FORECASTING EXCHANGE RATES

by

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Master of Management Studies

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"FORECASTING EXCHANGE RATES"

submitted by Michel Fuksa, B.Comm.
in partial fulfillment of the requirements for
the degree of Master of Management Studies

Thesis Supervisor

Director, School of Business

ABSTRACT

This study examines the efficiency of the Canada-US foreign exchange market through forecasting of the exchange rate. Generalized Additive Models (GAM), Neural Networks (NN) and linear models are used to forecast the point value of the one-month-ahead Canada-US foreign exchange rate and of the three and six months ahead trends in the exchange rate. The one-month-ahead exchange rate returns are also predicted. Structural models based on the Hooper-Morton model along with technical models based on the lags of the dependent variable are used in forecasting the exchange rate. The results suggest that the Canada-US exchange rate market may be inefficient in the weak form.

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1 Introduction

1.1 Background

In the global economy, international trade is an important part of any company's revenues. Trading internationally exposes a firm to currency or exchange rate risk. Because of the increasing amount of international trade it is important to understand, manage and control the exposure to exchange rate risk. In order to understand how to manage exchange rate risk, one needs to understand the behaviour of exchange rates

Although several differences exist between stock and foreign exchange markets, there are some similarities between the two. First, both are organised free markets where the laws of supply and demand fix prices of the goods traded. Next, the market participants are well informed and rational and, therefore, make decisions which will maximise their expected utility. There exist many other similarities between the stock and foreign exchange markets since they are driven by the same underlying rationale. The only notable difference between the two is the good traded: one market trades stocks which are ownership claims on company assets (and profits), and the other trades currencies. All the principles underlying these markets are the same. Investors gather information on the state of the universe in which they operate and make rational investment decisions. The investment and uncertainty problems facing the two market participants tend, therefore, to resemble each other. This suggests that the prices in the

two markets reflect all the available information and, thus, that the Efficient Markets Hypothesis (EMH) must apply.

The EMH proposes that, for markets to be efficient, security prices must reflect all relevant information. Fama (1970) operationalizes this hypothesis and defines three types of efficiency:

- ◆ Weak form efficiency: no investor can earn excess returns by developing trading rules based on historical price or return information.
- ◆ Semi-strong form efficiency: no investor can earn excess returns from trading rules based on any publicly available information
- ◆ Strong form efficiency: no investor can earn excess returns using any information, whether publicly available or not

The EMH maintains that assets' prices follow a random walk and that any systematic departure from a security's equilibrium price will be corrected by the rational and well informed market participants through arbitrage. The implication of this hypothesis is that forecasting of security prices is a futile exercise since all information is already discounted in the security price. Over the years, many tests of the EMH have been conducted in the academic literature, often with contrasting results (Black (1971), Fama and Blume (1970), French (1980)). To this day, it is unclear whether this theory holds

(Note that the rejection of any one of the three hypothesis based on a model, signifies that any stronger hypothesis is false, but does not mean that a less strong hypothesis is false. Market efficiency is thus asymmetric). At the same time, a relatively large number of studies have focused on the predictability of prices in the financial markets, but with little success. The results seem to point out that, while it is difficult to forecast financial asset prices, it is possible to do so to a limited degree.

1.2 The Study

This study represents yet another test of the semi-strong form market efficiency hypothesis in the foreign exchange (FX) market by attempting to forecast the Canada / US foreign exchange rate based on historical data. The impetus for the study has been the appearance of new modelling techniques which allow for the capture of non-linear relations between variables - a notable advantage over traditional and frequently used statistical tools.

The modelling tools chosen for the study are Neural Networks (NN) and Generalized Additive Models (GAM), techniques which have become popular only recently because of their computer intensive-nature. These modelling techniques have been applied successfully to financial and non-financial modelling by several researchers (Kuan and Liu 1995; Lachtermacher and Fuller 1995; Elman 1990; Lee and Park 1992;

Friedman and Silverman 1989), and have been used with some success in forecasting the stock market (Lee and Park 1992; Krzyzanowski, Galler and Wright 1993).

There are many benefits from this study. It adds to the already considerable body of literature examining the semi-strong form market efficiency in the foreign exchange market, and by introducing the use of two new methodologies for the purpose of forecasting exchange rate movements. The results from this study will help theoreticians to better understand the behaviour of the foreign exchange markets by allowing them to examine non-linear relationships in the data. This new perspective will enable them to construct an empirical framework encompassing the non-linear structure of the foreign exchange markets. The new techniques to be used in modelling relationships in this study will ultimately help researchers to better understand the financial markets in general.

This study will also be of use to practitioners who are in contact and have to deal with the foreign exchange markets by providing them with a better understanding of the dynamics of the market. By helping theoreticians develop new theories of the FX market, practitioners will benefit from their improved knowledge by applying it to hedging and investment management as well as speculation. The ability to forecast exchange rates and better understand their behaviour will help managers in aggregate, to perform their tasks better.

The remainder of this study is organised in the following manner. Chapter 2 provides a literature review on the subject of foreign exchange modelling and forecasting. Chapter 3 describes the proposed research in detail, while Chapter 4 describes the methodology to be followed. Chapter 5 presents the results of the study. Contribution to the existing literature is discussed in Chapter 6. Chapter 7 presents the conclusions, including the benefits and limitations of the study.

2 Literature Review

Meese and Rogoff (1983) (M&R), in a seminal study that has influenced researchers for over a decade, evaluated the forecasting performance of the most popular structural models (Frenkel-Bilson, Dornbush-Frankel and Hooper-Morton models as presented in Appendix 4) against a random walk model for three currencies (the British Pound, the Mark, and the Yen). The methodology was as follows: the three models' coefficients were estimated on a training sample, and their forecasting performance measured on realised values of the underlying economic variables. This approach allowed Meese and Rogoff to verify the predictive power of the models without having to forecast the underlying variables. The results were disappointing: the random walk model performed better than any of the three structural models. Additional time-series models were constructed in the hope that they would outperform the structural models. These models included vector autoregression and univariate autoregression models.

The vector autoregression model consisted of lagged independent variables stemming from the structural models together with lagged values of the spot exchange rate. The univariate autoregression consisted only of lagged values of the exchange rate. The performance of these time series models was also evaluated based upon the realised values of independent variables. None of these models outperformed the random walk model. Meese and Rogoff concluded that these results pointed to either mis-specification

of the models or the inability of the models to account for non-linearities in the data.

Another possible cause would be the possibility of a temporal structural shift in the underlying variables.

In order to account for the shortcomings of this study, several authors have taken on the task of expanding it in order to implement some of the proposed suggestions. In a follow-up study on the German mark, Somanath (1986) expanded the Meese and Rogoff (1983) study by modifying their models to include a 1 lag dependent variable (see Appendix 4). The same methodology as with Meese and Rogoff (1983) was used in order to estimate and test the models, with the exception of an expanded dataset being used. The models' performance was compared with a random walk model, on a test sample constructed of subsequent observations. The results of the study showed that the lagged structural models outperformed the random walk and simple structural models.

In another replication of the M&R study, Schinasi and Swamy (1989) tried to address the issue of parameter changes over time. M&R in their conclusions identified this possibility as an explanation for the poor performance of the structural models against the random walk. Swamy and Schinasi addressed this point by re-estimating the models at regular time intervals, thus allowing coefficients of the models to change over time. The methodology and the models used in their study were adapted directly from M&R's work. Schinasi and Swamy, inspired by Somanath (1986), also estimated their

models with one lagged variable. The results of the study were in direct contradiction with M&R's work: the variable coefficient models outperformed the random walk in the test period, and the lagged variable models presented a dramatic improvement over the simple variable coefficients model. Schinasi and Swamy concluded: "... once one is willing to relax the conventional assumption of fixed regression slopes, it is possible to estimate structural models of exchange rate determination which perform better in predicting out of sample values of exchange rates". This suggests, therefore, that the FX rate determination system might be a truly dynamic entity in that the exchange rate might not only depend on the underlying economic variables alone, but on time as well.

Beginning with the conclusions of the M&R study, several authors have examined the possibility that the relation between the underlying variables is non-linear in nature in the hope of improving the explanatory power of the models under investigation. In their study, Diebold and Nason (1990) use locally-weighted regression, a technique allowing for non-linear relations between variables, in order to predict the exchange rate for ten currencies from their past values. The study focused on finding the right model parameters, such as the size of the neighbourhood and testing with different lag lengths in order to obtain the lowest in-sample prediction error. Once the correct parameters were identified, the model was tested on out-of-sample data by trying to predict the next period exchange rate. At each time period, the model was re-estimated in order to allow the parameters to change over time. The results of this study were disappointing: the out-of-

sample testing showed that the model's performance was not better than that of a random walk model. Modelling was also performed for different prediction horizons into the future, but with no improvement. The authors concluded that the discouraging results were caused by over-fitting, resulting from the use of a non-linear modelling technique on data with linear relations.

Following the article of Diebold and Nason (1990), Chinn (1991) further explored the possibility of non-linear relationships between variables. The author elaborated on the fact that the "theory provides the fundamentals but not the form of the relationships", hypothesising that the forecasting failure might not indicate the failure of structural models, but that of linear structural models. In order to find the 'true' relations between the variables, Chinn proceeded to use the Alternating Conditional Expectations (ACE) non-parametric regression technique, a variant of the Generalized Additive Models. He focused on forecasting the DM/Y, USS/Y and USS/DM exchange rates. Linear modelling was also performed on the data in order to constitute a point of reference for comparing the performance of ACE. The methodology used by Chinn was the same as the one used by M&R, but new models were added to further exploit the modelling capability of ACE. The new models included the M&R difference models and an error correcting model consisting of level and difference elements for the same variables. Rolling forecasts were also performed in order to account for temporal changes in the data. In in-sample forecasts, the ACE models outperformed the linear and random walk models. In the out-

of-sample forecasts, the results were mixed. All of the non-linear models beat the random walk model in the root mean square error criterion, but some of them were outperformed by simple linear models. For the rolling forecasts, the linear models performed better than some ACE models, which again outperformed the random walk. The reason for this result seemed to be that ACE over-fit the data in the training stage.

Chinn and Meese (1994) returned to the Meese and Rogoff (1983) models and tried to estimate them using parametric and non-parametric techniques imposing theoretical constraints on the models. The structural models were found to be poor predictors of the short-term exchange rate for the DM, CS, BP and Yen. The long-term 12 month forecasts outperformed the random walk model.

Kuan and Liu (1995) attempted to forecast the exchange rate with the help of a neural network (NN). They focused on the pound Sterling, Canadian dollar, the mark, the yen and the Swiss franc using daily data. The model used in the study was a simple time-series model in which lagged values of the dependent variable were used as explanatory variables: up to 6 lagged variables were used. Kuan and Liu were interested in the capacity of the networks to forecast the direction of future price changes and estimate future values of exchange rates. They found that NNs can outperform the random walk model in sign and point forecasting in only two out of five FX series.

