Universidad Ramon Llull

DOCTORAL THESIS

Title	**A CONTRIBUTION TO EXCHANGE RATE FORECASTING BASED ON MACHINE LEARNING TECHNIQUES**
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To my family, with love

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Abbreviations and symbols used

ANN	Artificial Neural Networks
ARIMA	Autoregressive Integrated Moving Average
BPNN	Back-Propagation Neural Networks
CAB	Current Account Balance
CAD	Canadian Dollar
CI	Confidence Interval
CNY	Chinese Yuan
DG ECFIN	Directorate-General for Economic and Financial Affairs
EMA	Exponential Moving Average
ER	Exchange Rate
ESI	Economic Sentiment Indicator
EU	European Union
EUR	Euro
GA	Genetic Algorithms
GBP	Great Britain Pound Sterling
GDP	Growth Domestic Product
INR	Indian Rupee
JPY	Japanese Yen
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MLP	Multilayer Perceptron
MSE	Mean Squared Error
NMSE	Normalized Mean Squared Error
NN	Neural Networks
R	R Project for Statistical Computing
RMSE	Root Mean Squared Error
SMA	Simple Moving Average
SVM	Support Vector Machines
SVR	Support Vector Regression
US	United States
USD	US Dollar
UK	United Kingdom
VAR	Vector Autoregression

Symbols

\$: US dollar   £: Pound sterling   ¥: Japanese yen   €: European euro   ¥: Chinese yuan
\$: Canadian dollar

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Thesis Abstract

The purpose of this thesis is to examine the contribution made by machine learning techniques on exchange rate forecasting. Such contributions are facilitated and enhanced by the use of fundamental economic variables, technical indicators and business and consumer survey variables as inputs in the forecasting models selected. This research has been organized in a compendium of four articles. The aim of each of these four articles is to contribute to advance our knowledge on the effects and means by which the use of fundamental economic variables, technical indicators, business and consumer surveys, and a model's free-parameters selection is capable of improving exchange rate predictions. Through the use of a non-linear forecasting technique, one research paper examines the effect of fundamental economic variables and a model's parameters selection on exchange rate forecasts, whereas the other three articles concentrate on the effect of technical indicators, a model's parameters selection and business and consumer surveys variables on exchange rate forecasting.

The first paper of this thesis has the objective of examining fundamental economic variables and a forecasting model's parameters in an effort to understand the possible advantages or disadvantages these variables may bring to the exchange rate predictions in terms of forecasting performance and accuracy. The second paper of this thesis analyses how the combination of moving averages, business and consumer surveys and a forecasting model's parameters improves exchange rate predictions. Compared to the first paper, this second paper adds moving averages and business and consumer surveys variables as inputs to the forecasting model, and disregards the use of fundamental economic variables. One of the goals of this paper is to determine the possible effects of business and consumer surveys on exchange rates.

The third paper of this thesis has the same objectives as the second paper, but its analysis is expanded by taking into account the exchange rates of 7 countries. The fourth paper in this thesis takes a similar approach as the second and third papers, but makes use of a single technical indicator. In general, this thesis focuses on the improvement of exchange rate predictions through the use of support vector machines. A combination of variables and a model's parameters selection enhances the way to achieve this purpose.

Resumen en español

El propósito de esta tesis es examinar las aportaciones al estudio de la predicción de la tasa de cambio basada en el uso de técnicas de aprendizaje automático. Dichas aportaciones se ven facilitadas y mejoradas por el uso de variables económicas, indicadores técnicos y variables de tipo *'business and consumer survey'*. Esta investigación está organizada en un compendio de cuatro artículos. El objetivo de cada uno de los cuatro trabajos de investigación de esta tesis es el de contribuir al avance del conocimiento sobre los efectos y mecanismos mediante los cuales el uso de variables económicas, indicadores técnicos, variables de tipo *'business and consumer survey'*, y la selección de los parámetros de modelos predictivos son capaces de mejorar las predicciones de la tasa de cambio.

Haciendo uso de una técnica de predicción no lineal, el primer artículo de esta tesis se centra mayoritariamente en el impacto que tienen el uso de variables económicas y la selección de los parámetros de los modelos en las predicciones de la tasa de cambio para dos países. El último experimento de este primer artículo hace uso de la tasa de cambio del periodo anterior y de indicadores económicos como variables de entrada en los modelos predictivos. El segundo artículo de esta tesis analiza cómo la combinación de medias móviles, variables de tipo *'business and consumer survey'* y la selección de los parámetros de los modelos mejoran las predicciones del cambio para dos países. A diferencia del primer artículo, este segundo trabajo de investigación añade medias móviles y variables de tipo *'business and consumer survey'* como variables de entrada en los modelos predictivos, y descarta el uso de variables económicas. Uno de los objetivos de este segundo artículo es determinar el posible impacto de las variables de tipo *'business and consumer survey'* en las tasas de cambio. El tercer artículo de esta tesis tiene los mismos objetivos que el segundo, pero con la salvedad de que el análisis abarca las tasas de cambio de siete países. El cuarto artículo de esta tesis cuenta con los mismos objetivos que el artículo anterior, pero con la diferencia de que hace uso de un solo indicador técnico.

