foreign exchange loss when they convert the domestic currency into foreign currency once their investment is mature. But as long as the *expected* foreign exchange loss (the expected rate of domestic currency depreciation) is less than the nominal interest rate differential, risk-neutral investors will continue investing in the domestic country until the expected rate of domestic currency depreciation is just equal to the nominal interest rate differential. Only when the expected rate of domestic currency depreciation is greater than zero in an absolute value, will there be a differential between the two nations' nominal interest rates. So we can infer that the initial appreciation of domestic currency has overshot its long run equilibrium. In the medium run, domestic prices will start to fall to respond to the relatively fixed level of outputs (output is assumed at its natural level) and the reduced nominal money supply. Once domestic prices go down, and then the real money supply rises, more outputs can be consumed. This results in a decrease in the interest rate, the capital inflow will be reduced, and the domestic currency will start to depreciate to its long run equilibrium. In summary, a cut in the nominal domestic money supply causes interest rates to rise, and consequently leads to a dramatic increase in the value of the domestic currency. But when the prices gradually fall, the domestic currency depreciates somewhat to reach the long run equilibrium.

In the stick-price monetary model, the exchange rate is positively related to the relative money supply and expected long run inflation rate differential, and negatively related to relative real GDP (real income) and nominal short run interest rate differential.

2.3.3.2 Flexible-Price Monetary (Frenkel-Bilson) Model (FPMM)

The flexible-price monetary model was originally developed by Frenkel and Bilson in the late 1970s. This model assumes that prices are perfectly flexible, and are determined by the domestic money supply because the output level is relatively fixed (output is also assumed at its natural level). Moreover, in the flexible-price monetary model, purchasing power parity is assumed to hold. Therefore, it is concluded that the domestic money supply determines the exchange rate. Hence, if the domestic money supply is reduced, then in this model, the domestic currency will appreciate. On the other hand, if real income falls, then the demand for domestic money stock will shrink. In this case, real money supply is excess real money demand, residents will expand their consumption and prices will go up because of a relatively fixed level of outputs. Since domestic prices are higher, which implies that the inflation rate in the domestic country is higher; consequently, the value of the domestic currency will be reduced in the long run according to the theory of purchasing power parity.

In the flexible-price monetary model, the exchange rate is positively related to the relative money supply, nominal short run interest rates differential and expected long run inflation rates differential, and negatively related to relative real GDP (real income).

2.3.3.3 Comparison of SPMM and FPMM

In the stick-price monetary model, changes in the nominal interest rates imply monetary policy is changing. However, in the flexible-price monetary model, changes in nominal interest rates directly reflect that the expected inflation rates are changing.

The flexible-price monetary model is more suitable to describe the cases of large inflation differential. For example, FPMM successfully captured the main features in the German hyperinflation of the 1920s (Frenkel, 1976). While the stick-price monetary model is more realistically applied in the opposite case of having a relative small inflation differential such as the Canadian Dollar against the United States Dollar in the 1950s (Mundell, 1964 and 1968).

2.3.3.4 General Equilibrium Model

The general equilibrium model is an extension of the flexible-price monetary model that additionally takes multiple trade goods and real shocks across countries into account. In this model, we consider that in a two-country, two-goods world that prices are flexible; but in contrast to the flexible-price monetary model, domestic and foreign goods are *not* perfectly substitutive. If the domestic money supply is extended, then the domestic currency will depreciate. Also, if domestic real income increases, then the demand for money will arise and hence induce a relative contraction of the money supply; consequently domestic prices will fall as well which implies that domestic currency will appreciate under the circumstances that purchasing power parity is held. These analyses are the same as in the flexible-price monetary model, but the case of preference shift is beyond the capability of FPMM. A shift in preference away from foreign goods to domestic goods caused by an increase in domestic productivity (output per capita) results in 'relative price effect' and 'money demand effect'. The former effect implies the relative domestic goods prices are reduced, and then domestic currency will tend to depreciate. The latter effect implies that the demand for domestic money increases as a result of an appreciation of domestic currency. Whether the exchange rate appreciates or depreciates is determined by the relative size of these two opposite effects. In other words, the degree of substitutability between domestic and foreign goods highly influences the relative value of the two currencies concerned. If the degree of substitutability is high, then the relative price effect will be small (Obstfeld and Stockman, 1985); that is, the money demand effect dominates the relative price effect, and therefore the domestic currency will appreciate eventually.

2.3.3.5 The Empirical Findings of Monetary Models

Macroeconomic fundamentals (such as money supply, industrial production, interest rate and inflation rate) seem important in determining exchange rate movements over relatively *long* horizons, the substantial and often persistent movements in exchange rates in the *short* run (even *medium* run), especially within one year or less, are largely unexplained by macroeconomic fundamentals (Sarno and Taylor, 2002). Many empirical studies have strong evidence to support this statement. For example, Diebold, Gardeazabal and Yilmaz (1994)[31] incorporated the cointegration relationship among exchange rates, which is demonstrated in Bailie and Bollerslev (1989 and 1994), to build an error correction model (ECM), but it had found no improvement upon the accuracy for out-of-sample forecasts within one-year (1-, 21-, 42-, 63-, 84-, 105- and 126-days). The remaining unexplained parts of exchange rate movements could be logically attributed to innovations in unobservable fundamentals such as

[31] This paper uses daily observations of the Canadian dollar, French franc, German mark, Italian lira, Japanese yen, Swiss franc and UK pound.

productivity shocks, or non-fundamental factors such as speculative bubbles (Frankel and Rose, 1995).

Regarding the accuracy of exchange rate out-of-sample forecasting with short forecasting horizons, a short run model (ARIMA (autoregressive integrated moving average) model) does perform better than a long run model incorporating economic fundamentals. This ARIMA model utilises only past values of exchange rates to generate future values of exchange rates based on criteria MAE (mean absolute error) and RMSE (root mean square error). For most of the forecast horizons from 1 to 12 months, the ARIMA model out-predicts a long run monetary based model (Hock and Tan, 1996)[32]. However, we cannot jump to conclude that in the foreign exchange market, the investors who believe the exchange rate will converge to the long-run equilibrium will *not* be at more of an advantage than those who only have the information of past values of spot exchange rates in a relatively longer horizon (Hock and Tan, 1996). In fact, the investors can substantially gain greater economic value based on monetary fundamentals than those who only use a random walk model across a range of horizons from 1 to 10 years, and more important is that the longer the forecast horizon, the more the economic value (Abhyankar, Sarno and Valente, 2004)[33].

A special model (Baharumshah, Sen and Ping, 2003) consisting of a linear combination of a long-run function (based on purchasing power parity) and a short-run function (based on its time series) does outperform the naïve random walk model in terms of out-of-sample exchange rate forecasting for all the forecast horizons ranging from 1 to 14 quarters. Introducing a short-run function, which captures the deviations of the exchange rate from its long-run path, is critical for the research (Baharumshah, Sen and Ping, 2003) to achieve the thrilling result that a monetary fundamentals based model can overturn the result of Meese and Rogoff (1983) even in a *short* (within one year) forecast horizon. Although Baharumshah, Sen and Ping (2003) focuses on the currencies[34] that are not free-tradable, the positive results

[32] This paper uses monthly observations of the US dollar, UK pound, German mark and Japanese yen.
[33] This paper uses monthly observations of the US dollar, Canadian dollar, UK pound and Japanese yen.
[34] The chosen currencies are the Malaysian ringgit, Singapore dollar, and Thailand baht, which were pegged to a basket of currencies (Among these currencies, the US dollar had the highest weight).

encourage us to use a fundamental monetary model with an ingenious adaptation, such as incorporating more dynamic econometric specifications (Edison, 1991; Chinn and Meese, 1995; Conway and Franulovich, 2002) to obtain a reasonably accurate forecast.

Similar satisfactory results, where the monetary fundamentals model dominates the random walk model for 13 out of 18 exchange rates at 1-quarter forecasting horizon and for 17 out of 18 exchange rates at 16-quarter forecasting horizon by employing a panel regression, and moreover the out-of-sample forecast accuracy of monetary fundamentals relative to the random walk model tends to improve with the prediction horizon (Mark and Sul, 2001)[35], also confirm the information that monetary fundamentals do contain significant prediction power especially in the long run.

2.3.4 Portfolio Balance Model[36]

It is assumed that domestic and foreign assets are *not* perfectly substitutive in the portfolio balance model, which is not the case in the stick-price monetary model or the flexible-price monetary model. The wealth of domestic residents consists of domestic money, domestic bonds and foreign bonds (dominated by foreign currency). If domestic monetary authorities decide to sell domestic bonds, then the domestic money supply will be reduced because domestic residents pay for the bonds with domestic money supply, and the price of domestic bonds will fall and domestic interest rate will rise (implying a higher yield or return to attract investors). The rise of the domestic interest rate causes domestic residents to hold fewer foreign bonds and more domestic bonds, and domestic money demand will be reduced. The reduced demand for foreign bonds leads to a decrease in the price of foreign bonds and an increase in the foreign interest rate. Since the foreign interest rate starts increasing, the capital outflow to foreign countries will increase, and thus will moderate the increase in the domestic interest rate. Moreover, the relatively higher demand for domestic bonds and relatively less demand for foreign bonds imply the demand for domestic

[35] This paper uses quarterly observations of the Australian dollar, Austrian schilling, Belgian franc, Canadian dollar, Danish krone, Finnish markka, French franc, German mark, Greek drachma, Italian lira, Korean won, Netherlands guilder, Norwegian krone, Spanish peseta, Swedish krona, Swiss franc, UK pound and US dollar.

[36] Same as Footnote 26

currency is relatively higher and the demand for foreign currency is relatively less; consequently, domestic currency will appreciate against foreign currency. From the simple analysis, we can see that the assets sector determines the spot exchange rate and the domestic interest rate.

The wealth effect positively related to asset demand strongly provides the evidence for the portfolio balance model (Lewis, 1988)[37]; moreover, three out of four bonds (Canadian dollar, German mark and Japanese yen) wealth elasticities are significantly different from zero. Karfakis and Kim (1995) stated that when there was an announcement that the Australian current account deficit was larger than expected then the Australian dollar would depreciate, which supports the theory of the portfolio balance model.

2.3.5 Artificial Neural Networks Model[38]

Artificial neural networks (ANNs) are inspired by biological systems, and are being used in wide research fields, including medical diagnostics, biological investigation, product selection, system control, pattern recognition, functional synthesis, computer science, and general business (Hu, Zhang and Patuwo, 1999), due to their special ability to learn from and generalize from experience.

Currently, one of main application areas for ANNs is forecasting because ANNs have some distinguishing features over the traditional model-based methods and which make them more suitable and useful in this area. First, ANNs are data-driven self-adaptive methods, and therefore they can capture the relationship between input and output data even if it is hard to specify the relationship by traditional methods. Therefore, very few *a priori* assumptions are required in ANNs approach, which saves a lot of the work required to build theoretical laws in the system. Second, ANNs have a high degree of capability of generalization. Having learned pattern(s) among the data on hand, ANNs are able to draw an accurate inference about the other data (out of the sample) in the population regardless of whether the data in the sample are

[37] This paper estimated foreign bonds demand equations from the portfolio balance model for five countries: the US, the UK, Germany, Japan and Canada.
[38] The theory of this section is mainly based on Zhang, Patuwo and Hu (1998).

masked by noise or not. In this sense, it is believed with confidence that ANNs can do a good job of forecasting by predicting future behaviour (out-of-sample data) from learning about the existence of past behaviour (in-sample data). Third, the much more general and flexible functional forms obtained lead to ANNs being competent to describe precisely the extremely complicated underlying relationship between inputs (the past/current values) and outputs (the future values). On the other hand, traditional methods do not have this advantage of being universal functional approximators. Finally, ANNs are a general nonlinear mechanism. Many previous forecasting studies assume that the relationship between inputs and outputs is linear. This is not reasonable in that, in the real world, many given time series are generated nonlinearly and have too many possible nonlinear patterns. As mentioned firstly, ANNs can perform well without having *a prior* knowledge about the functional relationships among the data; therefore, ANNs are superior to the nonlinear models as well as linear models in the forecasting field from this point of view.

Although ANNs have several obvious advantages compared to traditional methods, the performance of ANNs for forecasting tasks over a large number of reports is not consistent. The primary reasons why ANNs could not compete with the traditional linear models in some cases are that the data is linearly generated with no or minimum disturbance (it is not rational to expect that ANNs forecast linear relationships more accurate than linear statistical models), and the data set is not trained under an ideal network structure. There is no an explicit guideline to choose a suitable network structure for a particular data set, and the only way of doing so is based on limited experiments.

It is realised that ANNs also have some weaknesses[39], and they can never be viewed as a universal panacea which is capable of predicting everything well in all situations. In other words, ANNs cannot replace the traditional statistical methods; instead they are a very useful supplementary tool for the latter: ANNs do perform much better when time series data with high frequency is available, and when the underlying relationship among the data is nonlinear (Gonzalez, 2000).

[39] The biggest one is that ANNs approach involves a considerable degree of uncertainty caused by the limited solid theoretical framework available (more detail will be discussed in the subsection 2.3.5.2 --- Strengths and Weaknesses of Neural Networks).

2.3.5.1 A Few Restatements of Neural Networks[40]

First, on the basis of economic theory, it can be inferred which explanatory variables should be included in the regression models. However, in specifying a functional form of a relation in a model there is generally a lack of theoretical ground. Therefore, building the architecture of a neural network model without the support from economic theory is not a *unique* shortcoming for the ANN modelling. Second, to some extent, many neural network models are theoretically equivalent to the standard statistical models. The conventionally distributional assumptions, which constrain the standard regression models, are also needed for neural network models to provide an optimal outcome to make sure that estimates are unbiased and consistent, and variance is minimised. Finally, neural networks can capture the features of the patterns (between input and output variables) well by applying an algorithm to minimise the error (the difference between actual and estimated output values); hence neural networks can provide more desirable estimated outputs compared to traditional regression models for the same data sets. The positive result is from the more advanced methods used in neural networks rather than the nature of neural networks themselves which are mistakenly called *intelligent systems*.

2.3.5.2 Strengths and Weaknesses of Neural Networks[41]

The neural network modelling has three major advantages compared to traditional statistical modelling. First, it is superior to linear regression models in terms of modelling nonlinear relations because nonlinear activation functions in the use of neural networks can more effectively capture the features of nonlinear patterns. Second, it relaxes *a priori* functional form assumptions which are required in the other nonlinear modelling. In reality, information about the function form of a relation is not always available. The lack of knowledge is likely to cause a mistake to be made by selecting a wrong function form in the regression model, which in turn, greatly reduces the accuracy of forecasts in the other nonlinear models. Finally, the architecture in neural networks is relatively flexible. The architecture of neural networks harmonises with a wide range of often used statistical techniques as long as

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[40] The theory of this section is based on Gonzalez (2000).
[41] Same as Footnote 40

these statistical methods modify their structures a little. This implies that a neural network modelling has a variety of capacities.

On the other hand, four undesirable aspects of the neural network are also detected. First, the existence of hidden layer(s) in the neural networks makes the impact of an individual input on the estimated output very complex and difficult to identify, and hence the weights from the estimated neural networks are hard to interpret. Second, the global minimum is likely to be masked by some local minima and hence not easily found. This often happens when using all nonlinear estimation methods since some local minima are very close to the global minimum. Third, a large sample is particularly necessary for neural networks to provide a high quality forecast because too many weights involved in the neural networks (compared to standard regression modelling) reduce the degrees of freedom. Finally, to design and estimate a neural network architecture is a time-consuming task owing to the complicated experiment-based procedure of building neural networks.

2.3.5.3 Empirical Findings of Artificial Neural Network Technique

It is generally accepted that exchange rate dynamics cannot be fully captured by standard linear models largely due to linear modelling misspecification[42]. Theoretically, the causal relation between economic fundamentals and exchange rates is very likely to be too inherently complicated to be specified accurately. Therefore, traditional linear models (and some traditional nonlinear models) fail to capture the features of exchange rate dynamics adequately, although economic fundamentals are essentially important in driving exchange rates (Qi and Wu, 2003). The existence of too many possible nonlinear patterns between exchange rates and their fundamentals makes it extremely difficult to formulate a particular nonlinear model that can effectively capture all nonlinear features in a given data set (Zhang, Patuwo and Hu, 1998).

In order to further exploit the relation between exchange rates and fundamentals, and explain better the exchange rates movements and hence provide more accurate

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[42] For more detail, see the discussions of Qi and Wu (2003) and Gradojevic and Yang (2000).

exchange rates forecasts, artificial neural networks (ANN) technique --- a very powerful tool capable of approximating almost any nonlinear function (Franses and Dijk, 2000; Gradojevic and Yang, 2000) --- has been widely used in the area of exchange rate forecasting. The ANN model is a typical case of the flexible functional forms that do *not* specify any functional form of the relationship (Medeiros, Terasvirta and Rech, 2002). Moreover, ANN models, which are distinguishable from traditional nonlinear models, are good at performing nonlinear modelling without the requirement of *a priori* knowledge about the underlying relationships between explained and explanatory variables (Gonzalez, 2000), and hence they can be viewed as a more general and flexible modelling for the purpose of forecasting (Zhang, Patuwo and Hu, 1998).

Unfortunately, very few articles have been published on the application of ANNs with a foundation of a structural exchange rate modelling. Most studies, which aim to forecast exchange rates more accurately by ANNs, have *not* employed a theory-based structural model. On the contrary, these studies either are keen on more generally nonlinear and/or nonparametric issues (Deboeck, 1994) or are restricted to the purely empirical nature of ANN itself (Refenes, Azema-Barac, Chen and Karoussos, 1993; Kuan and Liu, 1995). Here, we only choose some examples which implement structural exchange rate models accompanied by the ANN technique.

Three structural models (the flexible-price monetary model, the stick-price monetary model and the portfolio model) employing ANN specification (Plamans, Verkooijen, and Daniels, 1998)[43] generally could not produce satisfactory short run one-step-ahead forecasts (forecast horizon is 1 month). Similarly, ANN procedures employed by (Oi and Wu, 2003)[44] and chosen, with the guidelines of economic theory, a set of monetary fundamentals could not out-predict a random walk model or a simple linear monetary model with no ANN technique at 1-, 6- and 12-months forecast horizons. These studies suggest that neither market fundamentals nor nonlinearity can improve the performance of exchange rates forecasting. The negative results may largely be attributed to the problems that the true potential power of the ANNs has not been fully

[43] These papers use monthly observations of the Dutch guilder, German mark, Japanese yen, UK pound and US dollar.