Meese and Rogoff (1988) re-examined the problem of forecasting the exchange rate again by looking at the relation between real exchange and real interest rates. They found very little evidence of any explanatory power in the real interest rates: their model was unable to outperform the random walk model. They concluded that the disturbance in real interest rates might explain some of the exchange rate volatility.

In an attempt to formulate a better structural model for exchange rate determination, Dooley, Isard and Taylor (1995) added the price of gold to the Frankel-Dornbush model mentioned in M&R. This new variable was added since gold is an asset without a country, and that any change in a country's economic condition would be reflected in the price of gold. The reason for this linkage is that gold is a 'sure asset', meaning that when economic uncertainty pushes investors to divest from one country, the affected funds 'take refuge' in other countries and in gold. Dooley et. al., after testing their hypothesis empirically by estimating and fitting the models with the gold variable, concluded that it is significant when it comes to explaining changes in the exchange rate. Gold was found to be the most statistically significant variable in the model.

Engel and Hamilton (1990) examined the long swing hypothesis of foreign exchange rates to determine its validity. This hypothesis states that the exchange rate is characterised by long term trends and swings. They could not reject the hypothesis of the existence of such trends and argued that the exchange rate is characterised by non-linear

serial dependence. They further argued that the exchange rate could follow long term trends even though the spot rate could deviate from them.

Cumby and Obstfeld (1981) tested the Fisher hypothesis of exchange rates. The Fisher hypothesis states that given two bonds similar in all respects but the currency denomination, any nominal rate of return differential between them will be offset by an expected exchange rate change over the holding period. The authors tested this hypothesis and ended up rejecting it.

In an article describing the floating exchange rate experience beginning in 1973, Frankel (1989) contrasted theoretical predictions with the practice. The following points summarise his observations:

- ◆ Theory predicted that the exchange rate would change at the same speed as economic fundamentals: this was proven not to be true.

- ◆ Speculation is not a stabilising phenomenon, and most market participants pay scant attention to fundamentals. Surveys have reported that the most profitable FX forecasters were using technical rather than fundamental analysis. ('in 1985: 97% of banks and 87% of securities houses supported the belief that "the use of technical models has had an increasingly significant impact on the market"')

- ◆ De Long (1987) presents a model in which a class of traders plays on the 'noise', but is prospering. (there exists a riskier asset that pays a larger return in order to compensate

the rational investor: the 'noise traders' have a mistaken idea of the risk return trade-off and hold more of this asset, and thus prosper over time)

- ◆ The FX market reacts to something else than just the fundamentals: the fundamentals are just not changing fast enough to explain the changes in the exchange rate. Frankel suggests that the movements originate from trader interactions: French and Roll (1986) conducted a study on stock price movement: on days when the New York Stock Exchange was closed, the price moved less than during the days it was open.

- ◆ The trading volume in the FX market is bigger than the international trade in goods and services and the volume of international trade in long term capital.

- ◆ Banks believe that taking long term positions based on fundamentals is risky, but allow traders to take large open positions as long as they are closed at the end of the day: these operations are profitable in aggregate.

- ◆ One forecasting service provides forecasts every 15 minutes.

- ◆ The economic rule that the long run is the sum of a series of expected short runs is not working: the fundamentals are not used by the majority of traders.

- ◆ The market moves in speculative bubbles.

Ten years earlier, Goodman (1979) had expressed the same concerns as Frankel (1989) when examining the American commercial exchange rate forecasting services market. The author studied the forecasting performance of 10 out of the 23 commercial

services which provided forecasting information on the future behaviour of exchange rates. He segmented the providers of this service into three groups:

- ◆ firms using judgmental forecasting (13 firms)
- ◆ firms that rely on economic models (6 firms)
- ◆ companies using exclusively technical models (4 firms)

Goodman excluded the first category of forecasting firms from the study on the basis that these firms did not employ any formal models of exchange rate determination, but rather, relied on experts' opinions. The remaining services were providing point estimates of the exchange rates and trend estimates for the technical services. The economic services relied on models similar to those described by M&R, while the technical services relied on mathematical models relating past prices to future prices and on the chartist approach. All of the economic services stressed that their forecast should only be used for planning purposes and not to manage or hedge portfolios or assets. The technical services on the other hand, mentioned that their forecasts were intended for use in hedging programs. Goodman measured the performance by examining the recommendations for 6 currencies against the U.S. dollar for January 1976-June 1978. The results showed that, although forecasting services based upon economic modelling provided a good forecast on the average, they were not able to significantly outperform the buy and hold strategy. Forecasting services based upon technical analysis, on the other hand, did extremely well compared to the buy and hold strategy, outperforming it

by at least 7.28% per year, with the performance of the worst technically-oriented service being far better than that of the best economic-oriented one. These results indicate that the foreign exchange market may not be efficient in the weak form, a conclusion that has clear implications for corporations exposed to foreign exchange risk.

Hakkio (1986) examined the random walk hypothesis of the foreign exchange markets. He examined the contradictory evidence present in many studies relating to the exchange rate following a random walk and tried to settle the issue with the help of a Monte Carlo study on the power of four common tests of random walk. The methodology centred on the ability of the tests to reject the hypothesis of a random walk for time series that were 'close' to a random walk, but that did not follow one. The author determined that none of the tests were very powerful: they rejected the random walk hypothesis at the most only 30% of the time when, in fact, the time-series was not a random walk. Hakkio maintained that this fact explained the numerous contradictory study results: the conclusion that the exchange rate follows a random walk was caused by the test for the random walk not being powerful enough to reject the null hypothesis of a random walk. Hakkio concluded that the findings that the exchange rate followed a random walk should not be taken at face value.

Satchell and Timmermann (1995) provided a new approach to evaluating the performance of out-of-sample forecasts of non-linear exchange rate models. They

proposed to look at the economic value of the forecast instead of the standard evaluation criteria like MSE (mean square error) or MAE (mean absolute error). They tested their theory on fifteen exchange rates using daily data for twelve years. They used a non-parametric forecasting algorithm to forecast the daily changes in the exchange rates, and evaluated the forecasting performance of the model using error as well as economic value criteria. They found out that even though the non-linear model was less precise in predicting the exchange rate based on the error criterion than the random walk model, the non-linear model outperformed the random walk model based on the economic value criterion, with a higher mean return than the random walk model. They have also proved that the economic value criterion of forecasting performance was closely related to the tests of market timing.

2.1 Conclusion

As the literature review might indicate, forecasting the exchange rate is not a small task. The large number of studies often with inconclusive and contradictory results indicates that further work needs to be undertaken in order to explain the behaviour of the exchange rate, let alone being able to forecast it.

Meese and Rogoff (1983), in a trend setting study which has influenced the international finance literature for over a decade, have examined a number of relatively

simple structural economic models of exchange rate determination. The goal of their study was to test the performance of these models in determining the ex-post exchange rate for a number of currencies. Even though none of the models outperformed the random walk benchmark, the authors managed to extract some very important conclusions from their results. The authors concluded that the cause for the bad performance of the models was either:

- ♦ a model mis-specification, or/and
- ♦ non-linearities in the underlying relations, or/and
- ♦ time related coefficient changes, or/and
- ♦ sampling error.

The last point is of little interest, although it might have contributed to the poor results of the study. The more interesting alternatives are the first three.

The model mis-specification argument has been picked by several researchers since 1983, and is motivated mainly by “technical” factors. The proponents of this explanation are Frankel (1989) and Goodman (1979), both of which tried to attribute the poor performance of structural models to the fact that economists are not taking “the real world” into consideration. Both researchers argued that markets move in non-rational, speculative bubbles, and that FX market participants pay only very little attention to economic fundamentals. They concluded, therefore, that model mis-specification was to blame for poor performance of foreign exchange models.

The shape of the relationship between variables has been examined by Chinn (1990) and Diebold and Nason (1991). Both authors argue that although the M&R models are correct as to the fundamental variables underlying exchange rate determination, they do not specify the exact shape of the relation linking the exchange rate to its economic determinants. The researchers in their respective studies try to find the right shape of the relations by using non-parametric regression methods. Only Chinn (1990) succeeded in forecasting the exchange rate better than the random walk benchmark. Both studies concluded that it is very difficult to fit a non-linear relation through the data because over-fitting might nullify any benefits from using a non-linear approach to modelling relations.

The third flaw mentioned by M&R has been addressed by Somanath (1986) and Schinasi and Swamy (1989). These researchers have taken on the task of repeating the M&R study by allowing the coefficients of the models to change with time. Somanath (1986) has further modified the models to include one lagged dependent variable (see Appendix 4). In both studies, methodologies have allowed for the models' coefficients to change over time by successive re-estimation in order to include the latest data points. The models in both of these studies have been able to outperform the random walk benchmark.

The results from the above studies lead to several observations. First, it is important to take "the real world" into account when modelling any phenomenon. This study assumes that the structural models described by Meese and Rogoff (1983), and by succeeding researchers, are accurate reflections of reality.

The second observation one could make is that it seems that the exchange rate can be modelled better with the help of non-linear techniques. One has to be careful, however, not to overuse this method, because of over-fitting. Also in order to successfully forecast the exchange rate one must allow for the model coefficients to change over time. This is very important in view of the fact that the exchange rate determination process might be a dynamic process as suggested by Schinasi and Swamy (1989) and Frankel (1989).

Finally, one must be able to objectively and correctly evaluate forecasting performance of the models used. As Satchell and Timmermann (1995) noticed, the correct way of evaluating a exchange rate prediction model is through the use of economic value assessment. The use of other criteria of model selection might flaw study conclusions: had the previous studies used the correct performance measure, very different conclusions might have been obtained.

In conclusion, the literature review suggests that in order to successfully describe the exchange rate, the empirical models must allow for three possibilities:

- 1) time-variant parameters
- 2) non-linear relations between variables
- 3) technical as well as economic factors

3 Research Design

3.1 The Research Question

The principal and secondary research questions that this study will attempt to answer are as follows:

- ♦ Is the Canada / U.S. foreign exchange market efficient in the semi-strong form?

The study will also attempt to answer the following secondary research questions:

- ♦ Is the shape of the relationship between the dependent and independent variables non-linear?
- ♦ Do model parameters vary with time?
- ♦ Do technical variables help in predicting the exchange rate?
- ♦ Is economic value assessment the right performance measure?

3.2 Model Specification

The study invokes a number of models in order to answer the research questions enumerated above. This section presents the models used in the study.

The first model that will be estimated will be a technical time series model (Time Series 1 model: TS1), whose purpose is to detect whether it is possible to predict the exchange rate from its past values. This model presents a direct test of the weak form market efficiency hypothesis. The model is as follows:

$$F_{t-1} = a_0 + \sum_{n=1}^{12} f(F_{t-1-n})$$

where $F(t)$ is the spot exchange rate between Canada and the U.S. defined as the number of Canadian dollars per U.S. dollar, and $f(x)$ is the function relating the independent variables to the dependent variable.