En general, el enfoque de esta tesis pretende examinar diferentes alternativas para mejorar las predicciones del tipo de cambio a través del uso de máquinas de soporte vectorial. Una combinación de variables y la selección de los parámetros de los modelos predictivos ayudarán a conseguir este propósito.

Resum en català

El propòsit d'aquesta tesi és examinar les aportacions a l'estudi de la predicció de la taxa de canvi basada en l'ús de tècniques d'aprenentatge automàtic. Aquestes aportacions es veuen facilitades i millorades per l'ús de variables econòmiques, indicadors tècnics i variables de tipus 'business and consumer survey'. Aquesta investigació s'organitza entorn d'una recopilació de quatre articles. L'objectiu de cadascun dels quatre treballs de recerca d'aquesta tesi és el de contribuir a l'avanç del coneixement sobre els efectes i mecanismes mitjançant els quals l'ús de variables econòmiques, indicadors tècnics, variables de tipus 'business and consumer survey', i la selecció dels paràmetres de models predictius són capaços de millorar les prediccions de la taxa de canvi.

Fent ús d'una tècnica de predicció no lineal, el primer article d'aquesta tesi es centra majoritàriament en l'impacte que tenen l'ús de variables econòmiques i la selecció dels paràmetres dels models en les prediccions de la taxa de canvi per a dos països. L'últim experiment d'aquest primer article fa ús de la taxa de canvi del període anterior i d'indicadors econòmics com a variables d'entrada en els models predictius. El segon article d'aquesta tesi analitza com la combinació de mitjanes mòbils, variables de tipus 'business and consumer survey' i la selecció dels paràmetres dels models milloren les prediccions del canvi per a dos països. A diferència del primer article, aquest segon treball de recerca afegeix mitjanes mòbils i variables de tipus 'business and consumer survey' com a variables d'entrada en els models predictius, i descarta l'ús de variables econòmiques. Un dels objectius d'aquest segon article és determinar el possible impacte de les variables de tipus 'business and consumer survey' en les taxes de canvi. El tercer article d'aquesta tesi té els mateixos objectius que el segon, però amb l'excepció que l'anàlisi abasta les taxes de canvi de set països. El quart article de la tesi compta amb els mateixos objectius que l'article anterior, però amb la diferència que fa ús d'un sol indicador tècnic.

En general, l'enfocament d'aquesta tesi pretén examinar diferents alternatives per a millorar les prediccions del tipus de canvi a través de l'ús de màquines de suport vectorial. Una combinació de variables i la selecció dels paràmetres dels models predictius ajudaran a aconseguir aquest propòsit.

Chapter 1: General introduction

1.1 Foreign exchange background

The most basic needs in life involve cash. Whenever someone goes to the supermarket, puts gas on his car, or goes shopping, that person will get in some sort of transaction in which money will be present. It matters a lot when a person's budget is limited because of a particular currency weakness. A weak currency can make the purchasing power of $500 US dollars be worth 350 € in Europe. It will matter the more so when that individual decides to go on travel to a country where his spending ability will be constrained because of an unfavourable exchange rate. Imagine a U.S. traveller who decides to exchange his entire travel budget at his European country of destination. He believes it will be fine to do it since the euro is used in that country and its value (euro) will be stable for the duration of his trip. Taking this for granted could be seen as acting unwisely and naively.

Exchanging your travel money at the last moment could be deemed as unsafe because your exchange options will be reduced considerably. Everybody knows that exchange rate merchants at El Prat de Llobregat airport in Barcelona, mostly of which are banks and local offices, charge a fee for their exchange rate transactions, and that charge has a considerable impact on your travel budget. While your money is exchanged, the advantageous or disadvantageous exchange rate fluctuations that have happened since you left your home country are not taken into account. These fluctuations are mostly discarded for exchange rate purposes for the simple reason that banks post a rate on a daily basis not on an hourly basis (Smeral, 2004). This means that the daily rate posted is not a real rate and this may reduce your travel money if the rate has become more beneficial for you. The best advice for a U.S. traveller going overseas would be to plan his travel well in advance, do a little bit of research about the exchange rates on the country of his destination and exchange small amounts of money at different times over the entire planning process. The figure 1.1 on next page will show a 10 year exchange rate fluctuation for the EUR USD currency pair.