[44] This paper uses monthly observations of the Canadian dollar, German mark, Japanese yen, UK pound and US dollar.

exploited (Gonzalez, 2000) because of only limited heuristic guidelines available for designing an appropriate ANN's architecture for a given data set (Zhang, Patuwo and Hu, 1998), or the forecast horizons are too short[45] (within one year in these cases). The latter problem can be confirmed with the empirical finding (Verkooijen, 1996)[46] that neural network models guided by monetary fundamentals provide more accurate out-of-sample forecasts than linear regression models and random walk forecasts for horizons varying between 1 and 36 months ahead (1-, 6-, 12-, 24-, and 36-months) especially for longer horizons.

2.4 The Outline of This Research

In order to successfully forecast, at least one of the following criteria should be met (Baharumshah, Sen and Ping, 2003; Granger and Newbold, 1977; Giddy and Duffey, 1975):

1. A superior forecasting model is employed;
2. A modifiable forecasting mechanism is used;
3. A consistent access to information is available; and
4. Small and temporary deviations from equilibrium can be exploited.

Accordingly, this research uses a stick-price monetary model together with the ANN technique to predict monthly exchange rates (NZ dollar vs Australian dollar; NZ dollar vs US dollar) movements for the period between January 1990 and December 2003.

The monetary model is chosen since the exchange rates between major industrialised countries in the floating system cannot move independently of macroeconomic fundamentals for a long time, and theory-based macroeconomic fundamental models with significant components do display explanatory power for the exchange rates prediction at long horizons over two years (Chinn and Meese, 1995; Mark, 1995).

[45] ANNs perform better as the forecast horizon increases (Hill, Marquez, O'Connor and Remus, 1994) which is as same as monetary fundamentals (discussed in subsection 2.3.3 --- Monetary Models).
[46] This paper uses monthly observations of German mark and US dollar.

And the stick-price monetary model is further confirmed in this research because it is more realistically applied in the case of a relatively small inflation differential which is suitable for our data set (New Zealand, Australia and US did not experience a high inflation differential over the last 14 years).

Having chosen the monetary model as a baseline for the forecasting model, we then also employ a universal nonlinear pattern detecting device (ANN technique) (Gonzalez, 2000) to adequately capture exchange rate deviations from the long run equilibrium. The reason we use monthly data[47] in our research is that ANN works better for the high frequency data (Hill, Marquez, O'Connor and Remus, 1994; Hill, O'Connor and Remus, 1996), where the underlying pattern between input and output variables has more chance of being masked by noisy factors such as irregularities[48] (seasonality, cyclicity, nonlinearity, noise) (Zhang, Patuwo and Hu, 1998). Also our data set is relatively large since ANNs perform better in a large data set (Gorr, 1994) and are less appropriate for a small sample (Teräsvirta, Dijk and Medeiros, 2004). In addition, this research will examine the percentage of correctly predicted exchange rate changes (PERC) of ANNs forecasts according to the positive empirical finding that ANNs forecasts can capture remarkably more tuning points (Kohzadi, Boyd, Kermanshahi and Kaastra, 1996).

The new microstructure approach does provide some hope of better mimicking and predicting exchange rates movements (Frankel and Rose, 1995), but this is beyond the scope of this research largely due to microeconomic data sets being not yet readily available (Lyons, 2002).

[47] All our data is from the same source to make sure that the information is consistent.
[48] ANNs perform even better for the time series with more irregularity (Sharda and Patil, 1992).

Chapter 3 Econometric Methods and Data

3.1 Introduction

This chapter will first discuss the methodology of this research employed with a focus on the techniques of artificial neural networks, and in turn introduce forecasting measurements followed by the outline of the report format which will be used in the next chapter. Then, the explanation of the economic theory supporting the selection of the explanatory variables is provided. Finally, the data are described in detail.

3.2 Methodology

3.2.1 Simple Linear Regression Model

It has been discussed in Chapter 2 (Literature Review) that it is extrêmely difficult to get the microstructure data of "order flow" due to this microeconomic variable not yet being readily available. This research, therefore, employs a macroeconomic model (Meese and Rogoff, 1983) excluding microstructure variable(s) to estimate exchange rates monthly. In other words, this model implies that the foreign market is efficient in the sense that information is widely available to all market participants and that all relevant and ascertainable information is already reflected in exchange rate movements, and microstructure variables hence do not contain information relevant to exchange rate determination (Sarno and Taylor, 2002).

The macroeconomic model to be used in this research is:

$$E_t = \Phi(M_t) + \varepsilon_t \qquad t=1,\ldots N \quad (3.1)$$

where E_t is in the logarithm of the spot exchange rate over the month of observations; and M_t is a vector of typical macroeconomic variables, namely, the relative money supply, relative GDP, nominal interest rate differential, and the long-run expected inflation differential; ε_t is a random error term under the conventional assumptions.

The exact specification used in this thesis is as follows:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \quad (3.2)$$

where X_1 = natural log of relative money supply (index) $\left(Ln\left(\frac{M3_{NZ}}{M3_j} \right) \right)$

X_2 = natural log of relative GDP (index) $\left(Ln\left(\frac{GDP_{NZ}}{GDP_j} \right) \right)$

X_3 = nominal interest rate differential ($Int_{nz} - Int_j$)

X_4 = long-run expected inflation differential ($Inf_{NZ} - Inf_j$)

j = Australia, USA

3.2.2 Introduction to Artificial Neural Network (ANN) Methods[49]

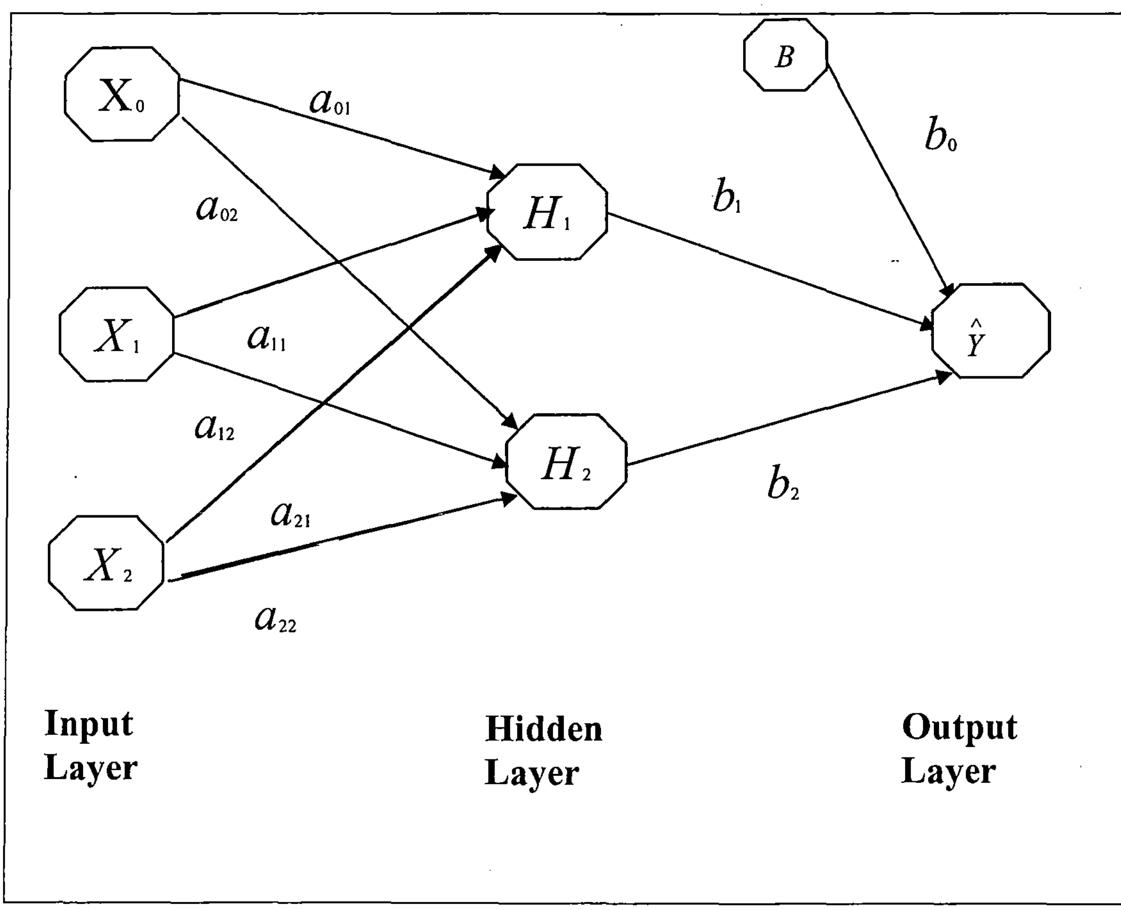
An artificial neural network, which collects a set of interconnected neurons, is like the human brain. The neurons in the networks are usually grouped in three layers, and information is continuously transmitted among these layers. By changing the neurons' connections and adjusting the connection weights[50], ANNs, a representation of a general class of non-linear models, are able to provide a much more accurate solution in a variety of areas and industries, including medical diagnostics, biological investigation, product selection, system control, pattern recognition, functional

[49] This overview of the ANN approach draws upon the discussions in Gonzalez (2000), Gradojevic and Yang (2000), Kaashoek and van Dijk (2001) and Zhang, Patuwo and Hu (1998).
[50] The various weights express the relative importance of a particular input to the output, and they are mathematically equivalent to the estimated coefficients of unknown parameters in a standard linear regression model.

synthesis, computer science and general business. One of the major applications for ANNs is forecasting, such as exchange rate forecasting. Although a lot of forecasting methods are available, generally the accuracy of their outcome is largely reduced when non-linear relationships and/or missing data are present, which often occurs when analyzing historical financial data. Neural networks, however, are a powerful and widely used technique for such complex prediction problems.

As mentioned above, the neurons (elements) are typically arranged into three layers: input layer, hidden layer and output layer. A general three-layer ANN model is described in Figure 3.1, which indicates the relationship among these three layers, and points out how each element in the previous layer contributes to the next layer with a different weight (Gonzalez, 2000).

Figure 3.1: A General Three-Layer ANN Model



The input layer receives data, and the elements in this layer are equivalent to the 'explanatory variables' in the standard linear model and each element represents one input. At the other end of the model, the element(s) in the output layer is (are) similar to the 'dependent variable(s)' in the standard linear model and each element represents one *actual* output. After the training process (mainly taking place in the hidden layer), an *estimated* output is supplied by the network in the output layer which can be interpreted as an in-sample forecast in response to the new input(s) that has (have) not been 'seen' by the network.

The hidden layer, being the bridge between the input and output layers, is critical for successful modelling since the signals have been continuously transmitted from the input layer to the output layer by the elements[51] in the hidden layer. The hidden layer, which is like the brain's interneurons, captures the correlations between the input and output data and further records this internal mapping. These functions of the hidden layer provide the network with an intuitive predictability and intelligence such as learning the present input-output patterns, adjusting the connection weights, and correctly inferring the new (unseen) input-output relations.

There is no theory-based rule for predetermining the optimal number[52] of hidden layers in a network. However, a trade-off between network learning ability and generalising ability[53] is recommended to be considered when the number of hidden layers needs to be decided. Too few layers will raise the problem that the network could not learn the input-output pattern well and hence reduce the network's power to accurately record the fact. On the other hand, too many hidden layers involved in a network could prevent the network from providing a good general solution for the 'unseen' parts of the data. In reality, the number of hidden layers in a particular network is purely data dependent and experimentally determined.

The elements in the hidden layer do not contain any real meanings, which are different from those in the input and output layers. But from the view of behavioural

[51] These elements in the hidden layer could be viewed as unobserved components in the linear model, and a sufficient number of hidden elements ensure that network can approximate almost any linear or nonlinear function to a desired level of precision.
[52] The number of hidden layer(s) can be more than one. However, one hidden layer is sufficient for most financial forecasting (Cybenko, 1989; Hornik, Stinchcombe and White, 1989), so the three-layered network is the most popular network to be applied for predicting.
[53] Generalization ability means to what extent a network can correctly infer the future 'unseen' parts of data by learning the present parts of data.

mannerisms, the elements in hidden layer are very similar to those in the output layer. Hidden elements compute the weighted sum of the input variables in the input layer by employing an activation function[54] and then provide an intermediate result in the hidden layer, and output elements calculate the weighted sum of the intermediate results in the hidden layer also by an activation function and then offer an *estimated* output value in the output layer.

During the learning[55] process, the connection weights are initially set to be a group of small random values and the inputs and *actual* outputs are introduced to the network. Then the model's *estimated* output is calculated and further compared to the *actual* output to produce a network error. Since they are the key to modifying the values of the connection weights in order to provide an accurate forecast in the network, the inputs weights in the hidden layer are changed several times. Consequently the hidden elements' weights in the output layer are also changed several times until the global minimum network error is found. After training, connection weights are re-determined and an input-output data pattern is revealed; ultimately, a much more precise *estimated* output can be obtained in analysing historical business data such as exchange rates forecasting.

3.2.3 Basic Principle of Artificial Neural Networks Model[56]

3.2.3.1 A Nonlinear Activation Function

It is necessary to introduce a nonlinear activation function for the potential of neural networks to be truly exploited. Some degree of nonlinearity brought by the activation function allows the neural networks to detect and further reproduce nonlinear patterns in the complicated data, which is a great advantage of using artificial neural networks. The ideal nonlinear activation function should have the characteristics of being continuous, differentiable, monotonic and bounded (Zhang, Patuwo and Hu, 1998)

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[54] The most common activation function is a logistic function.
[55] It is said that the network is learning when the connection weights are changing with each iteration.
[56] The basic principle of the ANN draws upon the discussions in Gonzalez (2000), Zhang, Patuwo and Hu (1998) and Qi and Wu (2003).

since these characteristics aid the network algorithm to find the appropriate connection weights.

In practice, there are a few well-behaved activation functions that have the characteristics discussed above:

- The sigmoid (logistic) function

  $$f(x) = \frac{1}{1+e^{-x}}$$

- The hyperbolic tangent (tanh) function

  $$f(x) = \frac{e^{x} - e^{-x}}{e^{x} + e^{-x}}$$

- Gaussian function

  $$f(x) = e^{x^2/2}$$

- The sine or cosine function

  $f(x) = \sin(x)$ or $f(x) = \cos(x)$

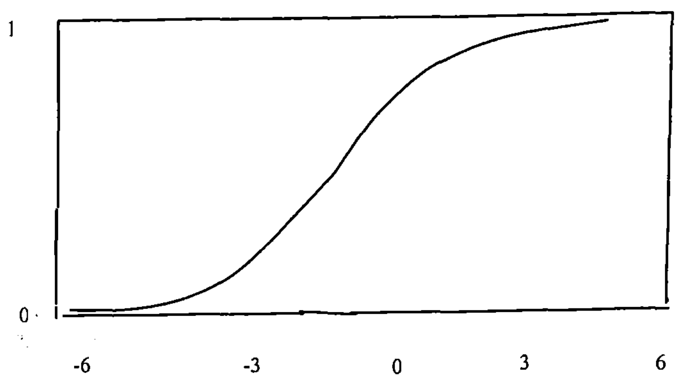
- Threshold function

  $f(x) = 0$ if $x < 0$

  $f(x) = 1$ if $x \geq 0$

Among these activation functions, the logistic cumulative distribution function is the most common one in the application of the neural network, and is depicted in Figure 3.2 below (for further detail see Gonzalez (2000)).

Figure 3.2: The Logistic Function



Through the use of the logistic function, which is mathematically bounded between 0 and 1, it is possible to mimic the way a real neuron from a human brain responds to the impulse received in order to further understand how an element from a data set responds to the information received. The level of an element in response to the information received monotonically increases from nearly nothing to highly activating as the value of the activation function increases nonlinearly from 0 to 1.

3.2.3.2 The Expression of Artificial Neural Network Model

Although many kinds of ANNs are available, the three-layer feedforward[57] network depicted in Figure (3.1) is the most popular network and is used widely. Within the three-layer feedforward network depicted in Equation (3.3), the vector of input variables is $X=\left(x_1, x_{2,\ldots,} x_k\right)'$ through the nonlinear function *g* and further using the linear or nonlinear function *f* to estimate the output variable. Therefore, a three-layer ANN model can be generally represented as:

$$Y=f\left\{\beta_0+\sum_{j=1}^{n}\beta_j g\left(\alpha_{0j}+\sum_{i=1}^{k}\alpha_{ij}x_i\right)+\varepsilon\right\} \quad (3.3)^{58}$$

where *k* is the number of input-layer units, and *n* is the number of hidden-layer units; a matrix of $\left\{\alpha_{ij}, i=1,2,\ldots,k; j=1,2,\ldots,n\right\}$ stands for the connection coefficients of the

[57] Forward refers to the activations propagated forward during the learning progress.
[58] In this equation, the reason that time subscripts are omitted is just for simplicity.

input-layer units to the hidden-layer units (α_{ij} denotes the weight that links input-layer unit *i* to hidden-layer unit *j*). Similarly, a vector of $\{\beta_j, j = 1, 2, ..., n\}$ indicates the connection coefficients of the hidden-layer units to the output-layer units (β_j denotes the weight that links hidden-layer unit *j* to output-layer unit *Y*). ε is the error term which usually has a Gaussian conditional distribution that is the same as in the standard linear model.

Note: Both α_{ij} and β_j are the parameters to be estimated in the equation.

The next two sections are going to further discuss the relationship between input, hidden and output layers under the condition of whether or not the dependent variable (output) is bounded.

3.2.3.2.1 The Dependent Variable Is Bounded (0, 1)

Similar to the standard linear model, one of input variables, which is called the bias (intercept term), is set to 1. In a simple input-output (two layers) neural network, it is assumed that X_0 is the bias, the output (Y) of the network is given as Y = $a_0X_0 + a_1X_1 + a_2X_2$, which is equivalent to Y = $a_0 + a_1X_1 + a_2X_2$. The same principle is also applied to hidden units.

In an explicit way, we assume that there are three input units (X), two hidden units (H), and one output unit (Y). If the dependent variable is bounded, the hidden units and the output unit generally use a logistic activation function. That is, both *f* and *g* are logistic activation functions.