The next model (Time Series 2 model: TS2), similar to the one above, will try to forecast changes in the FX rate:

$$\Delta F_{t-1} = a_0 + \sum_{n=1}^{12} f(\Delta F_{t-1-n})$$

where $\Delta F(t) = F(t) - F(t-1)$

The most general model used in the Meese and Rogoff (1983) study is the Hooper-Morton model (see Appendix 4). The principal structural model to be used in this study is a modified version of this model, a version which includes the price of gold as an additional variable (Dooley, Isard and Taylor 1995), and contains lags as suggested by Somanath (1986). The number of lags in the model is 4 for each variable. This

specification will allow for the inclusion of probable temporal effects, which will result in a more thorough description of the dependent variable. It is hoped that this model, because of its general nature, will be able to predict the exchange rate with greater success than the original Hooper-Morton model, and other models used in the post-M&R era. The model is as follows (Structural model 1: S1):

$$F_{t-1} = a_0 + \sum_{n=1}^4 f_1(F_{t-1-n}) + \sum_{n=1}^4 f_2(M_{t-1-n}) + \sum_{n=1}^4 f_3(Y_{t-1-n}) + \sum_{n=1}^4 f_4(R_{t-1-n}) + \sum_{n=1}^4 f_5(P_{t-1-n}) + \sum_{n=1}^4 f_6(TB_{t-1-n}) + \sum_{n=1}^4 f_7(G_{t-1-n}) + \sum_{n=1}^4 f_8(S_{t-1-n})$$

where:

- $F(t) = \log(\text{spot rate at time } t, \text{ expressed as the number of Canadian dollars per U.S. dollar})$
- $M = \log(M1c/M1a)$: the ratio of the Canadian (c) money supply to U.S. (a) money supply
- $Y = \log(Yc/Ya)$: ratio of real incomes
- $R = \log(Rc/Ra)$: ratio of the short-term (91 day) interest rates
- $P = \log(Pc/Pa)$: ratio of the expected long run inflation (usually taken as the average of the last 12 months CPI inflation rates)
- $TB = TBc/TBa$: ratio of cumulated trade balances
- $G = \log(\text{Price of gold in U.S. dollars})$
- $S = \log(\text{ratio of the return of the TSE300 to the DJIA stock market indexes})$

The next model (Structural model 2: S2) is the first differences variant of the preceding model:

$$\Delta F_{t-l} = a_0 + \sum_{n=l}^4 f_1(\Delta F_{t-l-n}) + \sum_{n=l}^4 f_2(\Delta M_{t-l-n}) + \sum_{n=l}^4 f_3(\Delta Y_{t-l-n}) + \sum_{n=l}^4 f_4(\Delta R_{t-l-n}) + \sum_{n=l}^4 f_5(\Delta P_{t-l-n}) + \sum_{n=l}^4 f_6(\Delta TB_{t-l-n}) + \sum_{n=l}^4 f_7(\Delta G_{t-l-n}) + \sum_{n=l}^4 f_8(\Delta S_{t-l-n})$$

where:

- $\Delta F(t) = \log[\text{spot rate at time } t] - \log[\text{spot rate at time } (t-1)]$, expressed as the number of Canadian dollars per U.S. dollar.

The following two models have the goal of forecasting the future trend in the exchange rate. The models used to forecast the trend will be time series models and the modified Hooper-Morton model. The first model (Trend model 1: TR1) has the following form:

$$T_{t+l} = a_0 + \sum_{n=l}^{24} f(F_{t-l-n})$$

where: $T(t+l)$ is the trend at time t for l periods, as defined in Appendix 3. Other variables have the same meaning as before.

The second model (Trend model 2: TR2) is a modified version of the modified Hooper-Morton model used in this study. The form of this model is as follows:

$$T_{t+l} = a_0 + \sum_{n=1}^4 f_1(F_{t-l,n}) + \sum_{n=1}^4 f_2(M_{t-l,n}) + \sum_{n=1}^4 f_3(Y_{t-l,n}) + \sum_{n=1}^4 f_4(R_{t-l,n}) + \sum_{n=1}^4 f_5(P_{t-l,n}) \\ + \sum_{n=1}^4 f_6(TB_{t-l,n}) + \sum_{n=1}^4 f_7(G_{t-l,n}) + \sum_{n=1}^4 f_8(S_{t-l,n})$$

where: $T(t+l)$ is the trend at time t for l periods, as defined in Appendix 3. Other variables have the same meaning as before.

3.3 The Variables

The variables used in the study are summarised in the following table:

Variable	Source	Frequency
Canada / U.S. spot rate expressed in C\$ per U.S.\$	CanSim	monthly
Canadian and U.S. M1 money supply	CanSim/FRE D	monthly
Canadian and U.S. real incomes (GDP)	CanSim/FRE D	quarterly
Canadian and U.S. 91 T-bill rate	CanSim/FRE D	monthly
Canadian and U.S. expected long run inflation (usually taken as the average of the last 12 months CPI inflation rates)	CanSim	monthly
Canadian and U.S. cumulated trade balances	CanSim/FRE D	quarterly
Gold price in U.S. \$	CanSim/Bank of Canada	monthly
TSE & DJIA stock market indices value	CanSim	monthly

Sources:

CanSim: Statistics Canada economic time series database

FRED: Federal Reserve Economic Database

4.1 Data Preparation

All model variables in this study were transformed into a logarithm with base 10, consistent with Meese and Rogoff (1983).

The models used in this study require monthly frequency data. Some of the variables, however, (like the GDP and trade balance statistics), do not fit this requirement because of the frequency at which they are reported by government agencies. In order to be able to use them in the study, they were transformed into monthly observations. This transformation was achieved through linear interpolation of data points. The use of linear interpolation is acceptable due to lack of a better alternative.

4.2 Sample Creation

In order to estimate and test the models, two samples were needed: the training sample and the testing sample. The data available for this study is of monthly frequency and spans over twenty years: from 1975 to 1995, i.e., 240 monthly observations. The training set consisted of 80% of observations, i.e., the first 190 observations, while the

testing set consisted of the remaining 50. This allocation allowed for enough data to be available for training the models and also left enough data for out-of-sample testing.

4.3 Modelling techniques

Three modelling techniques were used in the study: linear regression (LR), Generalized Additive Models (GAM) and Neural Networks (NN). This section describes the manner in which each of the proposed models were estimated.

4.3.1 Linear Regression

The first type of modelling technique used on the models is linear regression. This technique was used by Meese and Rogoff (1983) and by subsequent researchers. Its performance has been disappointing in general, but some studies like Somanath (1986) reported limited success by adding new variables to the models. The following table presents the models to be evaluated using the GAM technique:

<i>Models</i>					
TS1	TS2	S1	S2	TR1	TR2

After the full model was estimated, backward selection (see Appendix 1) was performed in order to identify the most influential variables for each of the models.

4.3.2 Generalized Additive Models

A variant of Generalized Additive Models, Alternating Conditional Expectations (ACE) was used by Chinn (1991) in order to model the exchange rate movements. Chinn was able to explain the exchange rate marginally better than a random walk model. The following models were estimated using this technique:

<i>Models</i>					
TS1	TS2	S1	S2	TR1	TR2

In contrast to Chinn (1991), the study proposes to estimate an expanded economic model which includes variables not used by Chinn (1991), and additional lags. Moreover, unlike Chinn (1991), the best nonlinear model was identified by using the backwards selection method (see Appendix 1).

4.3.3 Neural Networks

Two types of NNs were used in this study: the usual Feed Forward (FF) networks, and Time Delay NNs (TDNN) (see Appendix 2). The following models were estimated with this technique:

<i>Models</i>					
TS1	TS2	S1	S2	TR1	TR2

In order to allow the NNs to generalize the relations in the data instead of over-fitting the data, cross validation (CV) was used in the modelling process. CV is a process which allows for a testing sample to be used in the training stage, resulting in a better generalization capability (see Appendix 2).

The NNs used in this study have the following structure:

4 layers of nodes: 1 input layer, 2 hidden layers, and 1 output layer.

The first hidden layer has the variables in the model as the neurons. The second hidden layer consists of 12 neurons. The output layer consists of one neuron, corresponding to the output of the model. This study, in addition to one lagged variable model, as in Kuan and Liu (1995), also estimated economic models with the help of neural networks. It is therefore hoped that this approach will yield superior results than those of Kuan and Liu.

4.3.4 Looking for time related dependencies

Meese and Rogoff (1983) noted in their conclusions that it was possible that model parameters varied over time. In order to test this hypothesis, this study estimated GAM and LR models on a continuously updated training sample.

<i>Models</i>					
TS1	TS2	S1	S2	TR1	TR2

In order to test for time-dependent variations in the model parameters, the training sample was periodically updated in order to include the latest observations. The initial training sample for this test comprised 94 observations. The models were first estimated on this sample, which was updated with data at every 24 observations: the models were therefore, estimated on a training sample comprising 94 (Period A), 118 (Period B), 142 (Period C), and 166 (Period D), observations. The models were then compared to each other in search for time-related dependencies.

4.4 Performance Evaluation

In order to evaluate forecasting performance of the models, the following performance measures were used:

4.4.1 Error-Based Measures and Benchmarks

Two error-based performance measures were used: the MSE (mean square error) and MAD (mean absolute deviation).

$$MSE = \frac{\sum_{i=1}^n (Y_i - \hat{Y}_i)^2}{n}$$

$$MAD = \frac{\sum_{i=1}^n |Y_i - \hat{Y}_i|}{n}$$

Models evaluated based on this criteria in the following manner: the lower the MSE and MAD criterion, the better the performance of the model.

In order to evaluate any model objectively, a benchmark is needed. The 'random-walk' (martingale) model (RW1) of Pesando (1979) was be used as a benchmark. A random walk model assumes that the changes in the spot rate result from unanticipated information, and therefore the changes in a currencies' value are unpredictable (Giddy, 1994). The theory suggests that the best predictor of the future exchange rate is the current exchange rate. This theory has been implemented by Pesando (1979) in his random-walk model: $S(t+1)=S(t)$ (the expected exchange rate tomorrow is today's exchange rate).

4.4.2 Economic Value Performance Measures and Benchmarks

In addition to the usual error estimation techniques, economic value performance measures were also used. The purpose was to measure the economic value of forecasts. This technique is called the “switching portfolio” approach since the currency portfolio may switch from one currency to another (Satchell and Timmermann 1995).

This approach works in the following manner. At the beginning, the currency portfolio will start with a wealth of \$100 in Canadian funds (CS). After the first exchange rate prediction is made, the portfolio is re-balanced: if the prediction is that the CS will fall, the portfolio will be converted into US\$ at the current FX rate; otherwise, everything will stay as it is.