In general, the output unit (Y) is expressed as some function of the two hidden units (H_1 and H_2):

$$Y = f\left(b_0 + b_1H_1 + b_2H_2\right) \quad (3.4)$$

When Y is bounded this can then be formulated as a logistic function as follows:

$$Y=\frac{1}{1+e^{-(b_0+b_1H_1+b_2H_2)}} \quad (3.5)$$

Moreover, expressing each hidden unit as a logistic function of the X_j inputs, we have:

$$Y=\frac{1}{1+e^{-\left[b_0+\frac{b_1}{e^{-(a_{01}+a_{11}X_1+a_{21}X_2)}}+\frac{b_2}{e^{-(a_{02}+a_{12}X_1+a_{22}X_2)}}\right]}} \quad (3.6)$$

3.2.3.2.2 The Dependent Variable Is Not Bounded (0, 1)

On the other hand, if the dependent variable is not bounded, the hidden units employ a logistic activation function as usual, but the output unit often follows an identity activation function such as *f(x) = x*. That is, *g* is still a logistic activation function, but *f* is an identity activation function.

In this case, the output unit (Y) can still have the general form:

$$Y=f\left(b_0+b_1H_1+b_2H_2\right) \quad (3.4')$$

In contrast to Eq (3.5), here the unbounded output Y is a linear function of the hidden units (Namely, the value of the output can be expressed as the sum of the weighted hidden units):

$$Y=b_0+b_1H_1+b_2H_2 \quad (3.5')$$

However, as for Eq (3.6'), the hidden units are a nonlinear (logistic) function of the X_j input units:

$$Y=b_0+\frac{b_1}{1+e^{-(a_{01}+a_{11}X_1+a_{21}X_2)}}+\frac{b_2}{1+e^{-(a_{02}+a_{12}X_1+a_{22}X_2)}} \quad (3.6')$$

To sum up, the use of the logistic activation function and the identify activation function allows the network to produce a continuous, nonlinear, bounded or unbounded output.

Note: Both a_{ij} and b_j are the parameters to be estimated in the equations.

3.2.4 Important Techniques of the Artificial Neural Networks Model[59]

3.2.4.1 The Steps of the Network Development

1. Select a set of explanatory variables[60].
2. Choose a suitable architecture.
3. Set initial connection weights, the number of hidden layers, the number of units in each hidden layer and other foundational arrangements.
4. Organise the whole sample data in ascending time order, and then divide it into three sets (training set, validation set and test set) by the most common ratio of 6:2:2.
5. Get the predictions from artificial neural networks through software (NeuroShell 2 is used in this research).
6. Evaluate the performance of forecasting from ANN, and further compare it with other linear and/or nonlinear models.
7. Steps 3-6 are repeated until the error goal (the minimum of the mean square error in the validation set) is reached.
8. Steps 2-7 are repeated until the error goal (the minimum of MSE in all possible architectures) is reached.
9. Decide whether the existing explanatory variables need to be added and /or removed.

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[59] The important techniques of Artificial Neural Networks Model draw upon the discussions in Gonzalez (2000), Zhang, Patuwo and Hu (1998), Gradojevic and Yang (2000), Medeiros, Terasvirta and Rech (2002) and Software of NeuroShell 2 Help Menu (Ward Systems Group Incorporated).

[60] It is far more efficient to start using a linear regression model to experiment with different sets of explanatory variables. Once a satisfactory set of variables has been identified, the researcher can proceed to evaluate different architectures. Thus, one of the three levels of minimization identified can be greatly shortened through using a linear regression model.

10. Steps 1-9 are repeated until the error goal (the minimum of MSE associated with all possible sets of input variables) is reached.

3.2.4.2 The Technical Items of the Artificial Neural Networks

- **Data Normalization**

The logistic function being the representative of the nonlinear activation functions has the 'squashing' role of restricting the data into the range of (0, 1). Since nonlinear transfer functions are commonly used in the neural networks, data normalization is necessary for the output values as well as the input values, especially for the time series forecasting problems. Technically, normalising the data meets algorithm requirements that can aid the network to learn the data patterns more effectively and simultaneously largely mitigate computational problems. Having introduced the inputs and actual outputs into the network, immediately both minimum and maximum values for each variable are recognised by the network and then the software (NeuroShell 2) automatically scales the variables to lie between 0 and 1 before the training process begins. Later the same software automatically rescales inputs and outputs to the original range after estimation and/or forecasting as the result of providing convenience for measuring the performance and comparing the accuracy obtained by ANNs with other models.

- **Architecture Determination**

The major task of determining an appropriate architecture for an artificial neural network is to set some important parameters such as the number of layers, the number of elements in each layer, and the number of connection weights. However, selecting these parameters is basically dependent on the particular problem being considered through experiments to minimise the error because a solid theoretically-based method is not available. This research will use the exclusively fully-connected-feedforward network[61] as a basis with only one hidden layer for the forecasting purpose, since a single hidden layer is sufficient for the network to approximate almost any complex

[61] The exclusively fully-connected-feedforward network is a network which is fully connected in that all units in one layer are only fully connected to all units in the next layer except for the output layer.

nonlinear relation with a desired level of accuracy (Cybenko, 1989; Hornik, Stinchcombe and White, 1989). The exclusively fully-connected-feedforward network has been adopted for most forecasting applications.

For more detail, in this research recurrent networks (one type of backpropagation networks[62]) will be applied because recurrent networks are particularly good at learning sequences, so they are suitable for forecasting time series data to provide more accurate financial predictions. The reason is that the recurrent networks have a unique feature, in that they have an extra slab in the input layer, compared to the standard backpropagation networks. The extra slab is usually connected to the ordinary input layer, the hidden layer, or the output layer. In the case of forecasting, the recurrent networks with the extra slab linking to the hidden layer are chosen so that the hidden layer can introduce the features detected in all previous patterns into the new raw data in the input layer. Hence the network immediately grasps the feature about the last pattern, cumulates previous knowledge in a more timely way about the existing sequence data, more effectively adjusts the connection weights during the current training and ultimately enhances its forecasting ability.

- **Training Algorithm**

The backpropagation algorithm, which is characterized by hidden layers to extract the data patterns, is the most common training algorithm for the neural networks; hence it will be used in this research. For the training process, observations in the training set first enter into the input layer to be inputs, and next these inputs are sum weighted by an activation function and then are transformed into the hidden layer to produce estimated values for the hidden units. The same weighting and accumulating procedure is repeated for the hidden units and then these hidden units are transformed to the output layer to set the value for the estimated output. If there is a difference between the actual and the estimated output during the training process, then the backpropagation training algorithm will repeat the training process continuously, and

[62] Backpropagation is a widely used training algorithm in the neural networks which refers to the manner of a backward pass of error to each internal element within the network, and the standard backpropagation networks, which generalize well on a vast variety of problems, are exactly exclusively fully-connected-feedforward networks.

make the connection weights readjust to get this difference minimized for the entire sample.

The sequence of the patterns plays an important role in the successful training of the data sets in the recurrent networks to be successfully trained. In other words, for a given input pattern, a recurrent network tends to produce a different output pattern each time, which is largely influenced by the previous input patterns that have just been presented. This is completely different from the response of a standard backprogation network, which always provides exactly the same output pattern anytime as long as the given input pattern presented is the same. Therefore, the rotational pattern selection[63] must be used for both training set and test set, and the random pattern selection is not allowed when recurrent networks are employed in this research.

- **The Global Minimum**

Nonlinear estimation techniques do detect the nonlinear data patterns better due to the nonlinearity nature of the data itself, but the application of nonlinear models (artificial neural networks model employed in this research) has a unique difficulty during the estimation procedure compared to that of a linear model. That is, nonlinear models can hardly be sure whether the global minimum is attained because it is very likely to be masked by too many local minima with close mathematical figures. In order to reduce the possibility of introducing this problem into the estimation, which might ruin the potential performance of nonlinear models, it is necessary to repeat the process of neural network estimation as many times as possible with different blankets of random starting values for the initial connection weights in this research. Ultimately, the best estimation will be saved as the final one.

- **Sample Size**

Artificial neural networks models with more observations can detect more complex structure and more effectively handle irregularities in the data to achieve a higher

[63] The data patterns are presented in time order without gaps in the data set.

accuracy in modelling as long as the underlying relationship between inputs and outputs is truly nonlinear. On the other hand, a small sample could restrict the number of degrees of freedom in the ANN's model because of the existence of many weights (especially hidden units weights), which might induce an overfitting in the training set. Therefore, a relative large sample with 168 observations[64] (from 1990 January to 2003 December) will be used by applying the artificial neural network approach in this research.

- **Model Evaluation**

First, the final model, which has defined the potential variables and has selected a subset of them, should be evaluated by passing in-sample misspecification tests[65]. If the model does not pass any in-sample test, then, at least principally, it is necessary to reconsider the variables included and/or the functional form chosen in this model.

Out-of-sample forecasting[66], which is typically used for neural networks, is another method of evaluating a model. For carrying out this kind of model evaluation, the last observations in the series are saved to perform forecasting, and then the forecast results from different models[67] are compared and/or contrasted according to accuracy criteria.

- **Performance Measures**

As artificial neural networks are widely used for the application of forecasting, the most important performance measure[68] for an artificial neural network model is the prediction accuracy for out-of-sample observations. Practically, the degree of

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[64] ANN forecasting models can perform well even with a sample size of less than 50 observations (Zhang, Patuwo and Hu, 1998).

[65] The most important in-sample test is to test the assumption of no serial correlation in the errors, and this test will be taken in this research in the next chapter (Chapter 4 --- Empirical Results).

[66] The out-of-sample forecasting is the main purpose of this research, and it will be described in detail in the next subsection 3.2.5 --- Out-of-Sample Forecasting of Artificial Neural Networks Model, and will be further carried out in the next chapter (Chapter 4 --- Empirical Results).

[67] It is common to have at least one benchmark model for carrying out out-of-sample forecasting.

[68] The most frequently used performance measures for ANNs will be described in more detail in the following subsection 3.2.5.2.1 --- Accuracy Measures of Out-of-Sample Forecasting.

prediction accuracy is measured by the forecasting error, which is the difference between the actual value and the predicted value.

3.2.5 Out-of-Sample Forecasting of Artificial Neural Networks Model[69]

3.2.5.1 Introduction of the Problem of Overfit

The outstanding character of neural networks is their flexiblility which makes it convenient in building econometric models, but on the other hand over-flexibility can bring the problem of 'overfitting'[70]. Theoretically, more hidden layers and hidden units can better detect the data patterns, but there is no rule to determine the number of hidden layers and the number of hidden units, and it is really up to the nature of the application problem itself. If the number of hidden units is greatly increased without adding more input variables, then 'overfitting' in neural networks may occur because too many data patterns are drawn which make the neural network too specific to the *training* data set which worsens the ability to generalise. Once having acquired the 'overfitting' problem, a neural network model no longer accurately infers the real data generating process and consequently negatively affects the quality of the forecasts. This unique possibility of 'overfitting' for the neural networks makes it necessary to provide some principle for mitigating this problem in neural network modelling.

3.2.5.1.1 Pruning Technique

Since the existence of too many hidden units causes the problem of 'overfitting', pruning, a popular application technique, is introduced in the area of neural network forecasting. Pruning can dynamically eliminate insignificant weights and/or unnecessary hidden units during the *training* process and thus ensure a neural network has the appropriate size and can offer a good forecast as well as a good data fitting. Empirically, there are three frequently used pruning algorithms: information criterion pruning, cross-validation pruning and interactive pruning. However, this research

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[69] The out-of-sample forecasting of the ANNs model draws upon the discussions in Kaashoek and van Dijk (2001), Gonzalez (2000), Zhang, Patuwo and Hu (1998), Qi and Wu (2003) and Rech (2002).

[70] A network is said to overfit the data if too many input-output patterns are drawn from the data set, and an overfit network generally has low bias (small in-sample errors) but high variance (large out-of-sample errors which remarkably reduce the predictability of a network).

adopts a more common technique of "early stopping procedure", which will be discussed in more detail in the following section, rather than the pruning technique.

3.2.5.1.2 Early Stopping Technique

The purpose of employing the early stopping technique in neural networks application is exactly the same as that of the pruning technique. By using this technique, the whole data set needs to be split into three subsets in order: a training set, a validation set, and a test set. The training set is used to estimate the network connection weights, whereas the test set is used to yield the network out-of-sample forecasts. The validation set, which is never applied by the algorithm, is used as an indicator of the out-of-sample forecasting accuracy of the network by monitoring the error in this set during the estimation process. Having the validation set is the key for the early stopping technique to ensure the neural network model can successfully forecast.

An early stopping estimation technique can be described as in Figure 3.3, which depicts the inverse relationship between the number of iterations and the mean squared error (MSE) (Gonzalez, 2000).

Figure 3.3: Early Stopping Estimation Technique

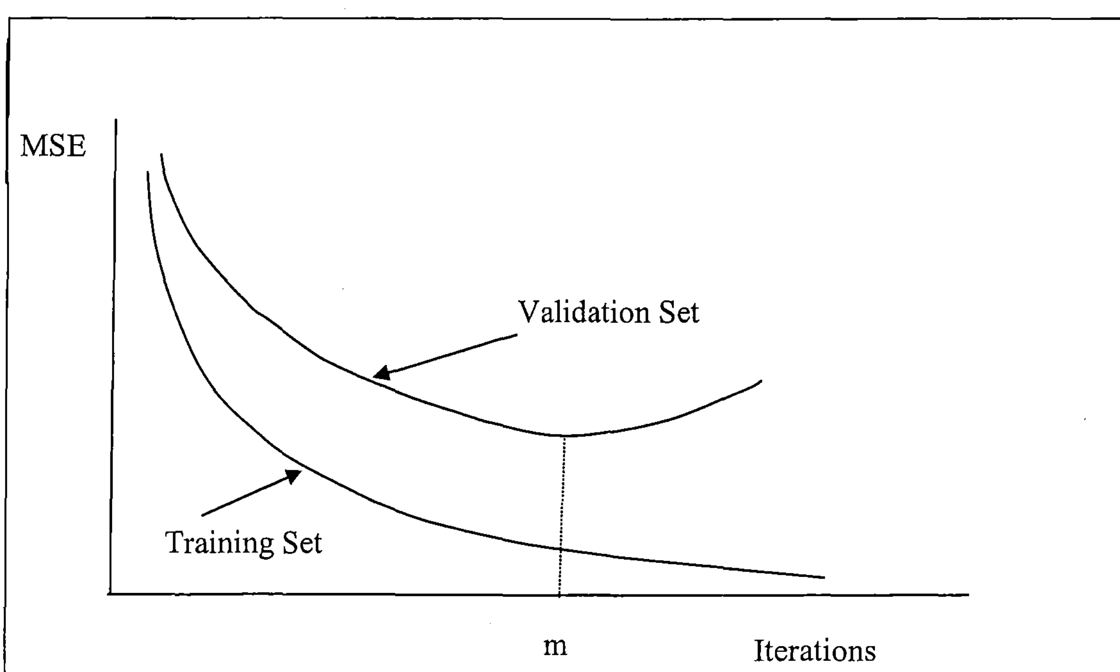

Figure 3.3 compares the development of the training set MSE with that of the validation set MSE throughout the whole estimation process. First, the MSE in both the training set and validation set continues falling by conducting more iterations. However, after a specific number of iterations (after *m* iterations in Figure 3.3), the MSE in the validation set begins to rise because the network starts to 'overfit' the data and hence significantly reduces its generality ability, while the MSE in the training set keeps declining since the network 'overfitting' the data is still 'fitting' the data. The estimation procedure must stop when it reaches the minimum error in the validation set rather than in the training set in order to avoid the network specialising in the observations of the training set, and to make sure that the network has the generalization capacity and can provide reliable forecasts.

Out-of-sample forecasts will be handled in the next stage after the coefficients estimated at the point that the error in the validation set just starts to increase have been saved as the final estimates. Using the early stopping technique causes the forecasting errors performed by the data in the validation set to be optimistically biased because the MSE in the validation set is already minimised before forecasting. Instead, out-of-sample forecasts from the data in the *test* set supply the given model with an unbiased estimate of the forecasting accuracy for the total population.

3.2.5.2 Out-of-Sample Forecasting

Generally, in order to provide artificial neural networks forecasts, time series data first need to be estimated through Eq (3.7) from the beginning until the observation $\left(X_{t_0}-h, Y_{t_0}\right)$ when forecasting starts from t_0 $\left(t_0<T\right)^{71}$ to produce forecasts with *h*-period forecast horizon. Then the first *h*-period forecast available is expressed as:

$$\hat{Y}_{t_0+h}=f\left\{\hat{\beta}^{h}_{0,t_0}+\sum_{i=1}^{n}\hat{\beta}^{h}_{j,t_0}g\left(\hat{\alpha}^{h}_{0j,t_0}+\sum_{i=1}^{k}\hat{\alpha}^{h}_{ij,t_0}x_{i,t_0}\right)\right\} \quad (3.7)$$

[71] It is assumed that a whole sample has *T* observations.

The same procedure should be repeated at time of t_0+1, $t_0+2,\ldots$, T-h to produce *N* (N=T- t_0-h+1) forecasts with *h*-period forecast horizon.

In this research, forecast accuracy is measured by the Root Mean Square Error (RMSE), Root Mean Square Percentage Error (RMS Percentage Error), Percentage of Correctly Predicted Turning Points (PERC), Pesaran-Timmermann test (1992, PT), and Diebold and Mariano forecast test (1995, DM). These measurements are described in detail in the following section.

3.2.5.2.1 Accuracy Measures of Out-of-Sample Forecasting

For both exchange rates (NZ-AU rate, and NZ-US rate) several measures are used to evaluate the forecasting accuracy of the empirical models (Pindyck and Rubinfeld, 1998, pp384-389; Preminger and Franck, 2005) because one specific forecast evaluation criterion is rarely suitable for any case (Perez-Rodriguez, Torra and Andrada-Felix, 2005). These evaluation measures include:

$$\text{RMSE (Root Mean Square Error)} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(Y_t^s - Y_t^a\right)^2} \quad (3.8)$$

$$\text{RMS Percentage Error (Root Mean Square Percentage Error)} = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{Y_t^s - Y_t^a}{Y_t^a}\right)^2} \quad (3.9)$$

where Y_t^s and Y_t^a are the estimated value and the actual value, respectively, and *T* is the number of periods in the data set.

In addition, we consider an indicator of PERC (Percentage of Correctly Predicted Turning Points) which is more suitable for the investors who usually focus on the total profits and are less interested in the technical accuracy of forecasts. The Pesaran-Timmermann test (1992) is a more formal test (compared to the PERC indicator) to check whether there exists significant economic value for a forecasting model in predicting the direction of change (Preminger and Franck, 2005). Also, these two measures can be viewed as the tools that check the forecasting accuracy about the direction of the change of the exchange rate in level. In other words, PERC and the PT test are the measures to examine which model can more accurately predict whether the exchange rate will go up or go down in the next period, but not necessarily the amount of the change.

$$\text{PERC (Percentage of Correctly Predicted Turning Points)} = \frac{N_1 + N_2}{N} \quad (3.10)$$

where N_1 and N_2 are the number of correctly predictions with positive sign, and negative sign, respectively, and N is the total number of the predictions.

$$\text{PT (Pesaran-Timmermann) Test Statistic} = \frac{\hat{P} - \hat{P}_*}{\sqrt{\hat{V}\left(\hat{P}\right) - \hat{V}\left(\hat{P}_*\right)}} \;\underset{\sim}{a}\; N(0,1) \quad (3.11)$$

where $\hat{P}$, which has the same concept as that of PERC, is the ratio of the number of times a forecasting model produces correct predictions of the sign of the actual series direction of change to the total number of times a forecasting model produces predictions of the sign of the actual series direction of change, and $\hat{P}_*$ is an estimate of $\hat{P}$ under the null hypothesis that the actual and the predicted series are independent of each other, and $\hat{V}\left(\hat{P}\right)$ and $\hat{V}\left(\hat{P}_*\right)$ are the estimates of the variance of $\hat{P}$ and $\hat{P}_*$, respectively[72].

Furthermore, the Diebold and Mariano (DM) forecast test (1995) is employed to examine the null hypothesis that the forecast accuracy of different models is the same.

$H_0 : E[d_t] = 0$ vs $H_1 : E[d_t] \neq 0$

[72] Pesaran and Timmermann (1992) provided more detail about the PT test. For a two-sided test, the null hypothesis of the PT test will be rejected if the PT test statistic is larger than 1.96 in an absolute value.

where d_t $\left(d_t = e^2_{0,t+h} - e^2_{a,t+h}\right)$ is the difference between the forecast errors (the squared forecast errors are adopted in this research) of the benchmark model $\left(e^2_{0,t+h}\right)$ and the alternative model $\left(e^2_{a,t+h}\right)$. (Note: h ($h \geq 1$) is denoted as the forecast horizon). The actual DM test statistic is then

$$\text{DM Test Statistic}^{73} = \frac{\frac{1}{T}\sum_{t=1}^{T} d_t}{\sqrt{\hat{V}\left(\frac{1}{T}\sum_{t=1}^{T} d_t\right)}} \quad (3.12)$$

where T is the total number of the forecasting periods, and $\hat{V}\left(\frac{1}{T}\sum_{t=1}^{T} d_t\right)$ is the estimate of the variance of $\frac{1}{T}\sum_{t=1}^{T} d_t$.

3.2.5.2.2 The Format for Reporting Forecasting Results

For our results we follow an important paper by Mark (1995) that focuses on different models' ability to predict exchange rates over a 'long run' horizon. Mark (1995) employs a regression model theoretically based on economic fundamentals to predict movements in exchange rates[74] with 1-, 4-, 8-, 12-, and 16-quarters forecasting horizons. His general conclusion is that changes in (the logarithm of) spot exchange rates over long-horizons (especially 12- and 16-quarters) are predictable by the regression model in comparison to a benchmark (Random Walk) model that is presented in Meese and Rogoff (1983).

Mark's regression model, which predicts the k-period-ahead change in the log spot exchange rates, is:

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[73] Diebold and Mariano (1995), Luger (2004) and Brand, Reimers and Seitz (2004) provide more detail about the DM test.

[74] This paper uses quarterly observations of the Canadian dollar, German mark, Japanese yen and Swiss franc vs US dollar from 1973 to 1991.

$$\Delta e_k = \alpha_k + \beta_k z_t + v_{t+k,t} \quad (3.13)$$

where Δe_k is the k-period-ahead actual change in the log spot exchange rate. We note that the z_t is actually an error correction term, that is, the deviation of the spot exchange rate (e_t) from the rate associated with economic fundamentals (f), which can be presented as $z_t \equiv f_t - e_t$[75], where α_k and β_k are linear least-squares regression coefficients, and $v_{t+k,t}$ is the prediction error. Hence, equation (3.13) can be viewed as an error correction model.

In our research, we compute f by relaxing Mark's restriction that $\lambda = 1$, and by incorporating two more economic fundamentals variables (interest rate and inflation rate) in our normal linear monetary model (see Eq (3.2)) rather than an error correction model. In other words, we predict the exchange rate movement in levels rather than in changes. Also we employ artificial neural network methods to form the nonlinear monetary model, and the reason for doing that is clearly stated in Chapter 2 --- Literature Review.

In Mark (1995) the data set started in 1973 when the observed exchange rates were already engaged in the floating system, and this is the prerequisite for examining the models' forecasting ability. Otherwise, the exchange rate movement was always within the target when the Bretton Woods System was prevalent, and was relatively independent of the economic fundamentals. Therefore, our data set chosen is also after the Bretton Woods System collapsed, which is from 1990 to 2003.

Mark (1995) presents empirical results including the ratio of RMSE of the regression model to that of the Random Walk model, as well as DM statistics for out-of-sample forecasting. He found, in general, the regression model based on economic fundamentals outperforms the Random Walk model for long-horizon (12-, and 16-quarters) forecasts. Hence, our research focuses on the accuracy of predictability in

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[75] $f_t \equiv \left(m_t - m_t^*\right) - \lambda\left(y_t - y_t^*\right)$ is the economic fundamentals with the restriction of $\lambda = 1$, and m and y stand for US money supply and income, respectively; and * denotes variables for the foreign countries.

terms of out-of-sample forecasting over the long-horizon, which is a 38-month horizon (from November, 2000 to December, 2003) in our case, from the different models. In addition to evaluating accuracy in predicting *levels*, we also evaluate the ability of the fundamentals' based model to predict *changes or turning points* relative to the Random Walk model. This is carried out with the PT test.

In the next chapter (Chapter 4---Empirical Results), we will first present the results for the NZ/AU exchange rate, then in turn for the NZ/US exchange rate.

3.3 Relevant Variables

3.3.1 Introduction

Since the monetary model (Sticky-Price Monetary (Dornbush-Frankel) Model) is chosen in this research (see Chapter 2 --- Literature Review for more detail), the independent variables, which explain exchange rates movements, are chosen as follows.

3.3.2 Dependent Variable

The natural logarithm of the spot exchange rate[76] (direct quotation: Home Currency/Foreign Currency)

3.3.3 Independent Variables

- Natural logarithm of the relative money supply
- Natural logarithm of the relative gross domestic production (GDP)
- Interest rate differential

[76] The spot exchange rate rather than the real exchange rate is chosen because of the forecasting purpose --- exploiting the true forecasting ability in the financial markets (Meese and Rogoff, 1983).

- Inflation rate differential
- Savings/investment balance (current account balance) differential

3.4 Data Description

The data in this research (from month 1 of 1990 to month 12 of 2003) are described as follows:

Spot rate: Monthly average market rate[77] of US Dollars per Australian Dollar and US Dollars per New Zealand Dollar, *International Finance Statistics (IFS).* The original data is then converted into New Zealand Dollars per US Dollar and New Zealand Dollars per Australian Dollar, and both are in *log* form.

Money supply[78]:. Monthly in millions of Australian Dollars, monthly in millions of New Zealand Dollars and monthly in billions of US Dollars, *International Finance Statistics (IFS).* The original data is then converted into index figures (2000 year is the base of figure 100), and all three are in *log* form.

Real GDP: Quarterly in billions of Australian Dollars of Gross Domestic Production, and Australian GDP Deflator (2000 year is the base of figure 100); Quarterly in millions of New Zealand Dollars of Gross Domestic Production, and New Zealand GDP Deflator (2000 year is the base of figure 100); Quarterly in billions of US Dollars of Gross Domestic Production, and US GDP Deflator (2000 year is the base of figure 100); *International Finance Statistics (IFS).* The Gross Domestic Production is first deflated by GDP Deflator, and is then converted into index figures (2000 year is the base of figure 100), and is further converted into monthly figures[79], and all three are in *log* form.

[77] Monthly average market rate chosen can almost eliminate the daily outliers.
[78] The data of money supply (broad money) with no seasonal adjustment are selected in order to exploit the true forecasting ability of the theory-based models (Meese and Rogoff, 1983).
[79] The quarterly-to-monthly conversion is done with the nonlinear interpolator feature in Eviews 5.1 software.

Short-run interest rate: Monthly average rate on the money market, *International Finance Statistics (IFS).*

Expected inflation rate: Quarterly index numbers of Consumer Prices of Australia and New Zealand, and Monthly index number of Consumer Prices of United States, *International Finance Statistics (IFS).* Quarterly index numbers are first converted into monthly index numbers[80], and then the percentage change of the consumer price within one month is worked out to get the approximator of monthly inflation rates.

Current Account Balance: Quarterly in millions/billions of US Dollars from Australia, New Zealand and U.S.A., *International Finance Statistics (IFS).* Quarterly original data is first converted into index numbers (2000 year is the base of figure -100), and is then converted into monthly numbers[81].

[80] Same as footnote 79
[81] Same as footnote 79

Chapter 4 Empirical Results

4.1 Introduction

In the early 1970s, the United States abandoned the fixed value of the dollar, which was pegged to gold, and allowed it to float/fluctuate against other currencies, and hence the fixed exchange rate system of Bretton Woods (major currencies were pegged to the US dollar) collapsed. Since then, the exchange rates among major industrialised countries have fallen into the floating system. In Australia, the fixed exchange rate system moved to a managed floating system in 1973, and further evolved into an independently floating system, which is market-determined, at the end of 1983. Similarly, the New Zealand Dollar was placed on a controlled floating basis in 1973, and then switched to a crawling-peg system in 1979, and ultimately engaged into the floating system as a part of a broad-based deregulation of the financial market in 1985.

This chapter presents the results from the three approaches to exchange rate forecasting, namely the Random Walk Model, the Monetary Model in linear form, and the Monetary Model estimated with nonlinear ANN methods. For each approach the data set (1990M01 – 2003M12) is partitioned into 130 'in sample' observations (1990M01 – 2000M10), which are used to estimate the parameters of each model; and 38 'out of sample' observations (2000M11 – 2003M12)[82]. The estimated models from the 'in sample' period are then used to produce *ex post* forecasts for the 'out of sample' period of 2000M11-2003M12. By comparing these 'forecasts' with the actual observed values of the exchange rates, we may evaluate the relative accuracy of each of the three forecasting approaches.

[82] The reason for dividing the whole data set in this way is based on the purpose of this thesis --- exploiting the forecasting ability of the ANNs technique with a long-run horizon, the horizon in this case is just over 3 years which is also convenient for approximately meeting the special rule of dividing the data set in the application of ANNs (more detail in Chapter 3 --- Econometric Method and Data).

4.2 Results for the New Zealand-Australia Exchange Rate

4.2.1 The Random Walk Model

As a 'benchmark' for comparing the possible improvements offered by the theory-based monetary model (linear and nonlinear cases), the Random Walk model may be written in the form

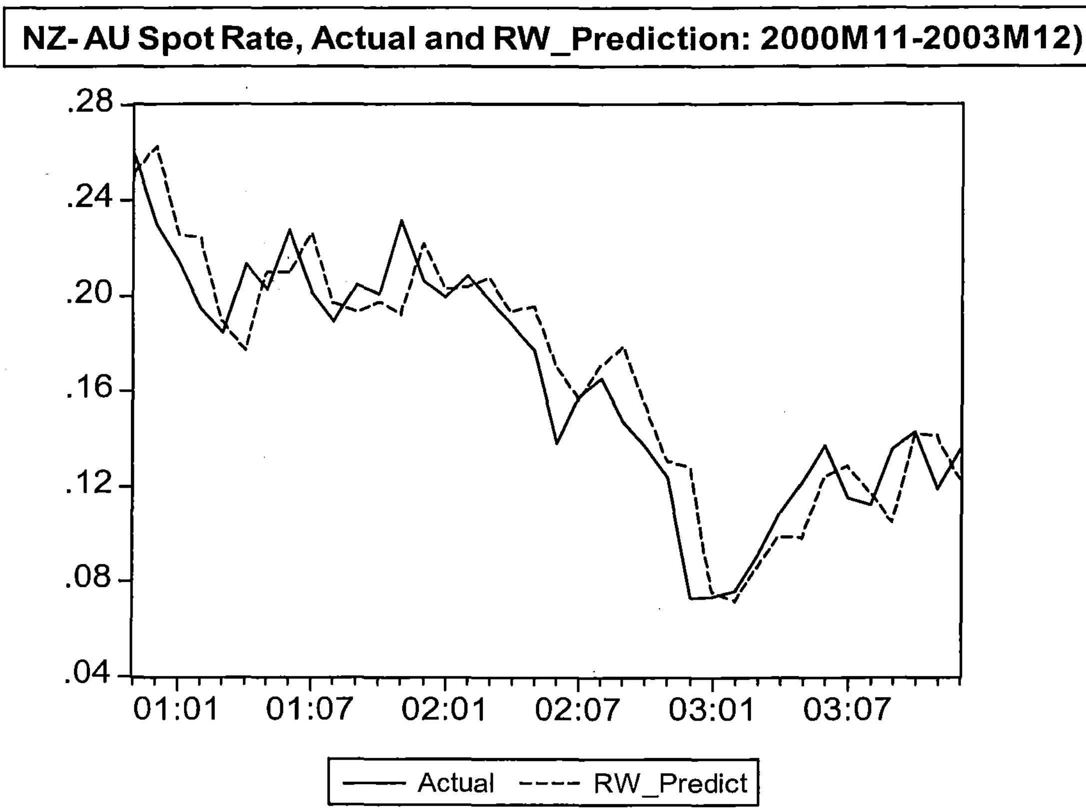
$$Y_t = \theta Y_{t-1} + \varepsilon_t \quad (4.1)$$

where Y_t is the spot exchange rate expressed as the price of foreign currency (direct quotation: Home Currency/Foreign Currency) at time t (in *natural log* form), $\theta = 1$ and ε_t is a random walk error process. According to this model, the current value of Y is equal to its previous value plus a random component, suggesting that all the relevant information regarding the value of Y is already incorporated in the data. Hence, the value of Y cannot be forecasted by using information on other economic/financial variables. In this thesis the *ex post* 'forecasts' of the exchange rate are produced by generating the random variable $\varepsilon_t \sim \text{Normal}(0, \sigma_\varepsilon^2)$ where σ_ε^2 has the same variance as the 'in sample' observations.

4.2.1.1 Ex Post 'Out of Sample' Forecasting

This section will discuss the empirical results of 'Out of Sample' forecasting from the Random Walk model for the period 2000M11-2003M12.

Figure 4.1: Random Walk (RW) Model 'Out of Sample' Forecasting (NZ-AU)



The predictions from the random walk model mimic the pattern of actual exchange rate movements quite well (R^2 = 0.85) with a relatively small error (RMSE = 0.02, and RMSPE = 0.16). However this model does not capture enough turning points (the percentage of correct predictions of the directional change = 49%, 18 out of 37). The forecasts from the two versions of the theory-based monetary models will be compared to the random walk forecasts.

4.2.2 Monetary Model (Linear Version)

As shown in Chapter 3, the Monetary Model may be expressed as

$$Y_t = \Phi(M_t) + \varepsilon_t \qquad t = 1,\ldots,N \quad (4.2)$$

where Y_t is in the logarithm of the spot exchange rate over the month of observations, and M_t is a vector of typical macroeconomic variables, and ε_t is a random error term under the conventional assumptions. From Chapter 3, the exact specification used in this thesis is as follows:

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \quad (4.3)^{83}$$

where X_1 = natural log of relative money supply (index) $\left(Ln\left(\frac{M3_{NZ}}{M3_{AU}} \right) \right)$

X_2 = natural log of relative GDP (index) $\left(Ln\left(\frac{GDP_{NZ}}{GDP_{AU}} \right) \right)$

X_3 = nominal interest rate differential ($Int_{nz} - Int_{AU}$)

X_4 = long-run expected inflation differential ($Inf_{NZ} - Inf_{AU}$)

The empirical 'in sample' estimated results are shown in Table 4.1.

[83] With the additional explanatory variable of the current account (Conway and Franulovich, 2002), the monetary model did not provide a reasonable result. That is, the variable of the current account did not have an expected sign, which was contrary to the theory. In other words, the currency of a wealthier nation tends to depreciate relative to the other. This is opposite to the macroeconomic theory.

This problem might come from the data set, or might be due to the odd economic event(s) happening in that period. Here we do not investigate the source of/reason for the problem. In order to provide a reliable analysis, we do not include the variable of current account in the monetary model (linear version). The same principle is applied in the ANN method.

Table 4.1: Monetary Model (Linear Version) 'In Sample' Estimating (NZ-AU)

Dependent Variable: Spot
Method: Least Squares
Date: 05/15/05 Time: 14:45
Sample: 1990:01 2000:10
Included observations: 130

Variable	Coefficient	Std. Error	t-Statistic	P-value
C (Constant)	0.222369	0524	16.44230	0.0000
M3 (Money Supply)	0.157974	0.160170	0.986290	0.3259
GDP (Gross Domestic Product)	-0.249710	0.234675	-1.064067	0.2893
INT (Interest Rate)	-2.874567	0.453804	-6.334386	0.0000
INF (Inflation Rate)	0.130324	2.616768	0.049803	0.9604

R-squared	0.294709	Mean dependent var	0.207577
Adjusted R-squared	0.272140	S.D. dependent var	0.072279
S.E. of regression	0.061665	Akaike info criterion	-2.696499
Sum squared resid	0.475321	Schwarz criterion	-2.586210
Log likelihood	180.2725	F-statistic	13.05798
Durbin-Watson stat	0.209138	Prob(F-statistic)	0.000000

In this model, all signs of explanatory variables are expected, but only the coefficient of the interest rate differential is statistically significantly different from zero. Moreover, an auto-correlation problem[84] is present in this model which is indicated by the Durbin-Watson statistic (0.21) that is far away from 2 (which indicates that there is no auto-correlation problem found).

Based on the 'in sample' estimation, the 'in sample' predicting for the period between January 1990 and October 2000 and the 'out of sample' forecasting for the period

[84] The error term in the model should follow the conventional condition, however a re-specification of the function that includes a lag of dependent variable to be an explanatory variable produces an even worse result with unexpected signs and non-significance although the auto-correlated problem is solved. Therefore we leave the linear model with the auto-correlated problem unchanged because the focus of our research is on the forecasting abilities of the models.