This rule can be written as follows:

If $PS(t+1) > PS(t)$, then do nothing: keep the funds in the currency that is appreciating

If $PS(t+1) < PS(t)$, then, switch into the other currency at the spot rate $S(t)$

PS - currency in which the portfolio is held

$W(t)$ - wealth of the portfolio at end of time t

$S(t)$ - spot exchange rate in CS per U.S.\$ at time t

The wealth of the final portfolio is the value of the currency portfolio after all periods, in Canadian dollars.

This benchmark enabled for the best evaluation of a model's performance in the sense that it measured the performance in terms of the amount of money each model produced, a measure by which any trading performance is evaluated. The reference trading rule to which this measure was compared is the buy-and-hold strategy.

4.4.3 Performance Measurement

Each model, estimated in this research, was evaluated using both error and economic value criteria. The models were then contrasted with the random walk benchmark models, and the best model and modelling technique was selected.

The criteria that was used in the model selection was the size of the MSE and MAD, and the economic value of the models. Models were judged in the following manner: the lower the MSE or MAD criteria, the better the model is. The higher the economic value created by the forecast the better the model. The following table presents the performance measures which were applied to various models. The trend models are not evaluated for economic value performance because of the difficulty of interpretation

of the forecast. The trend forecasts should only be considered as general indications of the movement of the FX rate, and should be used for planning purposes, not for portfolio management.

Model	<i>TS1</i>	<i>TS1</i> <i>b</i>	<i>TS2</i>	<i>TS2</i> <i>b</i>	<i>SI</i>	<i>SI</i> <i>b</i>	<i>S2</i>	<i>S2</i> <i>b</i>	<i>TR</i> <i>1</i>	<i>TRI</i> <i>b</i>	<i>TR</i> <i>2</i>	<i>TR</i> <i>2b</i>
Modelling method												
Linear Regression	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E	E	E	E
GAM	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E	E	E	E
Feedforward NN	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E	E	E	E
Time Delay NN	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E,V	E	E	E	E

E: Error based model evaluation, V: economic value model evaluation, *b*: backward selection

4.4.4 Market Efficiency

The principal goal of this study was to determine whether the Canada/U.S. foreign exchange market is efficient in the semi-strong form by trying to forecast the exchange rate based on historical data. The EMH stipulates that the exchange rates follow a random walk and, therefore, that any attempt at forecasting them will fail.

In order to reject the weak form market efficiency hypothesis (and therefore the EMH), a forecasting model will have to outperform the random walk model. The two tests of model performance used in this study are Pesando's (1979) "random walk" model, and the economic valuation approach.

First, if the random walk hypothesis held, the forecasting error of the “random walk” model should be smaller than that of any of the structural or time-series models.

The reverse would indicate that the markets are not efficient.

Second, the economic model valuation technique will also allow for the testing of this hypothesis: if the markets are efficient, the forecasting models should not be able to produce any value in excess of the \$US 100 starting portfolio, because no strategy should be able to outperform the random walk model (the buy-and-hold strategy). If any forecasting technique is able to produce excess wealth, market efficiency should be put in doubt.

Several factors, however, make forecasting the FX rate difficult. First, in the light of the EMH, prediction of the FX rate should be difficult by the simple fact that the actions of a large number of well-informed investors on the market, should eliminate every abnormal profit making opportunities. Secondly, technical reasons may not enable for the detection of any patterns in the data. For example, since the data in this study is of monthly frequency, short-term trends (and hence profit opportunities) may be completely enveloped by long term trends.

It is also possible that model variables might not be able to explain any of the movement in the exchange rates. This is probable in the light of the fact that only rarely

were these models able to explain movements in the exchange rate in studies undertaken over a period of 15 years. In the light of this fact, it is totally possible that the FX models proposed by economists are mis-specified.

4.4.5 The Methodological Process

5 Results

The study set out to test the semi-strong form of market efficiency in the Canada/US foreign exchange market. A number of additional issues were also examined such as the shape of the relationship between variables, the degree of parameter variation over time, the importance of technical variables in the models, and the consistency of economic value-based measures of performance. The study used monthly data spanning from 1976 to 1996 for eight fundamental variables. The study consisted of running 240 linear and GAM models, and 16 NN models to forecast one period ahead point values of the Canada/US exchange rate, the expected one period changes in the exchange rate as well as three and six month trends in the exchange rate. The Splus statistical package was used to perform all the linear and GAM modelling tasks, and the SNNS package was used for implementing the neural networks. Due to unexpected technical problems, some models could not be estimated, the reason being the number of variables in the structural models (32 variables) resulting in memory overflow during backwards selection. The full models were unaffected by this problem. The following models could not be estimated due to this problem and had to be eliminated from the study:

- Structural returns and point forecast models (S1G3B, S1G5B, S2G3B, S2G5B)
- Structural trend changes and trend point estimate models (TR23G3B, TR23G5B, TR26G3B, TR26G5B)

5.1 Data Analysis

All the graphs represent the ratios of Canadian time series to American equivalents. The analysis of time series plots for various model variables leads to the following conclusions:

5.1.1 The exchange rate

The Canada/US exchange rate is characterised by a lot of irregularities: the time-series is not smooth, even though it has a very clear long term trend. The training sample consisted of observations from January 1976 up to October 1992, and the testing sample

from November 1992 to January 1996. A careful examination of the FX time series can point to an important design problem for the models: shortly after the beginning of the testing period, the Canadian dollar devaluated very rapidly. The historical cause of this rapid devaluation was the recognition by the financial markets of the size of the Canadian debt. This event can be qualified as a structural change, and, therefore, models estimated using the training data, are not expected to show good predictive ability in the testing period. If the models are able to forecast the FX rate adequately during the test period, it will indicate the presence of learnable patterns in the data, perhaps emanating from fundamental structural factors.

5.1.2 Stock markets

The ratio of stock market indices is as irregular as the components themselves (TSE 300 and DJIA indices), and is similar in that respect to the FX time series. It clearly shows a downward trend for the Canadian stock market index. There are no clear cycles in the data.

5.1.3 Inflation

The inflation ration time series (CDN CPI/US CPI) is unexpectedly smooth, unlike any economic time series. There is no explanation for this phenomenon other than the fact that inflation is a managed variable, tracked very closely by government financial institutions (the Federal Reserve and the Bank of Canada). The time series indicates that the inflation ratio is very close to 1, which points to a high degree of integration in the fiscal/monetary policies in the two countries.

5.1.4 Money Supply

The M1 money supply ratio indicates a growing money supply in the US as compared to Canada during the 1980s. Beginning in the 90s, the money supply ratio stabilised. This also corresponded with the economic slowdown that has occurred during the early 90s in the United States and Canada.

5.1.5 Gross Domestic Product

The GDP ratio shows a very strong cyclical nature, but no clear trend. This lack of clear trend and the stability of the GDP ratio confirms the dependence of the Canadian economy on the US economy. The Canadian economy lags its American counterpart both on the upside as well as downside.

5.1.6 Interest Rates

The T-Bill ratio indicates that, over the last 20 years, the Canadian interest rates have been stronger as compared to US interest rates. Since the beginning of the 90s however, the Canadian interest rates have been falling, due to severe deficit cutting measures adopted by various levels of the Canadian government. A stronger Canadian dollar has resulted.

5.1.7 Trade Balance

The trade balance ratio, on the other hand, seems to be flat, with the exception of several spikes in the 1980s. The plot indicates that Canadian exports are not as successful as well as American exports, and shows a marginal decline in the total amount of Canadian exports since the beginning of the 1990s.

Cumulative Trade Balance: Exports - Imports

Canada:

Exports: global merchandise exports (Mill. \$, quarterly)
Imports: global merchandise imports (Mill. \$, quarterly)

US:

Exports: exports of goods and services (Bill. \$, quarterly)
Imports: imports of goods and services (Bill. \$, quarterly)

5.1.8 Gold

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Gold, after a tumultuous start in the early 80s, when the fears of inflation catapulted its price to very high levels, has since lost value, its price stabilised and is seemingly converging to a stable level. The price per ounce of gold in the recent history does not seem to be as volatile as it was in the 1980s.

5.2 Model Performance

The objective of this study was to test the semi-strong form efficiency of the Canada/US exchange market through forecasting of the exchange rate. Two type of models were estimated in order to forecast the exchange rate:

- technical models, which relied on FX lags to predict the exchange rate, and
- structural models, which relied on economic as well as technical variables to predict the exchange rate

In order to test for market efficiency, the models' forecasting performance was evaluated using two criteria:

- error measures, which relied on the MAD and MSE statistics to measure the forecasting error of the models
- economic value-based performance, which used the switching portfolio technique to calculate the amount of wealth created by a trading strategy based on a forecasting model.

The naive strategy (i.e. martingale, see Section 4.4.1) was used as a benchmark for models evaluated with the error measures criteria, while the buy-and-hold strategy was used as a benchmark against which the economic value-based performance of the forecasting models was evaluated. The naive strategy tested for the accuracy of the predictions, while the buy-and-hold strategy tests for the market timing/accuracy of the predictions. The two measures are complementing each other.

5.2.1 Neural Network Models

Neural networks were used in this study in the hope that their inherent nonlinear nature and self-learning would result in superior forecasting performance. The results of the neural networks performance were disappointing in this respect: the neural networks were not able to learn any pattern from the data, and thus, were unable to perform any forecasting.

Table 1 presents the economic value of NN forecasts over the full testing period. As one can see, the performance is very poor, none of the models being able to outperform the buy-and-hold strategy for the period. The cases when the NN performs the same as the buy-and-hold strategy are cases when the NN learning process broke down so severely that the network behaved as the buy-and-hold strategy.

Table 1					
Returns Forecast	C\$	US\$	Point Forecast	C\$	US\$
FF-TS1	125.02	91.29	FF-TS2	136.95	100.00
TD-TS1	124.50	90.91	TD-TS2	136.95	100.00
FF-S2	136.95	100.00	FF-S1	122.55	89.49
TD-S2	136.95	100.00	TD-S1	122.23	89.25
Buy and Hold	136.95	100.00	Buy and Hold	136.947	100.00
Optimal Strategy	158.05	115.41	Optimal Strategy	158.05	115.41

The poor results for the NN forecasting model can be attributed to the design of the network architecture. The network architecture used in the study was too large as

compared to the amount of data on which the learning took place. The estimation dataset consisted of 190 observations in the case of both technical and structural models. The neural networks used in the study were structured as follows:

- the size of the input layer varied according to each model, and was either 12 or 32 neurons
- the first hidden layer had the same number of neurons as the input layer (i.e. 12 or 32 neurons)
- the second hidden layer consisted of 12 neurons
- the output layer consisted of one neuron, corresponding to the dependent variable

The network used in this study was fully interconnected for a minimum of 300 ($12*12+12*12+12$ weights) and a maximum of 1420 weights ($32*32+ 32*12+12$ weights). Because of the relatively small amount of data available for training compared to the large number of parameters to estimate, none of the networks was able to learn adequately. This resulted in the inability of these networks to predict adequately during the testing phase, thus producing results similar to those of the buy-and-hold strategy. In retrospect, considering the number of parameters in the neural networks model and the size of the sample set, these results could have been anticipated. Table 2 presents the prediction error for all NN models, while Table 3 presents the error from the naive forecasting strategy.