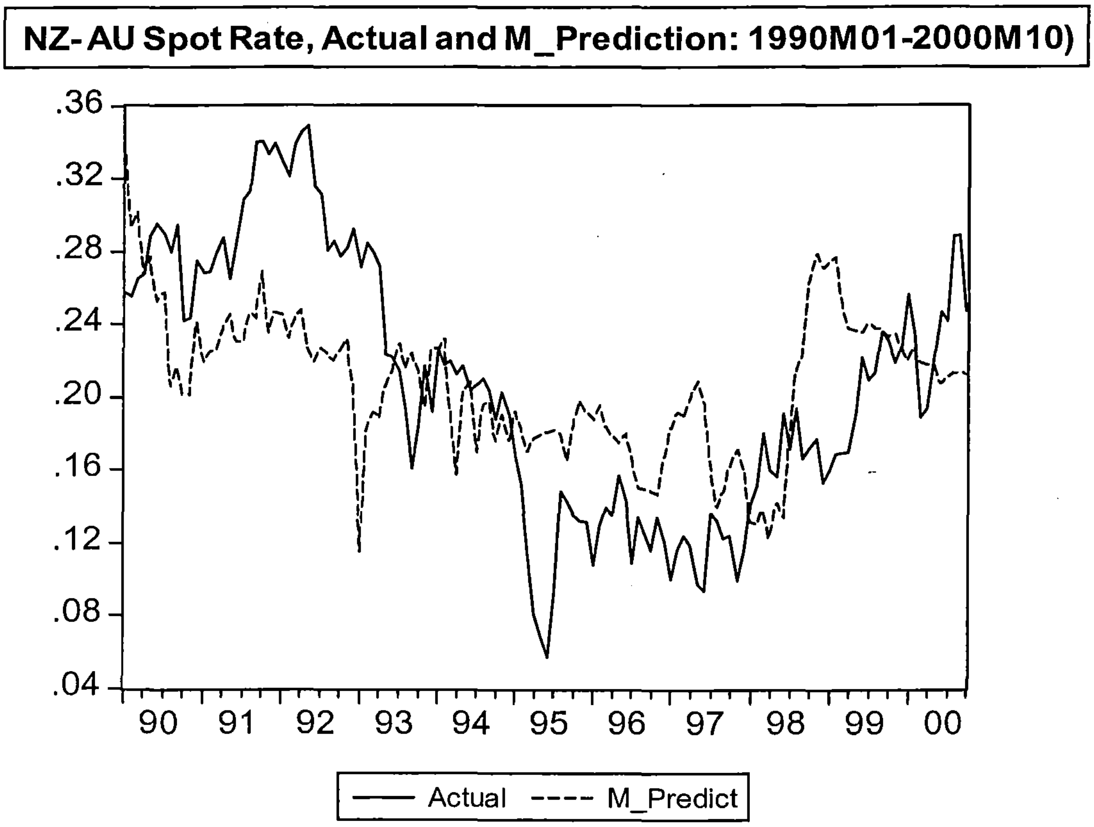
The same principle of the error term is also applied to the artificial neural network. However, in this case, we choose to leave the auto-correlated problem in the ANN models, which theoretically reduces the accuracy of the prediction in the application of the ANN model.

between November 2000 and December 2003 from the monetary model (linear version) are then produced.

4.2.2.1 'In Sample' Predicting

This section is going to discuss the empirical result of 'In Sample' predicting from the Monetary Model (Linear Version) for the period 1990M01-2000M10.

Figure 4.2: Monetary (M) Model (Linear Version) 'In Sample' Predicting (NZ-AU)

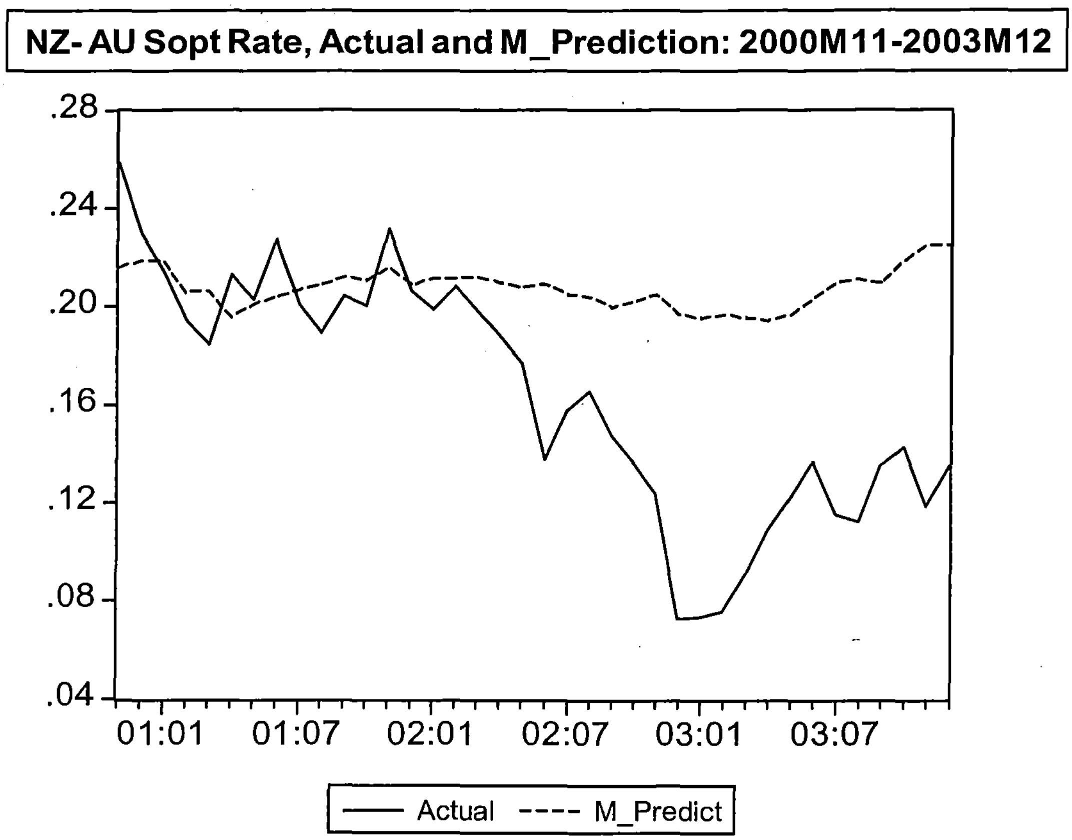


From the graph above, we can see that for the 'in sample' period of 1990M1 – 2000M10 the linear monetary model cannot mimic the pattern of exchange rate movement well in general (R^2 = 0.29), and only provides 47% (61 out of 129) correction rate of prediction of the next period's directional change. From January 1990 to December 1994, the monetary model under-predicted the spot rate, while it tended to over-predict the spot rate after then and until October 2000.

4.2.2.2 Ex Post 'Out of Sample' Forecasting

This section is going to discuss the empirical result of 'Out of Sample' forecasting from the Monetary Model (Linear Version) for the period 2000M11-2003M12.

Figure 4.3: Monetary Model (Linear Version) 'Out of Sample' Forecasting (NZ-AU)



Obviously, in the 'out of sample' data set, the linear monetary model performed even worse (R^2 = 0.18) than for the 'in sample' data set. Moreover, the deviations (RMSE = 0.06, and RMSPE = 0.64) from the actual spot rates become remarkably larger when the forecast horizon is extended (especially beyond one year). After one year, the forecasts from the linear monetary model totally lose the ground of prediction ability. Moreover, the linear monetary model provides only 42% (16 out of 38) correct predictions of the directional change in the out of sample, which is similar to that in random walk model (49%, 18 out of 37).

In summary, the monetary model (linear version) cannot beat the simple random walk model in terms of providing a better forecast, especially in a long horizon.

4.2.3 Nonlinear Monetary Model (Artificial Neural Networks Version)

The Monetary Model (Artificial Neural Networks Version) has the same specification as that of the monetary model (linear version)

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \quad (4.3)$$

where the variables are as defined previously.

The only difference between these two monetary-based models is that with ANN methods[85] we have a nonlinear approach which employs the universal nonlinear pattern approximator (artificial neural networks), while the monetary model (linear function) is a traditional linear function. The empirical 'in sample' estimated results are shown in Table 4.2.

Table 4.2: Monetary Model (Artificial Neural Networks)
'In Sample' Estimating (NZ-AU)

Contribution Factors[86]:	
M3 (Money Supply)	0.23673
GDP (Gross Domestic Product)	0.29277
INT (Interest Rate)	0.27544
INF (Inflation Rate)	0.19506

[85] In this research, one hidden layer of artificial neural network is employed because a single hidden layer is good enough to detect any nonlinear pattern for most forecasting problems.
[86] In the non-linear modelling, the contribution factor can never be as precise as that in the linear model due to the inherently complicated nature of the non-linear model, and actually the contribution factor only provides the guideline of the relative importance of independent variables to the dependent variable.

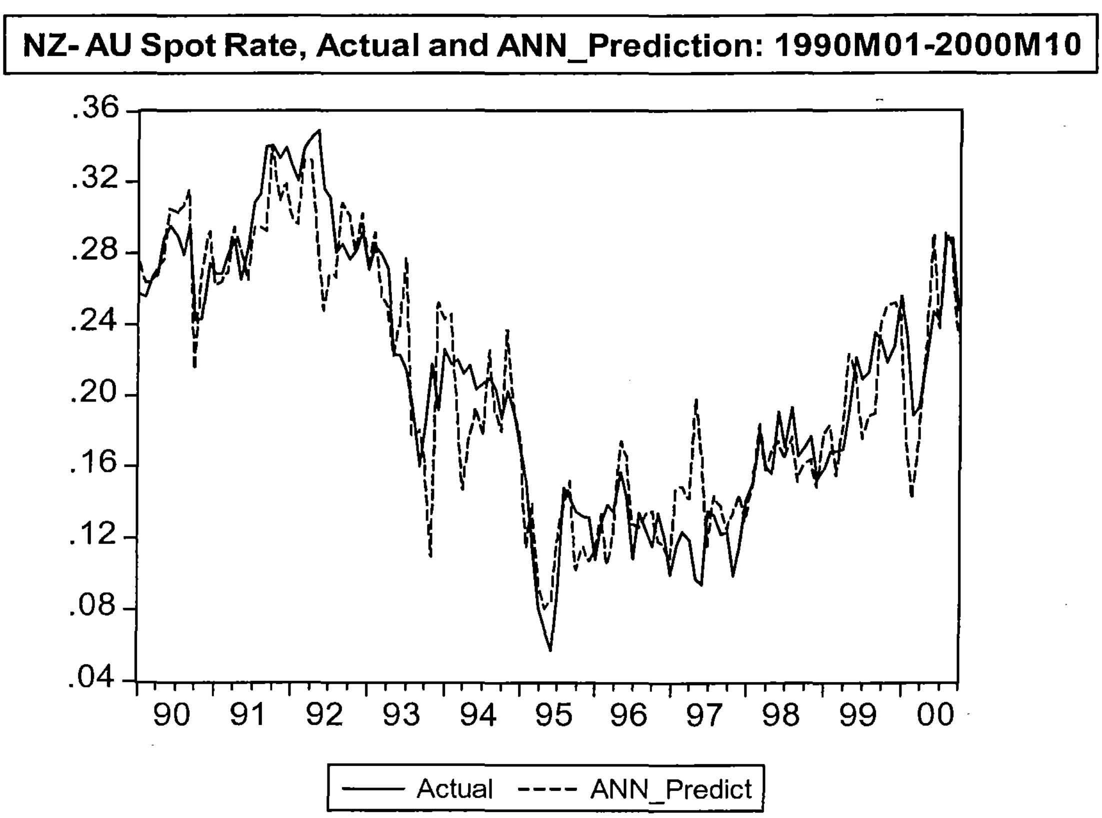
In this model, the effects from the four explanatory variables on spot rate movement are relatively equal, which is not the case in the linear version where the relative interest rate has the biggest impact on the exchange rate movement.

Based on the 'in sample' estimating, the 'in sample' predicting for the period between January 1990 and October 2000 and the 'out of sample' forecasting for the period between November 2000 and December 2003 from the monetary model (artificial neural networks) are then produced.

4.2.3.1 'In Sample' Predicting

This section will discuss the empirical result of 'In Sample' predicting from the Monetary Model (Artificial Neural Networks) for the period 1990M01-2000M10.

Figure 4.4: Monetary Model (Artificial Neural Networks) (ANN)
'In Sample' Predicting (NZ-AU)



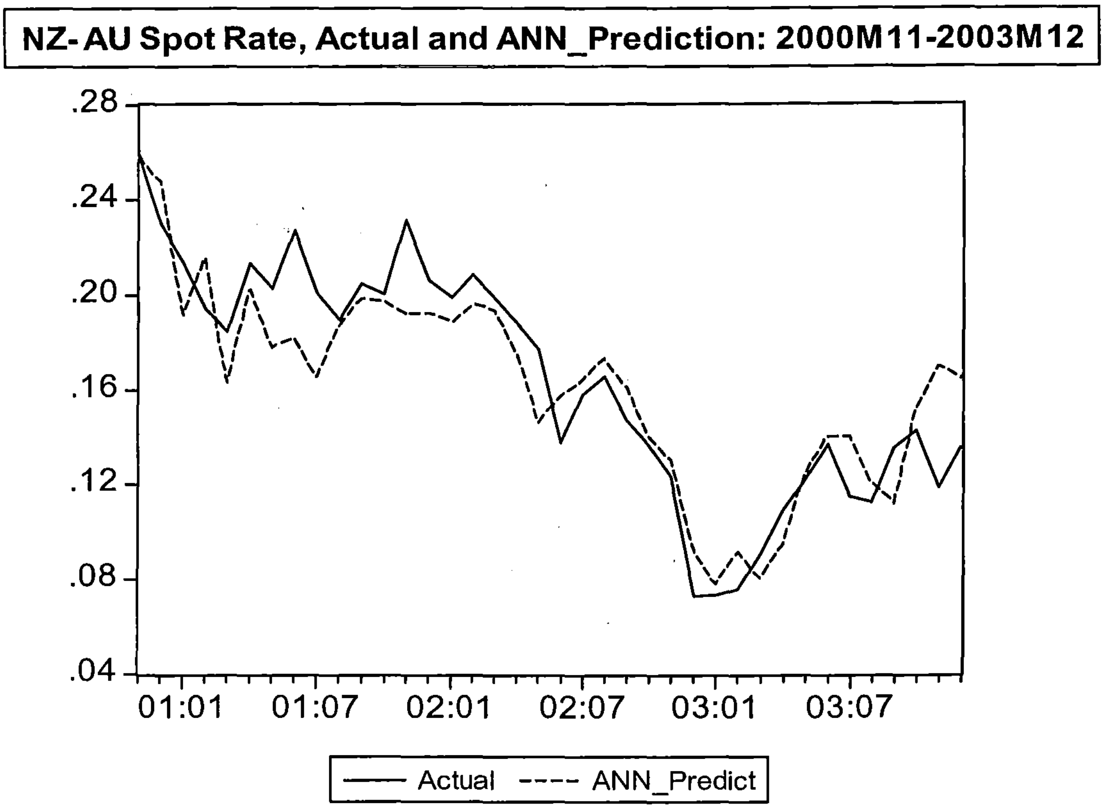
From Figure 4.4 above, we can see that the ANN model mimics the pattern of exchange rate movement well in general ($R^2 = 0.85$ which is much higher than 0.29 in the linear function). Moreover, the ANN model provides 67% (87 out of 129) correct prediction of the next period's directional change which is significantly higher than 47% (61 out of 129) in the linear version).

However, the predictions of spot rates are more volatile than those of actual ones. Intuitively, the predictions are good at grasping the directional changes (currency appreciation or depreciation) but tend to over-predict or under-predict, especially around the local maxima and minima. For example, the artificial neural networks over-predicted the spot rate as 0.085 in June 1995, instead of the actual rate of 0.057. That is, ANN greatly over-predicted the value of the Australian dollar, up to 50% at the point of June 1995.

4.2.3.2 Ex Post 'Out of Sample' Forecasting

This section is going to discuss the empirical result of 'Out of Sample' forecasting from the Monetary Model (Artificial Neural Networks) for the period 2000M11-2003M12.

Figure 4.5: Monetary Model (Artificial Neural Networks) (ANN)
'Out of Sample' Forecasting (NZ-AU)



Obviously, in the out of sample data set, artificial neural networks provide an even better forecast (R^2 = 0.83) (compared to in-sample predictions) because the networks have learnt the input-output pattern well in the in-sample data set, hence they use what they have learnt to better predict the future movement of the exchange rate.

Artificial neural networks provide 74% (28 out of 38) correct predictions of the directional change in the out of sample, which is higher than 67% (87 out of 129) in the in-sample data set. Moreover, the predictions are much less volatile and much closer to the actual ones (RMSE = 0.02, and RMSPE = 0.14) compared to those of the in-sample set, that is, the predictions just slightly over-predict or under-predict during the whole out of sample horizon. At the last point of time horizon, although ANNs over-predict, the two lines clearly suggest that they will converge into some point with the upward actual spot rate and the downward prediction one.

4.2.4 Summary

As this thesis is concerned with evaluating the forecasting abilities of the alternative approaches, we summarise the 'out of sample' results below.

Table 4.3: Forecasting Results Summary (NZ-AU)

Out_of_Sample	Rsq	RMSE	RMSPE	Turning Point	PT[87]
Random Walk	*0.8470*	*0.0199*	0.1637	0.4865	-
Linear Function	0.1813	0.0630	0.6374	0.4211	-0.5639
ANN Technique	*0.8307*	*0.0202*	*0.1368*	*0.7368*	*2.9223*

Note: These five criteria are R-Square, Root Mean Square Error, Root Mean Square Percentage Error, Percentage of Correctly Predicted Turning Points, and Pesaran-Timmermann Test Statistic from the left to the right..

Regarding out-of-sample forecasts, although the Random Walk Model provides a slightly higher R^2 and a negligibly smaller RMSE compared to ANN modelling, the monetary model with the ANN technique predicts the exchange rate (NZ-AU) significantly better than the Random Walk Model based on the criteria of RMSPE and Turning Point, and has market-timing ability based on the PT statistic. Overall, ANN provides a reliable forecast (containing economic value) with a good magnitude and a good directional forecast of exchange rate movement in a long horizon (more than 3 years) based on this case.

However, this general conclusion is not fully consistent with the results from the DM test. The DM test suggests that there is no difference between the Random Walk Model and the monetary model with the ANN technique in terms of forecast accuracy although the DM test shows that the Random Walk Model is more accurate than the monetary model with a linear function, and the monetary model with the ANN

[87] The Random Walk Model might either generate all positive or all negative series, making the PT statistic meaningless in such a case (Preminger and Franck, 2005); therefore, PT statistics do not apply in the RW model. In addition, PT test statistics in Table 4.3 suggest that the predicted spot rates are closely associated with the actual values in the ANN modelling ($|2.9223|>1.96$) but this does not happen (actually, the situation is the opposite) in the case of the linear model ($|-0.5639|<1.96$).

technique is superior to the monetary model with a linear function. This result from the DM test is supported by the evidence of error ratios.

Table 4.4: Error Ratios Summary (NZ-AU)

Out_of_Sample	Out/RW (RMSE)	Out/RW (RMSPE)
Linear Function	3.1683	3.8941
ANN Technique	1.0153	0.8357

Note: The figures in the first line are the ratios of the error from the linear function model to the error from the random walk model, and the errors are Root Mean Square Error and Root Mean Square Percentage Error from the left to the right; the figures in the second line are the ratios of the error from the ANN technique model to the error from the random walk model, and the errors are Root Mean Square Error and Root Mean Square Percentage Error from the left to the right.

It seems clear that the Random Walk model outperforms the monetary model with a linear function based on two error ratios that are much higher than 1 (even beyond 3), but it is hard to tell whether Random Walk model is better or the monetary model with the ANN technique is better, because one error ratio is higher than 1 (RMSE) but the other is less than 1 (RMSPE).

The detail of DM forecasting accuracy tests:

$$DM = \frac{\frac{1}{T}\sum_{t=1}^{T} d_t}{\sqrt{\hat{V}\left(\frac{1}{T}\sum_{t=1}^{T} d_t\right)}} \quad \text{where } d_t = e_{0,t+h}^2 - e_{a,t+h}^2$$

We use one-sided tests so that each model can be treated as the maintained (i.e., null) hypothesis.

(1) The Random Walk model tested against the linear monetary model

H_0^1: The RW model and the linear monetary model forecast equally well

H_a^1: The RW model forecasts better than the linear monetary model

The computed value of the test statistic and its P-value are:

$DM_1 = -2.4328\ [0.0075]$

Hence, the DM_1 test statistic favours the RW model over the linear monetary model.

(2) Now we reverse the previous null hypothesis and test the linear monetary model against the Random Walk model

H_0^2: The linear monetary model and the RW model forecast equally well

H_a^2: The linear monetary model forecasts better than the RW model

The computed value of the test statistic and its P-value are:

$DM_2 = 2.4328\ [0.9925]$

Hence, the DM_2 test statistic indicates that we do not reject H_0^2 in favour of H_a^2. That is, the test statistic unequivocally indicates that the linear version of the monetary model cannot forecast the NZ_AU exchange rate more accurately than the RW model.

In similar manner, we also tested the RW forecasts against those of the nonlinear ANN version of the monetary model. These results are summarised below:

(3) The RW model tested against the ANN model

H_0^3: The RW model and the ANN model forecast equally well

H_a^3: The RW model forecasts better than the ANN model

$DM_3 = -0.0976\ [0.4611]$ --- Not reject H_0^3

(4) The ANN model tested against the RW model

H_0^4: The ANN model and the RW model forecast equally well

H_a^4: The ANN model forecasts better than the RW model

$DM_4 = 0.0976\ [0.5389]$ --- Not reject H_0^4

Conclusion: In neither case does the DM test reject the equality of the forecasting accuracy of the RW and ANN models.

(5) The linear model tested against the ANN model

H_0^5: The linear model and the ANN model forecast equally well

H_a^5: The linear model forecasts better than the ANN model

$DM_5 = 2.3636$ $[0.9910]$ --- Not reject H_0^5

(6) The ANN model tested against the linear model

H_0^6: The ANN model and the linear model forecast equally well

H_a^6: The ANN model forecasts better than the linear model

$DM_6 = -2.3636$ $[0.0091]$ --- Reject H_0^6

Conclusion: The DM test statistic rejects the equality of the forecasting accuracy of the linear and ANN models, and favours the ANN model over the linear monetary model.

In summary, the RW model cannot be beaten by either the linear or nonlinear monetary model (although the nonlinear monetary model performs better than the linear version) in the case of the NZ_AU exchange rate.

4.3 Results for the New Zealand-United States Exchange Rate

4.3.1 The Random Walk Model

The Random Walk model can be written in the form

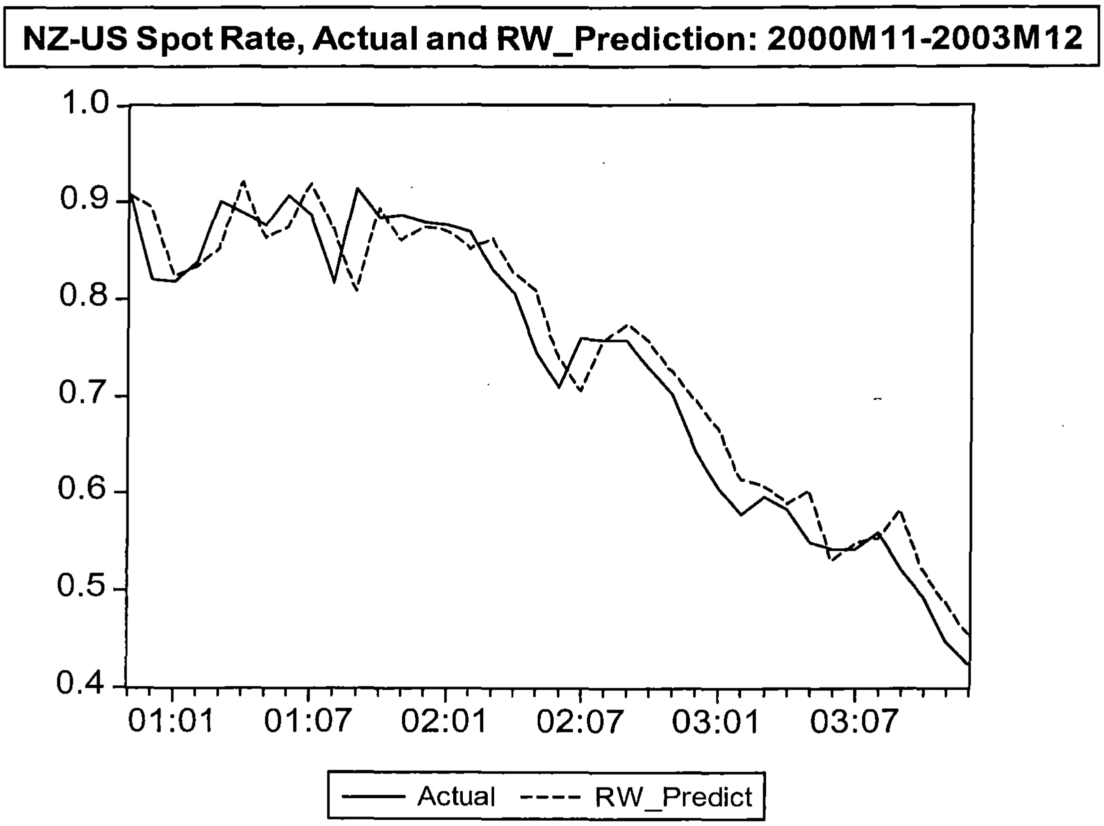
$$Y_t = \theta Y_{t-1} + \varepsilon_t \quad (4.1)$$

where the variables are as defined previously. The *ex post* 'forecasts' of the exchange rate are also produced by generating the random variable $\varepsilon_t \sim \text{Normal}(0, \sigma_\varepsilon^2)$ where σ_ε^2 has the same variance as the 'in sample' observations.

4.3.1.1 Ex Post 'Out of Sample' Forecasting

This section is going to discuss the empirical result of 'Out of Sample' forecasting from the Random Walk model for the period 2000M11-2003M12.

Figure 4.6: Random Walk (RW) Model 'Out of Sample' Forecasting (NZ-US)



The predictions from the random walk model mimic the pattern of the actual exchange rate movements quite well ($\bar{R}^2$ = 0.94) with a relatively small error (RMSE = 0.04, and RMSPE = 0.06), but this model does not capture enough turning points (the percentage of correct predictions of the directional change = 65%, 24 out of 37).

4.3.2 Monetary Model (Linear Version)

The Monetary Model (Artificial Neural Networks Version) has the same specification as that of the monetary model (linear version)

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \quad (4.3)$$

where the variables are as defined previously.

The empirical 'in sample' estimated results are shown in Table 4.5.

Table 4.5: Monetary (M) Model (Linear Version) 'In Sample' Estimating (NZ-US)

Dependent Variable: Spot
Method: Least Squares
Date: 05/30/05 Time: 21:35
Sample: 1990:01 2000:10
Included observations: 130

Variable	Coefficient	Std. Error	t-Statistic	P-value
C (Constant)	0.699641	0.008183	85.50239	0.0000
M3 (Money Supply)	-0.399553	0.042598	-9.379683	0.0000
GDP (Gross Domestic Product)	-3.733830	0.231450	-16.13235	0.0000
INT (Interest Rate)	-1.781092	0.280946	-6.339614	0.0000
INF (Inflation Rate)	6.943710	1.893070	3.667963	0.0004

R-squared	0.837038	Mean dependent var	0.550447
Adjusted R-squared	0.831823	S.D. dependent var	0.119151
S.E. of regression	0.048863	Akaike info criterion	-3.161896
Sum squared resid	0.298447	Schwarz criterion	-3.051606
Log likelihood	210.5232	F-statistic	160.5127
Durbin-Watson stat	0.438636	Prob(F-statistic)	0.000000

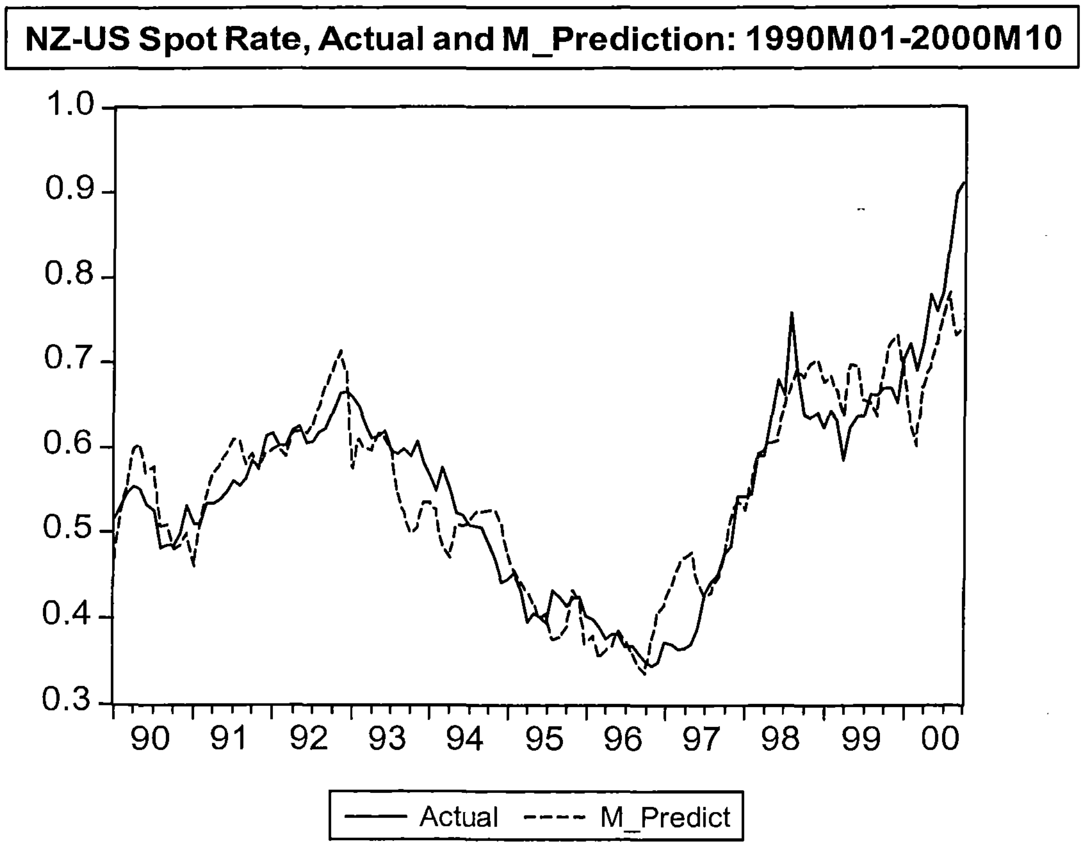
In this model, the signs of the three explanatory variables (except the variable of relative money supply) are expected, and all explanatory variables are statistically significantly different from zero. As in the case of NZ-AU, an auto-correlated problem is also present in this model, which is indicated by the Durbin-Watson statistics (0.44) that is far away from 2.

Based on the 'in sample' estimating, the 'in sample' predictions for the period between January 1990 and October 2000 and the 'out of sample' forecasts for the period between November 2000 and December 2003 from the monetary model (linear version) are then produced.

4.3.2.1 'In Sample' Predicting

This section is going to discuss the empirical result of 'In Sample' predicting from the Monetary Model (Linear Version) for the period 1990M01-2000M10.

Figure 4.7: Monetary (M) Model (Linear Version) 'In Sample' Predicting (NZ-US)



From the graph above, we can see that the linear monetary model can mimic the pattern of exchange rate movement well in general (R^2 = 0.84), and provides 64% (82 out of 129) correction rate of prediction of the next period's directional change). The difference between the actual spot rates and estimated ones is quite small, but it seems there is a big deviation in late 2000.

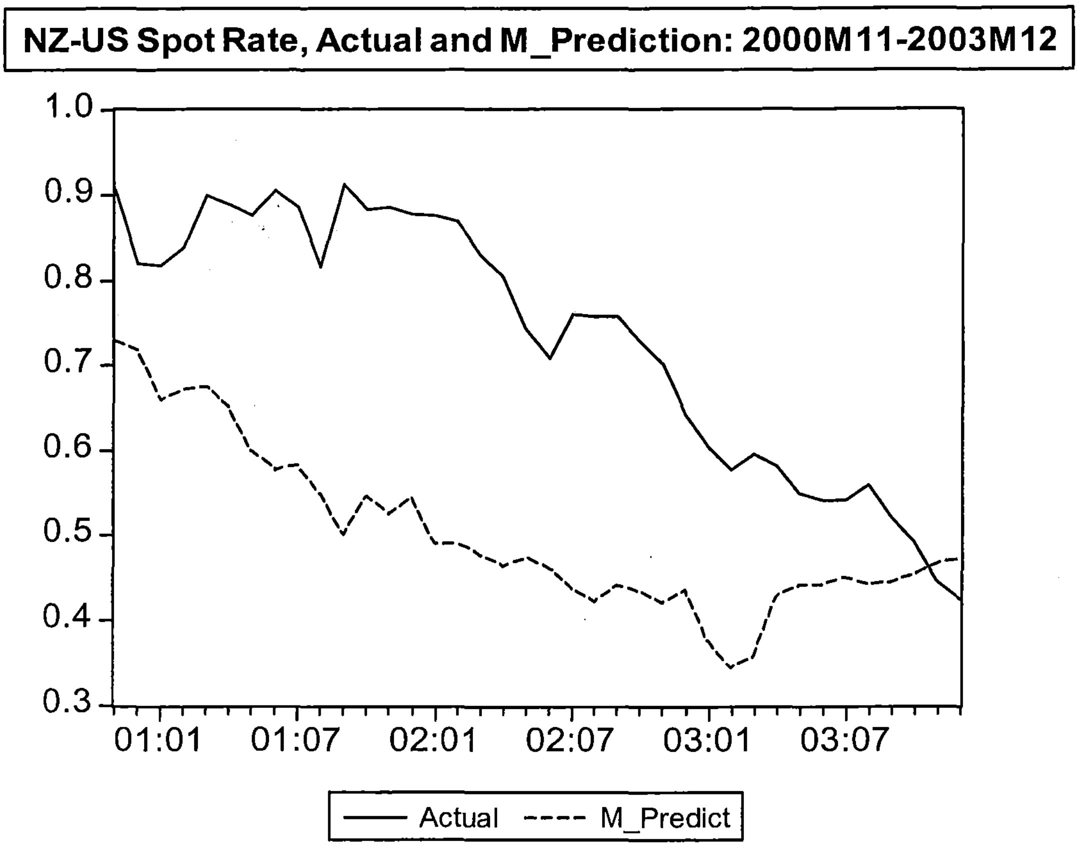
Generally speaking, these results suggest that the linear monetary model can far better explain the exchange rate of NZ-US than that of NZ-AU.

4.3.2.2 Ex Post 'Out of Sample' Forecasting

This section is going to discuss the empirical result of 'Out of Sample' forecasting from the Monetary Model (Linear Version) for the period 2000M11-2003M12.

Figure 4.8: Monetary (M) Model (Linear Version)

'Out of Sample' Forecasting (NZ-US)



Obviously, in the 'out of sample' data set, the linear monetary model performed much worse (R^2 = 0.41) than the 'in sample' data set. However, the huge deviation (RMSE = 0.26, and RMSPE = 0.33) from the actual spot rates was becoming smaller in late 2003. That is, from November 2000 to October 2003, the linear monetary model always remarkably under-predicted the exchange rate, but it tended to over-predict after November 2003. In general, the linear monetary model does not provide the evidence that it contains any prediction power at all.

Moreover, the linear monetary model provides only 47% (18 out of 38) correct predictions of the directional change in the out of sample, which is quite a bit lower than that in the random walk model (65%, 24 out of 37).

In summary, the monetary model with the linear version cannot beat the simple random walk model in terms of providing a better forecast even in a very short horizon.

4.3.3 Nonlinear Monetary Model (Artificial Neural Networks Version)

The Monetary Model (Artificial Neural Networks Version) has the same specification as that of the monetary model (linear version)

$$Y_t = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 X_{3t} + \beta_4 X_{4t} + \varepsilon_t \qquad (4.3)$$

where the variables are as defined previously.

The empirical 'in sample' estimated results are shown in Table 4.6.