Table 2					
NN Forecasts			NN Forecasts		
	MSE	MAD		MSE	MAD
FF-TS1	0.000145	0.009838	FF-TR13	0.000014	0.003034
TD-TS1	0.001338	0.032464	TD-TR13	0.001101	0.032962
FF-S1	0.000616	0.022571	FF-TR23	0.000023	0.004048
TD-S1	0.001716	0.036382	TD-TR23	0.000393	0.019472
FF-TS2	0.000029	0.004309	FF-TR16	0.000006	0.002142
TD-TS2	0.011608	0.107634	TD-TR16	0.007712	0.087784
FF-S2	0.000030	0.004421	FF-TR26	0.000008	0.002328
TD-S2	0.002790	0.052604	TD-TR26	0.004584	0.067663

Table 3		
Naive Forecasts		
	MSE	MAD
Point forecast	0.000026	0.004242
Return forecast	0.000034	0.004673
3 mo. trend forecast	0.000011	0.002667
6 mo. trend forecast	0.000002	0.001203

As can be seen, in some cases the NN models' errors are very small, and are comparable to those of the naive forecasts caused by the learning problem outlined above.

5.2.2 Linear Models vs. GAM

Two models were estimated, each with a different technique, for each technical and structural model as in Section 3.2. Linear models were used in predicting the FX rate because of their simplicity and their popularity, as well as a benchmark against which one could compare the performance of non linear models. Generalized Additive Models were also used in the study in the hope that their flexibility in modelling non-linear relationships would help in better capturing possible non-linear relationships between variables. Additionally, to estimate each model with the two techniques, backwards

selection of variables was performed on each model estimated with each technique, in order to identify the most influential variables. The linear and GAM models were estimated on 5 different sub-periods. Diagram 1 presents the design for the training and testing periods used in the study.

Diagram 2

Model:

This figure represents the models estimated during one period. There are in total 5 testing periods, and 40 models estimated per period for a total of 200 models.

For each period, all eight models designed in Section 3.2 have been estimated with linear regression, GAM and backwards selection. Diagram 2 presents all the calculations performed on the models from Section 3.2. In total, 200 models were estimated.

5.2.2.1 Overview

A priori, it was expected that the GAM would outperform the linear models in forecasting the FX rate because of their non-linear nature. The expectations were confirmed, and the GAM did quite well compared to the linear models. Tables 4 and 5 present the economic value performance of all linear and GAM models. Table 6 presents the overall best forecasting models according to the economic value criterion, and their forecast errors. Tables 4 and 5 show a notable difference between GAM and linear models: GAM models perform better on the overall economic value benchmarks for all but one linear model. When considering structural models however (Table 5), GAM do not perform as well as linear models and lose more money than linear models. None of the structural models are able to beat the buy-and-hold strategy. Surprisingly, it was easier for the models to predict returns than point values of the exchange rates. For the MAD and MSE measures for each of these models, refer to Appendix 7.

Table 4					
Point Forecast	CS	US\$	Returns Forecast	CS	US\$
TS1LM	133.68	97.62	TS2LM	133.93	97.80
TS1LMB	136.19	99.45	TS2LMB	138.33	101.01
TS1G3	137.39	100.32	TS2G3	132.67	96.88
TS1G3B	121.80	88.94	TS2G3B	139.21	101.65
TS1G5	128.99	94.19	TS2G5	118.72	86.69
TS1G5B	123.65	90.29	TS2G5B	138.07	100.82
Buy and Hold	136.947	100.00	Buy and Hold	136.95	100.00
Optimal Strategy	158.05	115.41	Optimal Strategy	158.05	115.41

Table 5					
Point Forecast			Returns Forecast		
	C\$	US\$		C\$	US\$
S1LM	131.41	95.96	S2LM	121.15	88.46
S1LMB	129.03	94.22	S2LMB	127.43	93.05
S1G3	105.06	76.72	S2G3	123.49	90.17
S1G5	99.54	72.68	S2G5	128.50	93.83
Buy and Hold	136.947	100.00	Buy and Hold	136.95	100.00
Optimal Strategy	158.05	115.41	Optimal Strategy	158.05	115.41

Legend: Model Labels

TS1 and TS2: technical, point forecast and returns models respectively

S1 and S2: structural, point forecast and returns models respectively

LM and G: linear and GAM models respectively (if GAM 3 and 5 indicate the # of degrees of freedom in the model)

B indicates whether this model has been selected with backwards selection

Returns Forecast: a forecast of the returns to be realized during period $t+1$ given returns data from periods $t, t-1, \dots$

Point Forecast: a point estimate forecast of the exchange rate at the end of period $t+1$ given data from periods $t, t-1, \dots$

5.2.2.2 The best models

Table 6 presents the best models, i.e. the models that were able to beat the buy-and-hold strategy for the full testing period. Figures 1, 2 and 3 present the model plots.

Table 6					
Model	C\$ Payoff	US\$ Payoff	MSE	MAD	
TS2G3B	139.21	101.65	0.00106	0.00489	
TS2LMB	138.33	101.01	0.0011	0.00532	
TS2G5B	138.07	100.82	0.00108	0.00531	
TS1G3	137.39	100.32	0.00109	0.00467	
Buy and Hold	136.947	100			
Optimal Strategy	158.05	115.41			

Figure 1: Model TS1G3 - a technical GAM model on 3 degrees of freedom.
The vertical lines represent the concentration of observations

Figure 1 presents the model TS1G3, the only full model able to outperform the buy-and-hold strategy with excess gains of \$0.32. The relationships between the dependent and independent variables are very non-linear which seems to confirm Chinn's (1991) intuition as to the shape of the dependence. As the model is estimated on 3 degrees of freedom, the fit represents fairly well the true shape of the dependence (i.e. there is no overfitting).

Figure 2 presents the model TS2G3B, which outperforms the buy-and-hold strategy by \$1.65 and which, therefore, is the best model elaborated in this study. This

model has been profiled through backwards selection, which yielded 6 variables (Table

Figure 2 : Model TS2G3B - a technical GAM model on 3 degrees of freedom.

7). The model contains 5 linear elements and one non-linear relationship. Figure 3

presents the model TS2G5B, i.e. the

same model as Fig. 1, but estimated on 5 degrees of freedom. This model contains the same variables as the TS2G3B model, and the only difference between the two is the level of non-linearity of the relationship of the L12 variable with the dependent variable.

The model TS2G5B performs worse than its more restrictive version. This clearly indicates a certain degree of overfitting in the less restrictive model: the non-linearity level in the L12 variable is significantly greater than in the TS2G3B model. The

remaining variables' relationship with the dependent variable seems to be the same across the models. In conclusion it seems that 5df yields a model which overfits the data, and therefore GAM models with less than 5df should give better results. It is however not clear what the optimal number of degrees of freedom should be.

Figure 3 : Model TS2G5B - a technical GAM model on 5 degrees of freedom.

The best forecasting models are able to outperform the buy-and-hold strategy by up to US\$ 1.65. It is interesting to see that the major characteristic of the best performing models is that they have been estimated using GAM. This indicates that there exist non-linearities in the data which linear modelling techniques are unable to model.

Additionally, the best-performing models were found to be technical exchange rate return forecasting models, using only the lagged dependent variable as explanatory variables.

The probable cause for the bad performance of structural models is the fact that none of them could be selected using backwards regression due to the computational problems outlined previously: since the most significant variables could not be extracted from the models, the structural models performed poorly because of the noise introduced by unimportant variables.

When tracked over time (over the 4 sub-periods), the positive EV models seem to display smaller errors than any other models considered: the TS2G5B model coming ahead, and outperforming any other model in three out of four testing sub-periods, the close second being the TS2LMB model. This indicates that the models in question seem to truly be able to forecast the exchange rate, instead of just capitalising on chance over one testing period. The anatomy of the EV winning models, estimated on the full training sample, is as follows:

Table 7	
Model	Components:
TS2LMB	L1,L2,L3,L8,L10
TS2G3B	ns(L12,3),L1,L2,L3,L8,L10
TS2G5B	ns(L12,5),L1,L2,L3,ns(L8,5),L10
TS1G3	all 12 lags

Legend: L1 L2 etc. represent lags: i.e. L1 is the first lag of the dependent variable, L2 is the second lag (Please refer to section 3.2). NS(a,b) refers to the cubic spline function modelling the relationship between the dependent variable and the independent variable (a) on (b) degrees of freedom. (For a full printout see Appendix 5)

As one can see, it seems that the best technical models rely heavily on the following five components: lags: 1,2,3,8 and 10: the models rely on recent as well as 'old' information in predicting the FX rate. It is interesting to see that 10 month lags still have significance in predicting the next month's exchange rate return, since common sense would command that only recent information has value. Appendix 6 shows the components of the three best models from the above table (TS2LMB, TS2G3B and TS2G5B) as evaluated over the 4 sub-periods A, B, C and D. The first observation is that each of these models have a common component, which does not change from period to period. It looks as if that the models have found some significant trends in the data and that it uses them to forecast the exchange rate. It is a subtle indication that the EMH might not hold in the Canada/US FX market.

From the results presented in Table 6, it is clear that the models were able to forecast the exchange rate in a significant manner. The fact that these models are able to outperform the buy-and-hold strategy suggests that the Canada/US exchange rate can be predicted in a limited manner by a set of carefully chosen models. This in turn suggests that the Canada/US foreign exchange market is not entirely efficient, and is inefficient in the weak form, because the best performing models are technical models!

5.2.2.3 Conclusions

The following conclusions can be reached about the performance of structural models.

1. Returns are easier to predict than point values for the Canada/US exchange rate: all the best performing forecasting models are return forecasting models rather than point forecasting models.
2. Structural models do not perform as well as technical models: it is possible that the structural models are either mis-specified, or that because of the computational problems, they could not show their true potential in forecasting the exchange rate.
3. Linear models can perform as well as GAM models, and have to be considered as serious contenders in modelling exchange rates to other more advanced techniques.
4. It seems that two models (TS2LMB and TS2G5B) were able to beat the random-walk assumption of FX markets. Because the best forecasting models were able to outperform the buy-and-hold strategy, and because they are technical models, the Canada/US FX market is inefficient in the weak form.
5. Relationships between variables can be highly non-linear as demonstrated in the model plots.
6. It seems that the MSE and EV benchmarks are consistent in the sense that for the best models, the smallest MSE corresponds to the higher EV.
7. Model variables change over time, but the models always contain a set of “core” variables, which remain in the models from period to period. This seems to indicate to

the presence of persistent trends in the data. However it is not possible to say whether the individual importance of this core set of variables in predicting foreign exchange changes over time.

6 Contribution to the literature

The goal of the study was to establish whether the Canada/US foreign exchange market is efficient in the semi-strong form. The means of reaching this goal was to forecast the Canada/US foreign exchange rate, operationalized through the use of advanced modelling techniques such as Neural Networks and Generalized Additive Models.

The principal result of the study indicates that the Canada/US foreign exchange market is not efficient in the weak form. The results suggest that past price data contains information about the future movements of the foreign exchange rates.

In contrast to this study, Kuan and Liu (1995) have observed with the help of a NN methodology that it is not possible to forecast the foreign exchange rate: only two of their five models outperformed the random walk. The current study's design is different, however, from the one undertaken by Kuan and Liu. Their study has centred on the use of one methodology (neural networks) and a limited number of lags (six vs. twelve for the current study). From the current study's results, it is clear that distant lags do contribute significantly to the forecasting ability of a model. Thus, Kuan and Liu study was too limited in the scope in order to find significant results.

Goodman (1979), in his survey of foreign exchange forecasting services, has found that services using technical forecasting methods are able to outperform the buy-and-hold strategy significantly, in contrast to services using economic models. The current study seems to confirm this result: the technical models being able to outperform the buy-and-hold strategy and any structural model. Frankel (1989), in a review of the floating exchange rate period, has also noticed that practitioners seem more inclined to use technical forecasting models than economic models. He attributed this fact to the poor performance of economic models historically to explain the exchange rates. This conclusion is upheld by the current study: none of the structural models being able to forecast the exchange rate well based on either the MSE and MAD benchmarks.

In their study of the predictability of exchange rates, Schinasi and Swamy (1989) allowed the economic model's coefficients to change over time: the modified models were able to outperform the random walk. The current study, after allowing for changing coefficients, has found that technical models were the best performers in all testing sub-periods based on the MSE criterion.

The results of the current study concur with the observations made by previous researchers. First, given a significant number of lags, the technical models will outperform the random-walk, which indicates the presence of long-term dependencies in the data. Second, technical models are the best tools to effectively forecast the exchange

rate, as Goodman (1979) and Frankel (1989) have suggested, and are already the standard among practitioners. Finally, changing parameter models might help in forecasting the exchange rate.

This study has extended significantly existing research in several ways. First, it is the first study on the topic of exchange market efficiency which used concurrently three techniques in forecasting exchange rates. This allowed for a better understanding of the exchange rate behaviour through a more precise modelling of the relationships between variables.

The linear regression technique was used as a benchmark in order to test the performance of non-linear models (GAM and NN). This study was the first one to use GAMs as a modelling technique in forecasting exchange rates. The result was that new relationships and structure in the data were found. NNs were used as a means of testing the non-linear modelling performance of the GAM. In addition to the innovative modelling techniques used, backwards variable selection has been performed on each of the models in order to find the most influential model attributes. No study has previously attempted to find the most significant variables in this manner.

The models used in the study differ significantly from the ones used in literature in several aspects. First, the models in this study have been expanded through the

inclusion of variables that have been found to be significant in the literature, but that have never been included in a single cohesive model. Second, the models used in the study include a large number of lags (12 for the technical models, and 4 for the structural models): no study found in the literature has used such a number of lags. The number of lags is one of the elements of success of this study because it has allowed for the discovery of structure in the foreign exchange data that other studies have overlooked.

The implementation of the above-mentioned improvements has lead to a study distinctly different from the literature.

7 Conclusion

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In conclusion, it can be said that the models considered in this study, and principally, the technical models, were able to successfully forecast the exchange rate, based on the EV criterion. The EMH states that all relevant information is reflected in asset prices, and therefore that an attempt to forecast any asset price is futile. The results from this study contradict the theory: the technical models were able to forecast the Canada/US exchange rate changes and beat the buy-and-hold strategy over the testing period. The weak-form market hypothesis is therefore rejected for the Canada/US exchange rate market!

In contrast, economic models, which were expanded by technical factors were unable to beat the market. This may have been caused by:

- Insufficient number of lags in the economic models may not allow for the right models to be found: i.e. the model is mis-specified.
- The true explanatory variables may not have been selected because of computational problems

What does this say about the efficiency of the FX market in general? It is very probable that because the Canada/US FX market has been found to be inefficient, other currency markets may be inefficient to a certain degree as well. It is likely because other

economies may be not as well integrated as the Canada-U.S. economies, and transactions in those currencies may be not as frequent as in the Canada-U.S. foreign exchange market.

The existence of trading costs can, sometimes, make market inefficiencies persistent, since the presence of costs may not allow investors to exploit every inefficiency. Because the best strategy in the study yields only \$1.65 over a period of 50 months involving less than 50 trades, the strategy will be profitable only if the trading costs are less than 3 cents per trade (the worst case scenario assuming 50 trades have been made). The costs per trade in the FX market (bid-ask spread), however, are not this high: they rarely go beyond 1 cent per trade. This means that unless there are other variable costs to trading exchange rates, this strategy will be profitable. Ignoring the additional risk exposure implied in the switching strategy based on the models compared to the buy-and-hold strategy, trading strategies based on the models outperform the buy-and-hold strategy. This implies that the Canada/US FX market may be inefficient in the weak form.

7.1 Benefits and Limitations

There are many benefits from this study. This study adds to the already considerable body of work concerning weak form market efficiency in the foreign

exchange market, and by introducing the use of two new methodologies for the purpose of forecasting exchange rate movements. The results from this study will help theoreticians to better understand the behaviour of the foreign exchange markets by allowing them to examine non-linear relations in the data. This new perspective will enable them to construct new theories encompassing the non-linear structure of the foreign exchange markets to better reflect reality. This study will also open researchers' horizon to the new type of techniques to be used in modelling relations, which will ultimately help researchers to better understand the financial markets in general.

This study will also be of use to practitioners who have to deal with the foreign exchange market by providing them with a better understanding of the dynamics of the market. Practitioners will benefit from their improved knowledge of foreign exchange behaviour by applying it to hedging and investment management as well as speculation. The ability to forecast exchange rates and understand better their behaviour will help managers, in aggregate, to perform their tasks better.

7.2 Future Directions for Research

While this study has contributed to the foreign exchange rate literature, there still remains a number of unanswered questions. First, while the best model in the study has outperformed the buy-and-hold strategy, it is uncertain by how much can the forecasting

performance be further increased, and by which means. Second, the NN methodology should be further examined and tested.

The NN models elaborated in the study have failed for a specific reason: there were not enough training examples in order to estimate all the parameters in the model. In order to solve this problem, a new network architecture should be designed, in order to achieve a reasonable ratio of training examples to weights.

The good forecasting performance of the models in this study could be improved by several means. First, a broader range of technical and economic models should be examined: while the literature and this study suggest that technical models are the best forecasters, there is no proof that no economic model exists which could not achieve an equal or better performance. Some of the possibilities which should be examined are:

- a greater number of lags,
- various economic variables,
- judgmental/behavioural variables,
- higher frequency forecasts (daily, hourly, up to the minute).

While these guidelines present a possible avenue of future research, they are but one of many possible directions. Another such direction is a more thorough and detailed search of the space of possible models. While this study has examined a large number of

models (around 200 models), it has not examined every possible combination of variables.

Future research should look into new techniques of modelling and model selection. First, research should concentrate on non-linear modelling techniques in order not to constrain the models to a local solution. A good modelling technique should allow the data to speak for itself and not force any peculiar structure onto it, and let adjust model parameters freely. Second, a possible area of study is bootstrap variable selection, a method which allows for the minimization of cross-validated prediction error. The same method can also help in finding correct model parameters. Finally, advanced model-space search techniques should be examined such as genetic algorithms, in order to maximize the chance of finding the true model.

APPENDIX 1: Generalized Additive Models

The general idea behind GAM is to “let the data show us the appropriate functional form” (Hastie and Tibshirani 1991), which makes them a very good modelling tool. The general form of GAM is: $Y=f(X)$, where $f(x)$ is a function relating the independent variable to the dependent variable. In the case of multiple independent variables, the function can be expressed in an additive form: $Y=f(x_1, x_2, x_3)$ is re-mapped into the standard GAM form as $Y=f(x_1) + f(x_2) + f(x_3)$. The assumption underlying such a model is that the dependent variable is an additive function of the independent variables.

In order to “let the data show us the appropriate functional form”, the GAM first needs to extract the form of relations from the data. The GAM accomplishes this through the use of scatterplot smoothers which smooth the data into revealing a functional form. An example of a smoother is the moving average:

$$s(x_i) = \text{average}_{j \in N^s(x_i)} (y_j)$$

Where $s(x_i)$ is the smoother, and N^s is the smoothing neighbourhood. The smoothing neighbourhood is one of the most important variables in a GAM model. It defines the amount of smoothing that will be performed on the data: a large amount of smoothing will be equivalent to performing a linear regression on the data, while a small amount will result in the data points being interpolated. The smoothing neighbourhood must be chosen very carefully when smoothing data.

Once the data is smoothed, the GAM can be now estimated. The estimation of the GAM is performed by a procedure called backfitting which is equivalent to the iterative smoothing of residuals. The algorithm for backfitting is as follows:

1) Initialise: $\alpha = \text{average}(y_i)$, $f_j = f_j^0$, $j=1 \dots p$

2) Cycle:

$j=1 \dots p$, $1 \dots p$, ...

$$f_j = S_j(Y - \alpha - \sum_{i \neq j} f_i | x_j)$$

3) Continue 2 until individual functions do not change

where: The GAM model to be estimated is: $E(Y | X_1, X_2, \dots) = f(X_1) + f(X_2) + \dots$

S_j = the selected smoother function

α = constant in the model

f_j = j-th function to be estimated

x_j = j-th data point

In this study, natural splines will be used in modelling the exchange rate. Natural splines are just another type of smoother available, but possess properties which make them very useful in any type of modelling. First, natural splines allow for a functional representation of the data and are, therefore, nicer to handle. Second, natural splines are linear beyond the domain of the data. Third, natural splines are resistant to outliers at the extremities of the data: outliers will not bias function estimates at the data extremities.

This is a very important consideration in view of the fact that outliers sometimes do exist in the data.

As with any other smoother, the right size of the neighbourhood will have to be chosen in order not to overfit or underfit the data. With natural splines, the size of the neighbourhood is selected with one parameter: the number of degrees of freedom for the smoother. In the present study, two GAM models will be run for each model specification: one with 3 df and the other one with 5 df. The reason for this selection is caution: the model should neither overfit nor underfit the data. Three degrees of freedom for a smoother will allow the smoother to find a non-linearity in the data, but will not allow it to overfit it, unless the data is linear. This recommendation is given by Hastie and Tibshirani (1990) in the wake of the fact, that is the behaviour of the data is not well known, it is better to be careful in fitting the data for the first time. Over-fitting was one of the causes for the poor performance of the Chinn (1991) study and should be avoided. Five degrees of freedom will allow for a more precise fit to be performed on the data, but might lead to over-fitting. The 5 degrees of freedom was selected on an ad-hoc basis taking into consideration Hastie and Tibshirani's (1990) recommendation on overfitting, and the fact that over-fitting in non-linear regression can be very dangerous: it is better to stay on the side of caution. Separate results will be presented for each type of model.