Table 4.6: Monetary Model (Artificial Neural Networks)
'In Sample' Estimating (NZ-US)

Contribution Factors:	
M3 (Money Supply)	0.34905
GDP (Gross Domestic Product)	0.13224
INT (Interest Rate)	0.44542
INF (Inflation Rate)	0.07329

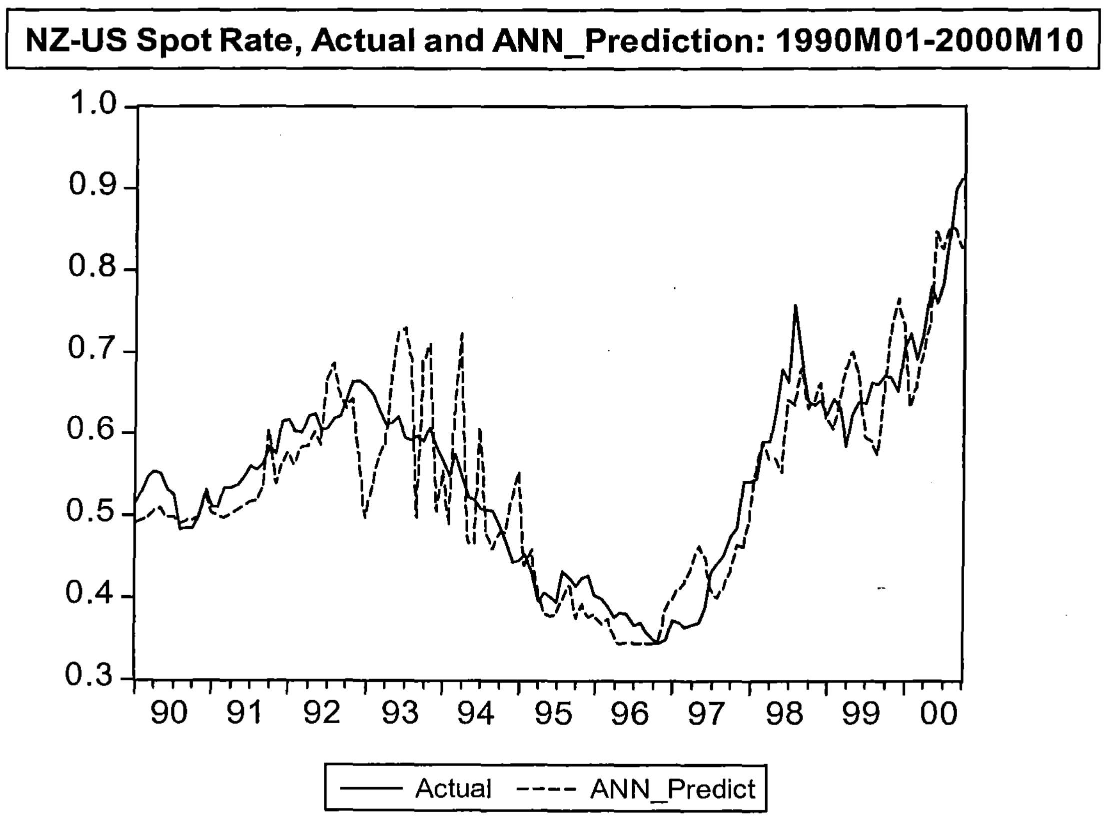
In this model, the effects from relative money supply and interest rate differential are much bigger than the other two, which is the opposite case in the linear version where the relative GDP and inflation rate differential have more influence on the exchange rate movement.

Based on the 'in sample' estimating, the 'in sample' predicting for the period between January 1990 and October 2000 and the 'out of sample' forecasting for the period between November 2000 and December 2003 from the monetary model (artificial neural networks) are then produced.

4.3.3.1 'In Sample' Predicting

This section will discuss the empirical result of 'In Sample' predicting from the Monetary Model (Artificial Neural Networks) for the period 1990M01-2000M10.

Figure 4.9: Monetary Model (Artificial Neural Networks) (ANN)
'In Sample' Predicting (NZ-US)

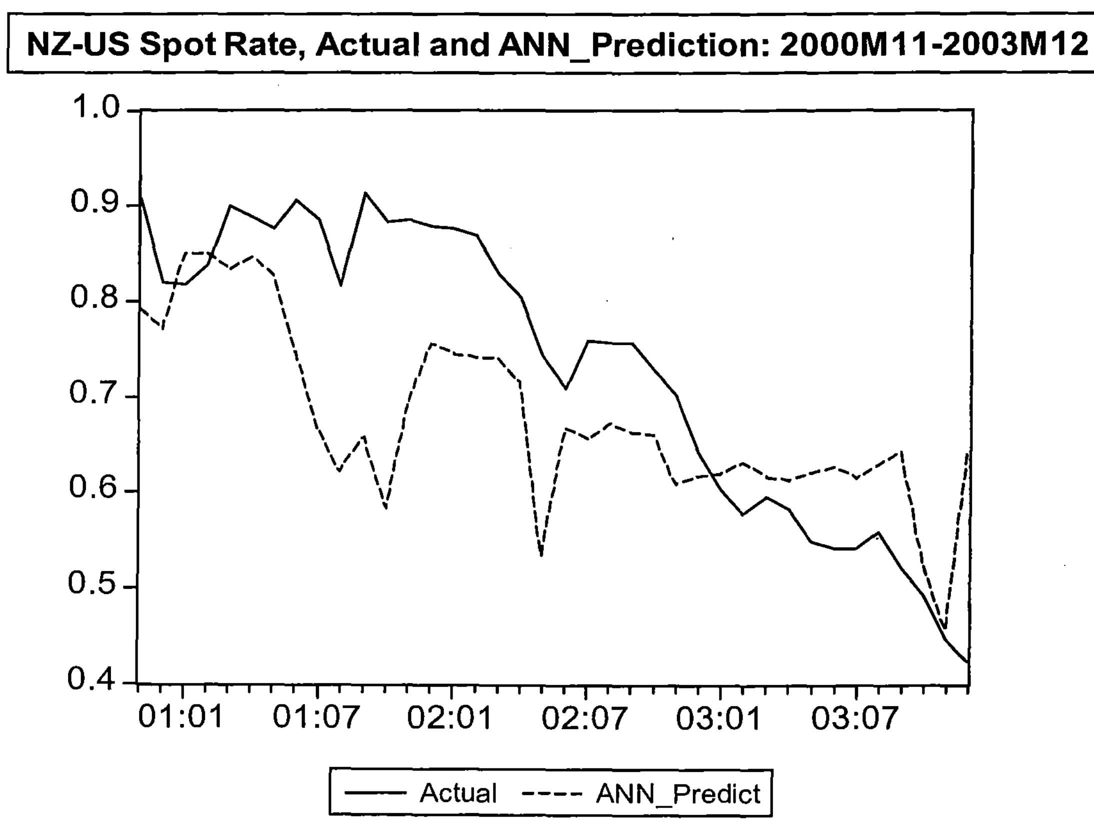


From the graph above, we can see that the ANN model performs worse than the linear function in general (R^2 = 0.80), and the ANN model provides 52% (67 out of 129) correct rate of prediction of the next period's directional change which is lower than 64% (82 out of 129) in the linear version. Moreover, the predictions from ANN are very volatile especially during the period 1992M12-1994M07. However, the deviation for late 2000 is significantly smaller than that in the linear function.

4.3.3.2 Ex Post 'Out of Sample' Forecasting

This section is going to discuss the empirical result of 'Out of Sample' forecasting from the Monetary Model (Artificial Neural Networks) for the period 2000M11-2003M12.

Figure 4.10: Monetary Model (Artificial Neural Networks) (ANN)
'Out of Sample' Forecasting (NZ-US)



Generally speaking, the pattern from ANN is quite similar to that of actual exchange rate movement (R^2 = 0.47), and the deviation (RMSE = 0.12, and RMSPE = 0.17) is much smaller than that in the linear function. However, ANN under-predicted the exchange rate before 2003, and then it tended to over-predict the exchange rate. Obviously, ANN has some prediction power (although the ANN model does not mimic very well in the case of NZ-US) and can capture more turning points (53%, 20 out of 38) compared to the linear function (47%, 18 out of 38).

In summary, ANNs provide a better forecast than the linear function in a long horizon (more than 3 years) based on this case. However, this performance is not very good.

4.3.4 Summary

The 'out of sample' results are summarised below.

Table 4.7: Forecasting Results Summary (NZ-US)

Out_of_Sample	Rsq	RMSE	RMSPE	Turning Point	PT
Random Walk	*0.9447*	*0.0381*	*0.0551*	*0.6486*	-
Linear Function	0.4169	0.2567	0.3273	0.4737	-0.6376
ANN Technique	0.4723	0.1224	0.1686	0.5263	-0.1303

Note: These five criteria are R-Square, Root Mean Square Error, Root Mean Square Percentage Error, Percentage of Correctly Predicted Turning Points, and Pesaran-Timmermann Test Statistic from the left to the right..

Regarding out-of-sample forecasts for NZ-US, where the situation is very different from the case of NZ-AU, all criteria are supportive of the Random Walk Model. But ANN modelling is still better than the linear function in terms of the four measurement criteria (excluding the PT test statistic) chosen. Overall, ANNs provide a better forecast (although with no significant economic value: the PT test statistic suggests that the ANN modelling could not forecast the exchange rate directional change well, and the percentage of successful capturing the Turning Point is also relatively lower (with just over 50%) than the linear function in a long horizon (more than 3 years) based on this case.

This general conclusion is supported by the results from the DM test. The DM test suggests that the Random Walk Model performs better than both monetary models with linear function and with ANN technique, but the monetary model with ANN technique no doubt beats the monetary model with linear function regarding the forecasting accuracy. This general conclusion is also consistent with the finding of error ratios.

Table 4.8: Error Ratios Summary (NZ-US)

Out_of_Sample	Out/RW (RMSE)	Out/RW (RMSPE)
Linear Function	6.7399	5.9423
ANN Technique	3.2150	3.6000

Note: The figures in the first line are the ratios of the error from the linear function model to the error from the random walk model, and the errors are Root Mean Square Error and Root Mean Square Percentage Error from the left to the right; the figures in the second line are the ratios of the error from the ANN technique model to the error from the random walk model, and the errors are Root Mean Square Error and Root Mean Square Percentage Error from the left to the right.

It is obvious that the Random Walk model provides more accurate out-of-sample forecasts with a long horizon than both monetary models with linear function and with ANN technique supported by the evidence of two error ratios that are much higher than 1 (even roughly around 6 and 3, respectively).

The details of DM forecasting accuracy tests:

(1) The RW model tested against the linear model

H_0^1: The RW model and the ANN model forecast equally well

H_a^1: The RW model forecasts better than the ANN model

DM_1 = -4.29626 $[0.0000]$ --- Reject H_0^1

(2) The linear model tested against the RW model

H_0^2: The linear model and the RW model forecast equally well

H_a^2: The linear model forecasts better than the RW model

DM_2 = 4.29626 $[0.9999]$ --- Not reject H_0^2

Conclusion: The DM tests reject the equality of the forecasting accuracy of the RW and linear models, and favour the RW model over the linear monetary model.

(3) The RW model tested against the ANN model

H_0^3: The RW model and the ANN model forecast equally well

H_a^3: The RW model forecasts better than the ANN model

$DM_3 = -2.61150\ [0.0045]$ --- Reject H_0^3

(4) The ANN model tested against the RW model

H_0^4: The ANN model and the RW model forecast equally well

H_a^4: The ANN model forecasts better than the RW model

$DM_4 = -2.61150\ [0.9955]$ --- Not reject H_0^4

Conclusion: The DM tests reject the equality of the forecasting accuracy of the RW and ANN models, and favour the RW model over the ANN monetary model.

(5) The linear model tested against the ANN model

H_0^5: The linear model and the ANN model forecast equally well

H_a^5: The linear model forecasts better than the ANN model

$DM_5 = 4.08188\ [0.9999]$ --- Not reject H_0^5

(6) The ANN model tested against the linear model

H_0^6: The ANN model and the linear model forecast equally well

H_a^6: The ANN model forecasts better than the linear model

$DM_6 = -4.08188\ [0.0000]$ --- Reject H_0^6

Conclusion: The DM tests reject the equality of the forecasting accuracy of the linear and ANN models, and favour the ANN model over the linear monetary model.

In summary, the RW model does forecast better than both linear and nonlinear monetary models (although the nonlinear monetary model performs better than the linear version) in the case of NZ-US exchange rate.

4.4 Summary

Based on the empirical analyses, the monetary model with the artificial neural networks method, which has a solid economic rationale, provides the best result with a good forecast in magnitude and a good forecast in direction associated with market timing ability for the NZ-AU case. Although the ANN technique cannot beat the Random Walk model for the NZ-US case, it does not perform worse than the Random Walk model and it still improves the performance compared to the linear function.

Therefore, although the ANN technique empirically provides a better forecast than a purely linear function, the general conclusion[88], that the artificial neural networks model can always beat the Random Walk model, does not hold. This means the result of Meese and Rogoff (1983) can not be overturned based on the mixed empirical results from this research.

[88] The empirical results obtained here largely depend on the observations in the particular forecasting period and might not allow us to hold a very general and consistent conclusion about these estimation models.

Chapter 5 Conclusion and Suggestions

5.1 Introduction

This chapter will summarise and discuss the empirical results from the previous chapter, and conclude whether the artificial neural networks technique can beat the random walk model to significantly improve the performance of exchange rate forecasting, and further provide suggestions for future studies in the same area.

5.2 Conclusion and Discussion

The central research question in this thesis is whether the artificial neural networks model can perform better than the random walk model in terms of long-run exchange rate forecasting. The overall answer for this question tends to be negative based on the empirical results in Chapter 4 --- Empirical Results.

In the NZ-AU case, the ANN technique can forecast better than the Random Walk model according to the criteria of RMSPE and Turning Point Accuracy, and has market-timing ability based on the PT statistic. However, DM test results suggest that there is no difference between the Random Walk Model and the monetary model with ANN technique in terms of forecast accuracy.

In the NZ-US case, all criteria support the Random Walk Model, and DM test results also suggest that the Random Walk Model produces more accurate out-of-sample forecasts with a long horizon than those from the monetary model with ANN technique.

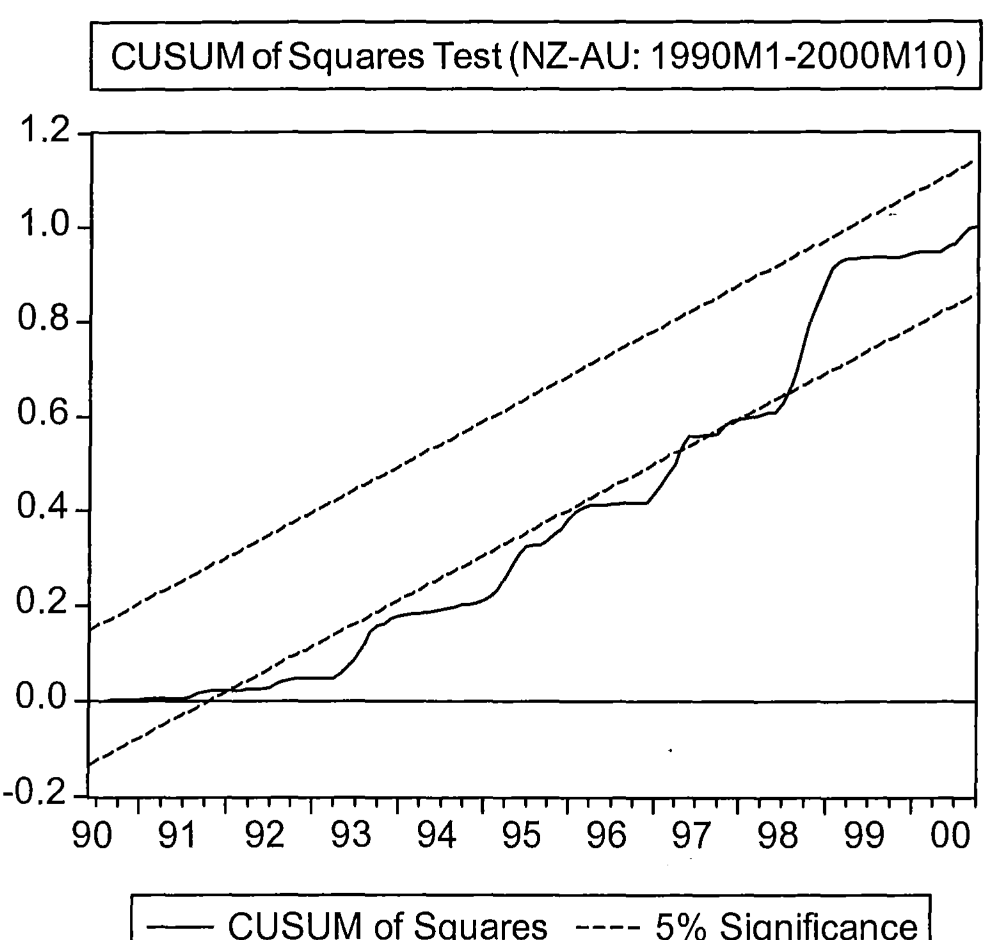
From these empirical results, we conclude that using the ANN technique does not significantly improve the performance over the Random Walk model. Does this conclusion suggest that nonlinear modelling is not entirely suitable for investigating the exchange rate movements?

5.2.1 Confirmation of the Use of the Nonlinear Modelling

As the appearance of nonlinearity can sometimes be due to the presence of instability in the empirical relationships within the data, it is necessary to check for evidence of such instability. Considering the linear version of the monetary model, a popular test for instability of an unspecified nature is the CUSUM test. The results are shown below.