Backwards selection which will be used in the case of linear and GAM models in this study, is a model-selection technique which tries to select the best model from a set of possible models, by choosing independent variables which explain best the dependent variable. The procedure starts by evaluating the full model (i.e. the model that contains all the variables), and next starts to refine it by throwing out variables with the least significance. It stops when the last evaluated model is the best: i.e. it stops at the model which explains the most of the dependent variable with the least number of independent variables. It is hoped that this model selection technique will help in identifying the most important variables, and will help in choosing the best possible model.

APPENDIX 2: Neural Networks

Neural Networks (NN) are artificial systems which try to model the human brain.

An artificial neural network, is a collection of artificial neurons, which, in turn, are mathematical representations of biological neurons.

An artificial neuron has the following structure:

The mathematical representation of a neuron is as follows:

$$u = \sum w_j x_j$$

$y = f(u)$, where $f()$ is the activation function.

where: x_i = neuron input, u = activation, w_j = weight parameter, y = neuron output

A neural network is a structure composed of similar neurons. NNs are often organised in layers:

Feedforward neural networks are networks in which the input maps directly into an output. In these networks, there is no feedback from the system. Recurrent networks, like the one shown above, have feedback loops which allow neurons to know how they are doing at performing the task of mapping the input into the output.

In this study, two types of neural networks are going to be used: feedforward neural networks (FFNN), and time delay neural networks (TDNN). FFNN are useful in mapping inputs to outputs in a static way. They do not allow for a time effect in the data to be captured. It has been shown in the literature review, however, that time effects do exist in financial markets, and, therefore, should be accounted for. It is also probable that FFNN will have a similar performance as GAM at the task of forecasting exchange rates.

In order to capture the time effect, TDNN must be used. TDNN are neural networks which have an adaptive structure, unlike FFNN. TDNN are by default recurrent networks in which the output of the network is mapped in as an input to the network. TDNN is, however, unlike simple recurrent networks, able to learn time dependent processes, i.e., processes which vary in time. They are, therefore, not only able to map the input to the required output, but also can learn the process by which the output and input change in time. This ability of TDNN comes from their adaptive structure. During learning, not only model parameters are estimated, but also the number of recurrent connections is calculated. This type of NN has, therefore, more degrees of freedom than its feedforward counterparts.

APPENDIX 3: Point and Trend Forecasts

A point forecast is a point estimate of the value that the dependent variable will take the next period (or another subsequent period). In the proposed study, quarterly point forecasts are going to be made for one year into the future. There will, therefore, be four forecasts made each year. The purpose of a point forecast is to help a potential user hedge risks involved in trading securities denominated in different currencies and goods and services internationally by providing a forecast of the level of the exchange rate at different points in time (Goodman, 1979).

A trend forecast will also be made on a quarterly basis. There will be two forecasts made each period, each with a different span. The first trend forecast is going to be performed for three months (one quarter) in advance of each period. The second trend forecast is going to be made for the next six months.

A trend is simply the average level of increase or decrease in a variable over a period of next three or six months and is expressed as the slope of a regression line estimated on the next three and six monthly observations respectively.

A three month trend is, therefore, defined as:

$$Y_i = \alpha + \beta X_i; i=1..3$$

$\min Q = \sum (Y_i - \alpha - \beta X_i)^2; i=1..3$ (Q is the residual square error to minimise)

$$\beta = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}; i=1..3 \text{ (Neter, Wasserman, Kutner 1990)}$$

where: $\bar{X}$ =average of X , X_i is the observation i , $\bar{Y}$ is the average of Y , and Y_i is the observation i .

but since X_i are integers: $i=1,2,3$ and because we want the average increase over a three month period (equidistant observations) we have:

$$\bar{X} = (1 + 2 + 3) / 3 = 2$$

$$\beta = \sum (X_i - 2)(Y_i - \bar{Y}) / \sum (X_i - 2)^2 ; i=1..3$$

when expanded:

$$\beta = [(1 - 2)(Y_1 - \bar{Y}) + (2 - 2)(Y_2 - \bar{Y}) + (3 - 2)(Y_3 - \bar{Y})]$$

$$/ [(1 - 2)^2 + (2 - 2)^2 + (3 - 2)^2]$$

$$= [-1 (Y_1 - \bar{Y}) + 0 (Y_2 - \bar{Y}) + 1 (Y_3 - \bar{Y})]$$

$$/ [1 + 0 + 1]$$

$$= [-Y_1 + \bar{Y} + Y_3 - \bar{Y}] / 2$$

$$= (Y_3 - Y_1) / 2$$

The average rate of change for the three month period (slope of the regression line) is

$$\text{therefore: } \beta = (Y_3 - Y_1) / 2$$

For the six month period the same logic can be applied (all variables conserve their meaning):

$$Y_i = a + \beta X_i ; i=1..6$$

$$\min Q = \sum (Y_i - a - \beta X_i)^2 ; i=1..6$$

$$\beta = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sum (X_i - \bar{X})^2}; i=1..6 \text{ (Neter, Wasserman, Kutner 1990)}$$

$$B = (-2.5 Y_1 - 1.5 Y_2 - 0.5 Y_3 + 0.5 Y_4 + 1.5 Y_5 + 2.5 Y_6) / 17.5$$

The slopes of the regression lines on 3 and 6 observations will, thus, be representing the trend of the exchange rate for the coming quarter or two quarters.

Goodman (1979) reports that certain FX forecasting firms do provide trend estimates for up to 6 months to clients for planning purposes. By using the above mentioned approach this study will provide forecasts similar with the ones existing in reality.

APPENDIX 4: Study Description

Meese and Rogoff (1983)

The three models used by Meese and Rogoff (1983) (Frenkel-Bilson, Dornbush-Frankel and Hooper-Morton models), are the most frequently encountered models in the FX determination literature, and have been used by a significant number of researchers in the post-Meese and Rogoff era.

These three models are subsumed into one general model of the following form:

$$s = a + b (m - m^*) + c (y - y^*) + d (r - r^*) + e (p - p^*) + f TB + g TB^*$$

where

s = spot exchange rate

m = money supply

y = real income

r = short term interest rate

p = expected long term inflation rate (preceding 12 months CPI inflation rate)

TB = accumulated trade balance

(Small caps indicate that the variable has been transformed with a log base 10; a $*$ indicates that the variable in question is the foreign-country variable equivalent; a

through g are parameters to be estimated)

The three models place the following restrictions on the coefficients:

Model	Restriction	Assumptions
Frenkel-Bilson	$e=f=g=0$	purchasing power parity
Dornbush-Frankel	$f=g=0$	slow domestic price adjustment
Hooper-Morton		

The Hooper-Morton model is the most general model in that it has no restriction on its parameters and allows for a great deal of flexibility in modelling the variables. Because of these limited restrictions, this model has been chosen as the general model to be used in the study.

Somanath (1986)

Somanath (1986) expanded the M&R (1983) models to include a lagged dependent variable. The general model specification is as follows:

$$s(t) = a + b(m-m^*) + c(y-y^*) + d(r-r^*) + e(p-p^*) + fTB + gTB^* + h s(t-1)$$

Variable definitions remain unchanged from the M&R (1983) study.

Appendix 5: The best performing models

Technical models:

Model: ts1.gam.model3

$LFX \sim ns(L1, 3) + ns(L2, 3) + ns(L3, 3) + ns(L4, 3) + ns(L5, 3) + ns(L6, 3) + ns(L7, 3) + ns(L8, 3) + ns(L9, 3) + ns(L10, 3) + ns(L11, 3) + ns(L12, 3)$

Model: ts2.lm.model.back

$LFX \sim L1 + L2 + L3 + L8 + L10$

Coefficients					
Intercept	L1	L2	L3	L8	L10
6.73559e-05	0.1651769	-0.1591385	0.10937	0.1967642	0.2722852

Model: ts2.gam.model3.back

$LFX \sim ns(L12, 3) + L1 + L2 + L3 + L8 + L10$

Model: ts2.gam.model5.back

$LFX \sim ns(L12, 5) + L1 + L2 + L3 + ns(L8, 5) + L10$

Structural Models:

Model: s2.lm.model.back

$LFX \sim L1 + L4 + LM1 + TB1 + TB3$

Coefficients					
Intercept	L1	L4	LM1	TB1	TB3

0.000139161	0.1516596	0.1302683	-0.1173476	-0.05939919	-0.02802284
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Model: s2.gam.model5

$LFX \sim ns(L1, 5) + ns(L2, 5) + ns(L3, 5) + ns(L4, 5) + ns(LM1, 5) + ns(LM2, 5) + ns(LM3, 5) + ns(LM4, 5) +$
 $ns(GDP1, 5) + ns(GDP2, 5) + ns(GDP3, 5) + ns(GDP4, 5) + ns(TB1, 5) + ns(TB2, 5) + ns(TB3, 5) + ns(TB4, 5) +$
 $ns(CPI1, 5) + ns(CPI2, 5) + ns(CPI3, 5) + ns(CPI4, 5) + ns(BAL1, 5) + ns(BAL2, 5) + ns(BAL3, 5) + ns(BAL4, 5) +$
 $ns(A1, 5) + ns(A2, 5) + ns(A3, 5) + ns(A4, 5) + ns(S1, 5) + ns(S2, 5) + ns(S3, 5) + ns(S4, 5)$

Model: s1.lm.model

Coefficients:

(Intercept)	L1	L2	L3	L4	LM1	LM2
-0.04162336	1.048438	-0.2503845	0.1851697	-0.05233917	-0.1544958	0.1182153
LM3	LM4	GDP1	GDP2	GDP3	GDP4	
0.04729595	-0.09853166	0.05026427	-0.08162856	0.01810632	0.0310335	
TB1	TB2	TB3	TB4	CPI1	CPI2	CPI3
-0.06025375	0.04326247	-0.02365315	0.00819646	0.36827	-0.4649752	-0.6898467
CPI4	BAL1	BAL2	BAL3	BAL4	A1	
0.6680583	-0.001275679	0.0003749396	0.0002492922	-0.0005228665	-0.003416036	
A2	A3	A4	S1	S2	S3	
0.01938835	-0.01473	-0.01649733	0.01794202	-0.02669765	-0.0005502318	
S4						
0.0285184						

Model: s1.lm.model.back

$LFX \sim L1 + L2 + L3 + LM1 + TB1 + CPI3 + A4 + S4$

Coefficients						
Intercept	L1	L2	L3	LM1	TB1	CPI3
-0.071255	0.982236	-0.193373	0.140758	0.085641	-0.0351217	-0.119785

Appendix 6: The Models and Time

This appendix presents the best backward selection models, and their composition through time.