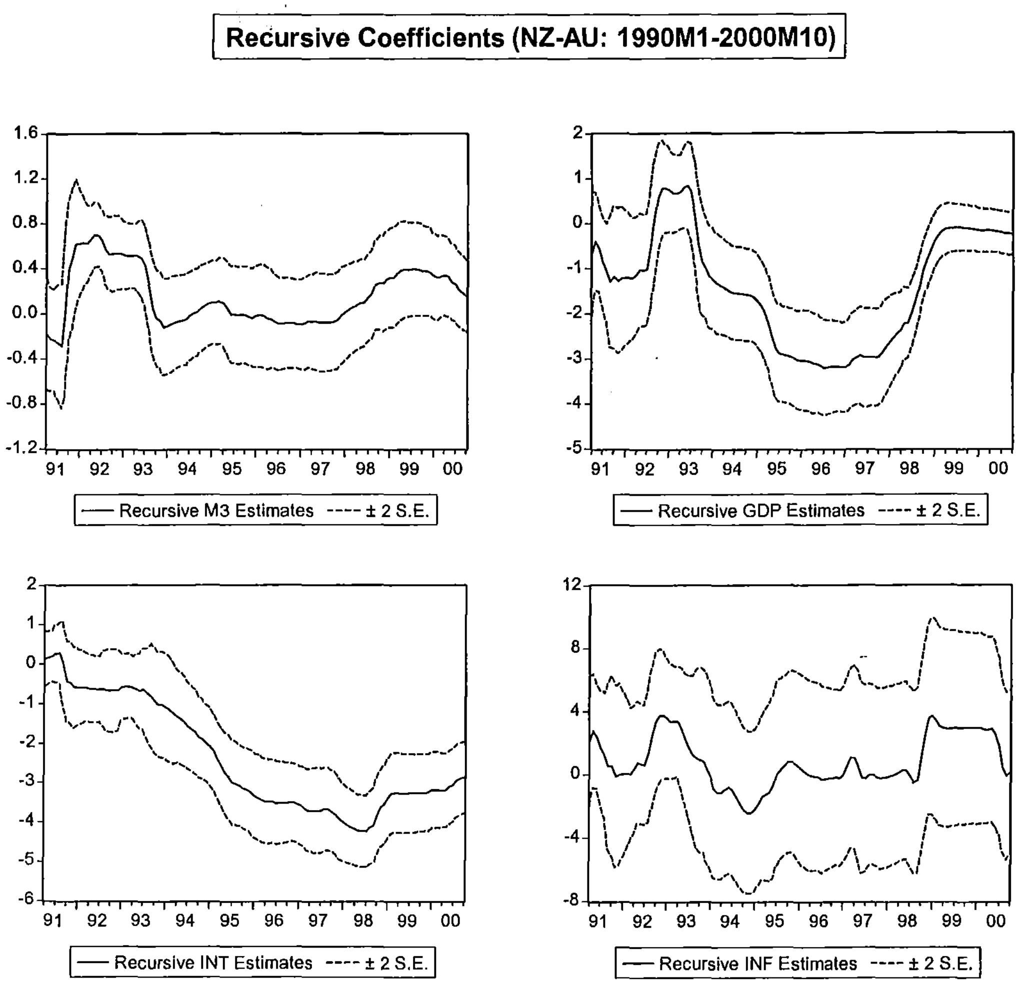
5.2.1.1 Testing for Instability in NZ-AU Relations

Figure 5.1: Parameter Instability Test (NZ-AU)



As shown in Figure 5.1, there is some evidence of instability in the linear relationship (NZ-AU) from 1992 to 1998. Hence, the next task is to try to pinpoint the possible source of this instability by examining the Recursive Least Squares (RLS) estimates for each parameter. The RLS coefficients are displayed in Figure 5.2 below.

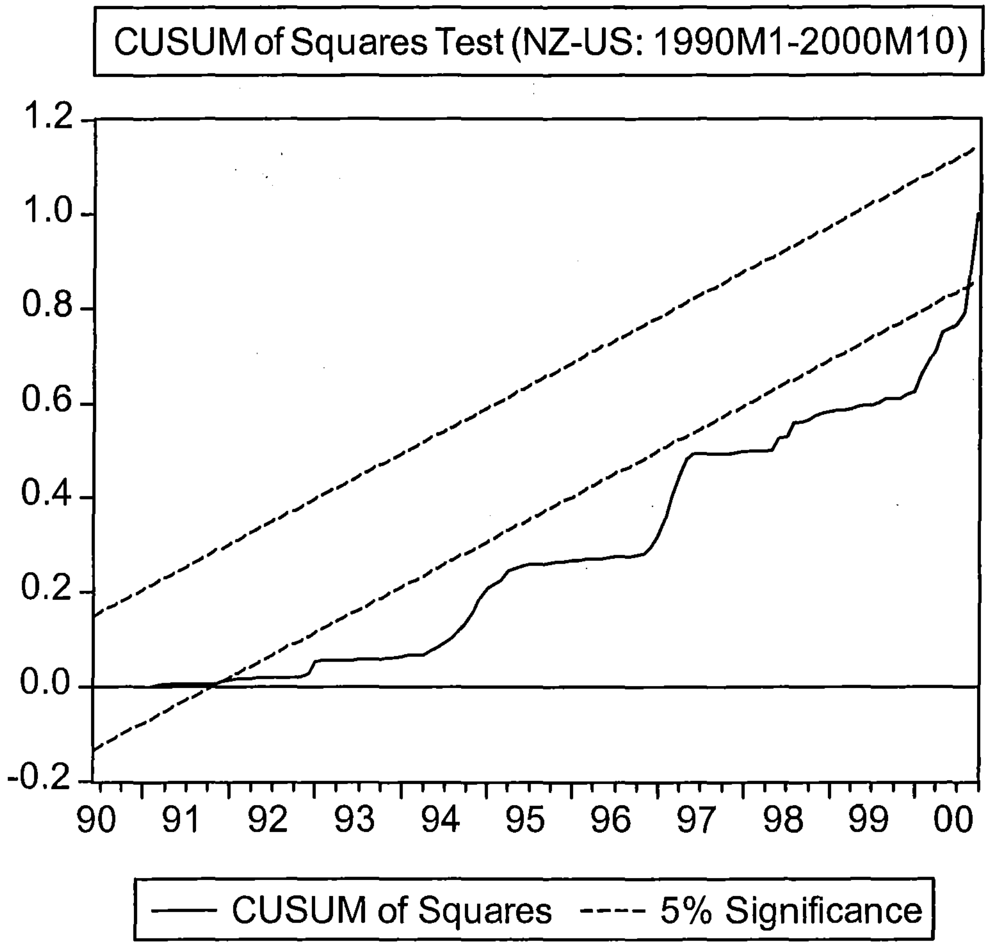
Figure 5.2: Parameters Estimation by RLS (NZ-AU)



From the graphs above, we can easily tell that at least the estimated parameters of the relative GDP (U shape) and the interest rate differential (continuously drops down) display clear evidence that there was some nonlinearity in the NZ-AU relations from 1990 to 2000.

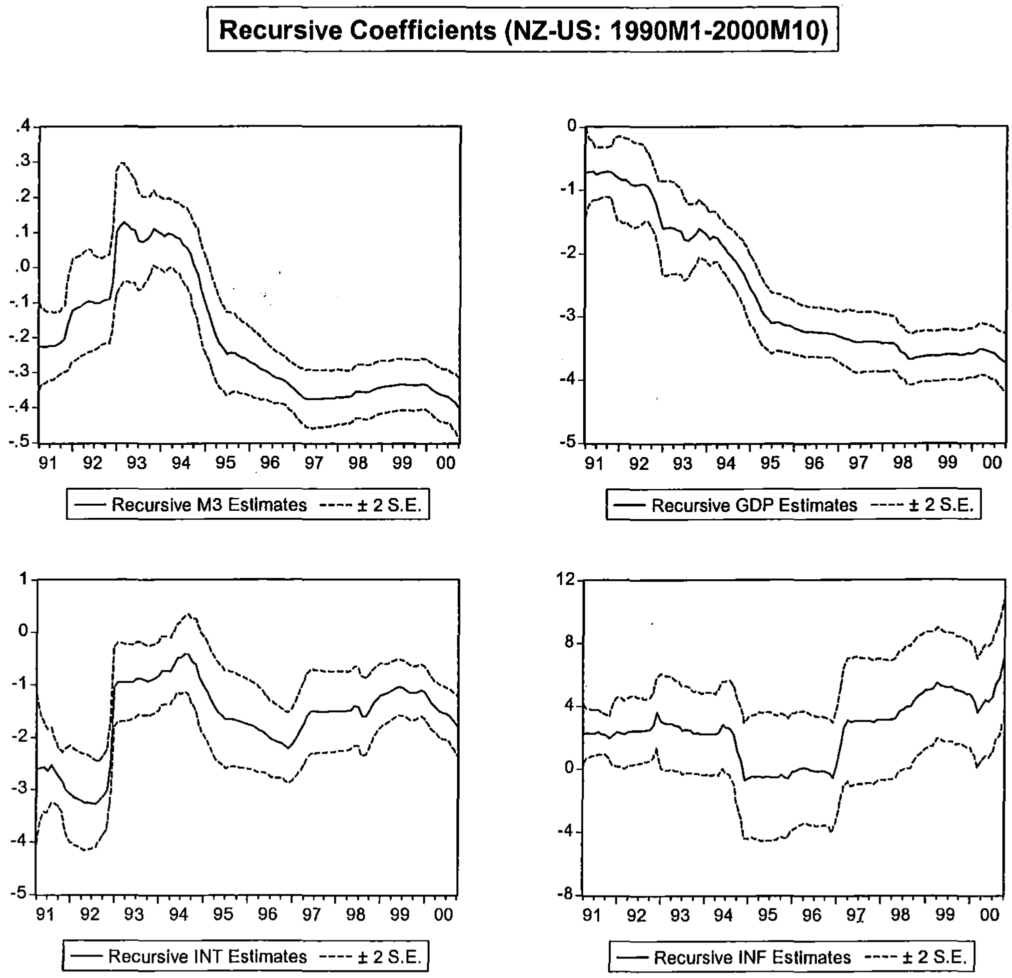
5.2.1.2 Testing for Instability in NZ-US Relations

Figure 5.3: Parameter Instability Test (NZ-US)



The results are similar to those of NZ-AU, but the graph shows that there is more percentage beyond the line of the 5% significance, which suggests that the evidence of instability in the data set from 1992 to 2000 is even stronger than that of NZ-AU case. The RLS results are shown below.

Figure 5.4: Parameters Estimation by RLS (NZ-US)



From the graphs above, we can easily tell that at least the estimated parameters of the relative money supply (inverted U shape), GDP differential (continuously decreases) and interest rate differential (inverted U shape) are non-constant, which may present themselves as evidence that there is nonlinearity in the NZ-US relations from 1990 to 2000.

It is clear that there is indeed nonlinearity in both data sets (NZ-AU and NZ-US) which confirms that the use of nonlinear modelling is correct and suitable. However, the performance of the nonlinear modelling, whilst improving on the linear models, is not entirely satisfactory. This outcome might well be attributed to factors other than inherent shortcomings in the nonlinear modelling methodology (ANN) itself. For example, the monetary model could be subject to specification errors (improper functional form, lack of dynamics, etc).

5.3 Limitations and Suggestions

5.3.1 Autocorrelation

In Chapter 4 --- Empirical Results, we have found that there is an auto-correlation problem in the linear monetary model. In order to solve the auto-correlation problem, we re-specified the function form that includes a lag of dependent variable to be an explanatory variable. Unfortunately, the re-specification function produced an even worse result with unexpected signs and non-significance although the auto-correlation problem was solved. Therefore we chose to leave the linear model with the auto-correlation problem unchanged because the focus of our research was on the forecasting abilities of the models.

The same principle was also applied to the artificial neural networks in order to make it easy to compare the performance from the ANN modelling with the linear monetary model. However, in this case, leaving the auto-correlation problem in the ANN modelling could theoretically reduce the accuracy of the prediction in the application of ANN models.

5.3.2 Stationarity

In a neural network model, all variables (inputs and actual output) should be stationary and bounded because the value produced by a hidden unit is bounded due to the use of the logistic activation function. If an input variable is non-stationary or grows continuously over time, then the hidden units could eventually reach the maximal or minimal value, which in turn causes the output to remain constant. Therefore, it is highly desirable to determine whether or not all inputs in our neural network models are stationary - if so, then the estimated output will automatically meet the same criteria. To this end, we employed two different tests regarding the stationarity status of each of the variables. However, we note the caution in Johnston and DiNardo (1997, pp223) that "... *the available tests have low power and so the distinction between the two types of series [stationary and nonstationary], although of theoretical importance, may be of little practical significance.*" The following tables present the results of the unit root tests.

Table 5.1: Unit Root Tests for NZ-AU Data

	ADF test Ho:Y~I(1)		KPSS test Ho:Y~I(0)	
Variable	Lags	Statistic	Band	Statistic
Spot (Spot Rate)	0	-2.212	10	0.222*
M3 (Money Supply)	0	-2.784	10	0.193*
GDP (Gross Domestic Product)	3	-2.655	10	0.133
Int (Interest Rate)	0	-4.067*	9	0.257*
Inf (Inflation Rate)	4	-6.881*	8	0.085

Note: Critical Values (ADF, 5%): -3.437 (Levels) (with trend and intercept term)
Critical Values (KPSS, 5%): 0.146 (Levels) (with trend and intercept term)
The value with * means that the null hypothesis is rejected at 5% significance level.

From Table 5.1, we can see that the results for the NZ-AU unit root tests (ADF and KPSS tests) are not consistent with each other. For the ADF test, the variables of spot rate, relative money supply, and relative GDP are detected to be non-stationary; but for the KSPP test, the variables of spot rate, relative money supply, and interest rate differential are detected to be non-stationary. The two unit root tests provide different results for the variables of relative GDP and interest rate differential, which suggests that these unit root tests are not able to unambiguously classify finite time series variables.

Table 5.2: Unit Root Tests for NZ-US Data

	ADF test Ho:Y~I(1)		KPSS test Ho:Y~I(0)	
Variable	Lags	Statistic	Band	Statistic
Spot (Spot Rate)	0	-0.471	10	0.181*
M3 (Money Supply)	0	-2.085	10	0.356*
GDP (Gross Domestic Product)	3	-2.418	10	0.120
Int (Interest Rate)	0	-2.007	10	0.194*
Inf (Inflation Rate)	1	-8.607*	7	0.077

Note: Critical Values (ADF, 5%): -3.437 (Levels) (with trend and intercept term)
Critical Values (KPSS, 5%): 0.146 (Levels) (with trend and intercept term)
The value with * means that the null hypothesis is rejected at 5% significance level.

Similar to those of NZ-AU unit root tests, the ADF test and KPSS test are also not consistent with each other in the case of NZ-US. For the ADF test, the variables of spot rate, relative money supply, relative GDP and interest rate differential are detected to be non-stationary; but for the KSPP test, only the variables of spot rate, relative money supply and interest rate differential are detected to be non-stationary. The two unit root tests provide different results for the variables of relative GDP, which also suggests that the unit root tests are not able to unambiguously classify finite time series variables. Again, Johnston and DiNardo (1997, pp 227) advises, "*Low Power in statistical tests is an often unavoidable fact of life, with which one must live and not expect to be able to make definitive pronouncements*."

Having received the message that the unit root tests have low power to unambiguously classify finite time series variables, we decided that it is better leave the variables unadjusted for the application of artificial neural networks in case all variables used in this thesis are possibly near the unit root process rather than the restricted unit root process.

5.3.3 Microeconomic Items

Empirical evidence does not unequivocally support that macroeconomic fundamentals have consistently strong effects on exchange rate determination and forecasting (Frankel and Rose, 1995), and hence the negative findings lead to a more updated branch (microeconomic approach) to attempt to better understand the deviations from macroeconomic fundamentals. The microstructure information is also called technical information, and it competes with fundamental information in terms of the ability to forecast foreign exchange rates. Rubio (2004) focused on technical analysis to forecast foreign exchange rates at different horizons in five different markets. His main findings, relevant to this research, were similar to those of Hutcheson (2000), Cheung and Chinn (2001), Menkhoff (1997), and Cheung, Chinn and Marsh (2004), namely that technical analysis models performed better in short horizons, whereas long-run exchange rate movements could be explained better by fundamentals based models.

The microstructure literature concerns a wide range of issues including *the transmission of information between market participants, the behaviour of market agents, the relationship between information flows, the importance of order flow and the heterogeneity of agents' expectations* (Sarno and Taylor, 2002, pp264). Among these microeconomic variables, order flow is the most important because order flow actually reveals aggregate market participants' expectation and therefore can be viewed as an approximate determinant of market price (Evans and Lyons, 1999).

It has been found that incorporating the 'non-public' information of order flow in a model is useful for forecasting exchange rates because this type of information cannot be widely attained by all market-makers contemporaneously, and thus causes the unanticipated exchange rate innovation (Evans and Lyons, 2005). The micro-based model, which mainly contains the information of order flow, forecasts exchange rates significantly better than both a standard macro-model and a random walk model at the various short horizons (1-, 5-, 10-, 15-, and 20-days), especially as the forecasting horizon rises (Evans and Lyons, 2005).

A mixed model that includes both a new variable (order flow) reflecting the microeconomics of asset pricing and macroeconomic fundamentals, is able to significantly improve on the pure macroeconomic models and produce more precise short run out-of-sample forecasts (one-day, one-week and two-weeks horizons) than a random walk model (Evans and Lyons, 1999)[89]. Similarly, but more elegantly, (Gradojevic and Yang, 2000)[90] introduced the variable of order flow along with a set of macroeconomic variables together with the use of an ANN technique. Their "hybrid" model yielded more accurate short run out-of-sample forecasts (one-day and one-week forecasts) compared to the standard linear and the random walk models in terms of criteria of root mean squared error (RMSE) and the percentage of correctly predicted exchange rate directional changes (PERC).

These results about the models which introduce the microeconomic variable of order flow are quite successful because they include the information indeed relevant to the exchange rate (Evans and Lyons, 1999), which is entirely ignored by traditional macroeconomic models. Actually, macroeconomic models are built on the assumption that markets are efficient and release all relevant information to every market participant (Sarno and Taylor, 2002), but macroeconomic models' information does not include microeconomic variables which are grouped as an error term in the macroeconomic models (Gradojevic and Yang, 2000). In conclusion, further studies of the microstructure of the foreign exchange market are necessary for attempting better understanding in this area (Frankel and Rose, 1995).

5.3.4 Conclusion

Throughout this thesis, we can not overturn the finding from (Meese and Rogoff, 1983) that random walk model performs no worse than other competing theory-based models in terms of exchange rates forecasting. For future research, the data sets should be examined and chosen carefully in order to avoid variable non-stationary and auto-correlation problems. By doing so, we can enhance the chance that nonlinear models forecast exchange rates more accurately than the random walk model. More importantly, microeconomic items should be incorporated (if the micro-information is

[89] This paper uses daily observations of the German mark, Japanese yen and US dollar.
[90] This paper uses daily observations of the Canadian dollar and US dollar.

valid and easy to get) in the nonlinear models in order to make the forecasting models more powerful.

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