Model:TS2LMB

Full period:

$$L1 + L2 + L3 + L8 + L10$$

Period A

$$L1 + L2 + L7 + L8 + L9 + L10 + L12$$

Period B

$$L1 + L2 + L7 + L8 + L9 + L10 + L12$$

Period C

$$L1 + L2 + L3 + L7 + L8 + L10$$

Period D

$$L1 + L2 + L3 + L8 + L10$$

The common set of variables for this model throughout the periods is: {L1, L2, L8, L10}.

One can also see, that as the model is estimated on a more and more updated dataset, the number of variables in the model decreases, the most significant ones remaining. There is a three-fold interpretation for the phenomenon:

- as the dataset increases, the models can be estimated with more confidence (they will not be overfitted), in this case, the other variables are considered as by-products of the estimation error

- the markets, as they evolve become more and more efficient, and significant trends (money making opportunities) disappear.
- the other variables in the model reflect local-temporal trends in the data

Model:TS2G3B

Full Period:

$$ns(L12, 3) + L1 + L2 + L3 + L8 + L10$$

Period A:

$$ns(L12, 3) + ns(L1) + L2 + L7 + L8 + L9 + L10$$

Period B:

$$ns(L12, 3) - L1 + L2 - L7 + L8 - L9 + L10$$

Period C:

$$ns(L12, 3) + ns(L1) + L8 + L10$$

Period D:

$$ns(L12, 3) + L1 + L2 + L3 + L8 + L10$$

The common set of variables for this model throughout the periods is: $\{L1, L8, L10, L12\}$

Model:TS2G5B

Full Period:

$$ns(L12, 5) + L1 + L2 + L3 + ns(L8) + L10$$

Period A:

$$ns(L12, 5) \sim L7$$

Period B:

$$ns(L12, 5) \sim ns(L2) \sim L7 \sim L10$$

Period C:

$$ns(L12, 5) \sim L1 \sim L8 \sim L10$$

Period D:

$$ns(L12, 5) \sim L1 \sim L2 \sim L3 \sim ns(L8) \sim L10$$

The common set of variables for this model throughout the periods is: $\{L10, L12\}$

Appendix 7: MSE and MAD Error Measures for All Models

MAD Benchmark						
Model	Full	Full 24mo.	Per. A	Per. B	Per. C	Per. D
s1.gam.model3.MAD	0.00467	0.00450	0.00987	0.00456	0.00348	0.00414
ts1.gam.model3.back.MAD	0.00519	0.00504	0.00641	0.00414	0.00460	0.00336
s1.gam.model5.MAD	0.00470	0.00536	0.02885	0.00402	0.00521	0.00330
ts1.gam.model5.back.MAD	0.00533	0.00509	0.02567	0.00425	0.00488	0.00328
s1.lm.model.MAD	0.00545	0.00464	0.00394	0.00352	0.00404	0.00307
ts1.lm.model.back.MAD	0.00499	0.00438	0.00404	0.00319	0.00350	0.00289
s2.gam.model3.MAD	0.00642	0.00538	0.00361	0.00497	0.00453	0.00272
ts2.gam.model3.back.MAD	0.00489	0.00376	0.00312	0.00458	0.00405	0.00297
s2.gam.model5.MAD	0.00630	0.00473	0.00652	0.00554	0.00381	0.00258
ts2.gam.model5.back.MAD	0.00531	0.00374	0.00393	0.00554	0.00338	0.00324
s2.lm.model.MAD	0.00532	0.00397	0.00378	0.00390	0.00404	0.00310
ts2.lm.model.back.MAD	0.00532	0.00411	0.00392	0.00411	0.00367	0.00260
s1.gam.model3.MAD	0.01315	0.00789	0.01530	0.03818	0.00613	0.00630
s1.gam.model5.MAD	0.15273	0.19484	0.19091	0.15036	0.15240	0.06170
s1.lm.model.MAD	0.00480	0.00509	0.00351	0.00518	0.00376	0.00278
s1.lm.model.back.MAD	0.00496	0.00618	0.00346	0.00535	0.00451	0.00357
s2.gam.model3.MAD	0.00738	0.00748	0.00897	0.01040	0.00650	0.00539
s2.gam.model5.MAD	0.01183	0.01114	0.01293	0.01259	0.01231	0.01977
s2.lm.model.MAD	0.00523	0.00496	0.00395	0.00490	0.00430	0.00185
s2.lm.model.back.MAD	0.00591	0.00613	0.00327	0.00504	0.00423	0.00242
tr13.gam.model3.MAD	0.00295	0.00337	0.01955	0.00430	0.00312	0.00399
tr13.gam.model3.back.MAD	0.00360	0.00276	0.00185	0.00304	0.00201	0.00277
tr13.gam.model5.MAD	0.00287	0.00243	0.03736	0.00685	0.00353	0.00398
tr13.gam.model5.back.MAD	0.00372	0.00270	0.05360	0.00260	0.00222	0.00280
tr13.lm.model.MAD	0.00324	0.00276	0.00276	0.00397	0.00235	0.00305
tr13.lm.model.back.MAD	0.00371	0.00333	0.00247	0.00420	0.00204	0.00194
tr16.gam.model3.MAD	0.00225	0.00142	0.00291	0.00412	0.00105	0.00279
tr16.gam.model3.back.MAD	0.00216	0.00201	0.00233	0.00230	0.00099	0.00283
tr16.gam.model5.MAD	0.00234	0.00241	0.08318	0.00401	0.00163	0.00364
tr16.gam.model5.back.MAD	0.00225	0.00205	0.03080	0.00231	0.00129	0.00286
tr16.lm.model.MAD	0.00219	0.00160	0.00167	0.00147	0.00089	0.00288
tr16.lm.model.back.MAD	0.00242	0.00146	0.00214	0.00178	0.00104	0.00275
tr23.gam.model3.MAD	0.00679	0.00494	0.00468	0.06971	0.01139	0.00332
tr23.gam.model5.MAD	0.05501	0.05741	0.06044	0.05145	0.05602	0.02220
tr23.lm.model.MAD	0.00297	0.00314	0.00286	0.00386	0.00229	0.00269
tr23.lm.model.back.MAD	0.00277	0.00338	0.00277	0.00399	0.00174	0.00258
tr26.gam.model3.MAD	0.00285	0.00361	0.00200	0.02829	0.00225	0.00233
tr26.gam.model5.MAD	0.00846	0.02653	0.02557	0.02529	0.02595	0.01324
tr26.lm.model.MAD	0.00216	0.00160	0.00264	0.00266	0.00145	0.00154
tr26.lm.model.back.MAD	0.00218	0.00192	0.00289	0.00326	0.00146	0.00126

MSE Benchmark						
Model	Full	Full 24mo.	Per. A	Per. B	Per. C	Per. D
s1.gam.model3.MSE	0.01442	0.01176	0.08528	0.07035	0.01502	0.00632
s1.gam.model5.MSE	1.92037	1.27543	1.62974	1.52055	1.05141	0.10003
s1.lm.model.MSE	0.00163	0.00103	0.00081	0.00043	0.00056	0.00046
s1.lm.model.back.MSE	0.00166	0.00108	0.00081	0.00075	0.00046	0.00050
s2.gam.model3.MSE	0.00474	0.00317	0.00247	0.00727	0.00143	0.00061
s2.gam.model5.MSE	0.00727	0.00383	0.00435	0.00446	0.00401	0.01384
s2.lm.model.MSE	0.00163	0.00082	0.00047	0.00079	0.00053	0.00039
s2.lm.model.back.MSE	0.00151	0.00080	0.00040	0.00070	0.00052	0.00036
tr13.gam.model3.MSE	0.00063	0.00042	0.00060	0.00026	0.00033	0.00039
tr13.gam.model3.back.MS	0.00069	0.00038	0.00017	0.00056	0.00025	0.00032
tr13.gam.model5.MSE	0.00052	0.00030	0.00046	0.00263	0.00046	0.00038
tr13.gam.model5.back.MS	0.00070	0.00039	0.23870	0.00066	0.00027	0.00033
tr13.lm.model.MSE	0.00063	0.00032	0.00029	0.00050	0.00018	0.00028
tr13.lm.model.back.MSE	0.00064	0.00032	0.00031	0.00051	0.00018	0.00026
tr16.gam.model3.MSE	0.00035	0.00021	0.00184	0.00022	0.00011	0.00021
tr16.gam.model3.back.MS	0.00033	0.00020	0.00015	0.00013	0.00006	0.00020
tr16.gam.model5.MSE	0.00032	0.00022	0.34982	0.00179	0.00030	0.00021
tr16.gam.model5.back.MS	0.00034	0.00021	0.07312	0.00023	0.00008	0.00020
tr16.lm.model.MSE	0.00029	0.00016	0.00009	0.00022	0.00003	0.00016
tr16.lm.model.back.MSE	0.00029	0.00016	0.00011	0.00022	0.00003	0.00016
tr23.gam.model3.MSE	0.00399	0.00220	0.00224	0.19400	0.00922	0.00491
tr23.gam.model5.MSE	0.11173	0.04744	0.04820	0.04323	0.04437	0.12169
tr23.lm.model.MSE	0.00174	0.00100	0.00039	0.00081	0.00045	0.00040
tr23.lm.model.back.MSE	0.00173	0.00098	0.00023	0.00096	0.00037	0.00036
tr26.gam.model3.MSE	0.00081	0.00023	0.00010	0.03247	0.00030	0.00519
tr26.gam.model5.MSE	0.05398	0.02318	0.02143	0.02122	0.02229	0.00647
tr26.lm.model.MSE	0.00134	0.00067	0.00012	0.00075	0.00018	0.00023
tr26.lm.model.back.MSE	0.00186	0.00078	0.00017	0.00080	0.00015	0.00021
ts1.gam.model3.MSE	0.00109	0.00066	0.00521	0.00048	0.00053	0.00047
ts1.gam.model3.back.MSE	0.00106	0.00055	0.00138	0.00084	0.00042	0.00043
ts1.gam.model5.MSE	0.00118	0.00066	36.56234	0.00140	0.00065	0.00048
ts1.gam.model5.back.MSE	0.00105	0.00056	0.05670	0.00096	0.00043	0.00044
ts1.lm.model.MSE	0.00142	0.00053	0.00042	0.00062	0.00043	0.00037
ts1.lm.model.back.MSE	0.00114	0.00053	0.00042	0.00065	0.00044	0.00034
ts2.gam.model3.MSE	0.00135	0.00060	0.00052	0.00084	0.00038	0.00044
ts2.gam.model3.back.MSE	0.00106	0.00047	0.00040	0.00084	0.00040	0.00035
ts2.gam.model5.MSE	0.00154	0.00059	0.00066	0.00152	0.00037	0.00051
ts2.gam.model5.back.MSE	0.00108	0.00044	0.00035	0.00098	0.00037	0.00034
ts2.lm.model.MSE	0.00114	0.00054	0.00040	0.00075	0.00041	0.00039
ts2.lm.model.back.MSE	0.00110	0.00050	0.00039	0.00077	0.00037	0.00037

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