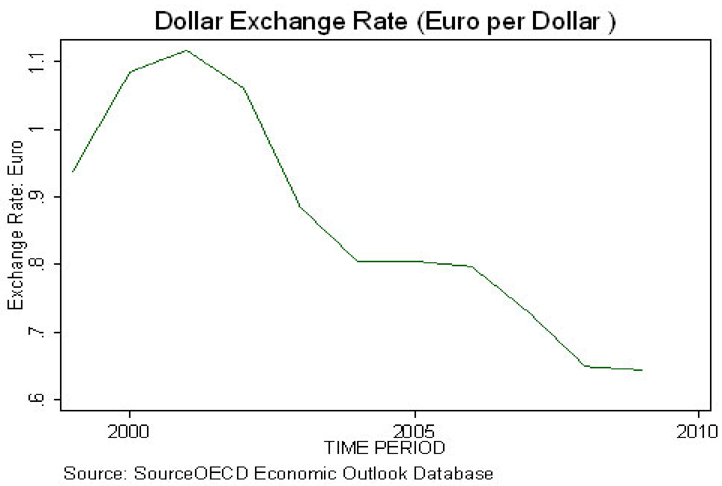


Figure 1.1: Euro per Dollar, 2000-2010. Source: OECD Economic Outlook Database

Monitoring exchange rates is of strategic importance not only for worldwide travellers, but also for export/import merchants (Evans, 2005). For instance, a U.S. merchant whose U.S. currency is strengthening as the days pass by will see how his products will be less competitive abroad. A strong U.S. currency will decrease the demand for U.S. products overseas. But at the same time, imported products from abroad will be cheaper, and U.S. local products will lose competitiveness in the domestic market to them. This situation will boost imports at the expense of exports. The other way around is the result of a weak U.S. currency. A weak U.S. dollar will decrease the cost of and increase the demand for U.S. products overseas. Imported products will be more expensive because U.S. importers will have to pay more for a unit of foreign currency. This will cause U.S. demand for overseas products to decrease. Imported products will lose competitiveness to locally produced U.S. commodities. This situation will cause exports to soar and imports to shrink.

Because of these and many other situations, such as an American Ph.D. Candidate financing his studies at a renowned business school in Europe through U.S. student loans, it is good to have a clear understanding of how the exchange rate mechanism works, and the precautions needed to avoid a lose-lose situation in the foreign exchange market. If we want to have a comprehensible picture of the exchange rate market, we need to understand the forces that cause these fluctuations and the mechanisms available to counter them.

1.2 Economic implications of exchange rates

Exchange rates serve a variety of purposes in the global business world. For instance, by helping in the translation and conversion of foreign currency, exchange rates expedite global commerce, the flow of products and services internationally (Truman, 2006). They also serve as economic indicators (McGregor, 1998). For instance, a strong exchange rate indicates a growing economy and political stability for a particular country. On the contrary, a weak exchange rate may indicate economic recession. Foreign exchange reserves can be used by politicians to exert an influence on currency rates and manage the economy (Kaplan, 2006). This happens when government officials use foreign exchange reserves to repurchase domestic currency and strengthen its value. Exchange rates can also be used as strategic instruments (Gandhi, 2006). This can be seen when dealing with currency derivatives such as options and futures contracts. Futures and forward markets are the commonplace setting where transactions with futures, forwards and options take place. In these markets, exchange rates are set for specified periods of time in order to manage risks. These unwanted risks can sometimes create financial havoc for currency traders in foreign markets (Butler, 2010). The causes for these risks will be explained in the next section.

1.2.1 Factors influencing exchange rates

Exchange rates are influenced by a variety of factors some of which are difficult to control and manage (Lowery, 2008). As for example, the demand and supply for money. Since exchange rates are based on the relative price of two national currencies, they are determined by the relative supplies and demands for these currencies (Frenkel & Johnson, 1978). These relative supplies and demands for money are in turn determined by the plans of private businesses and government policies. These policies have a direct impact on the economy of a nation. Other economic factors which exert an influence on exchange rates are productivity, equity flow, hedging activities, interest rate differentials, inflation, growth domestic product (GDP), current account balances (CAB) and trans-oceanic economic policies (Cushman & Zha, 1997). An interest rate differential usually reflects exchange rate expectations (Khor & Rojas-Suarez, 1991). The widely known purchasing power parity theory (PPP) links exchange rates to inflation. (Balassa, 1964; Juselius, 1995).

Surprisingly, in the European Union there is another variable which measures GDP growth on an aggregate level. This variable, which is called the Economic Sentiment Indicator (ESI), is part of the joint harmonized EU programme of business and consumer surveys (European Commission DG ECFIN, 2009). Business and consumer surveys reveal the opinion and expectations of financial and economic experts in the area about the current trend of the different sectors of the economy: industry, services, construction, retail trade and consumers. These business and consumer surveys provide important quantitative and qualitative information about the economic health, short-term forecasts and economic research for the euro-area. ESI, which is mostly of a qualitative nature, reflects the monthly judgments, anticipations, perceptions and expectations concerning diverse facets of economic activity in the different sectors of the economy.

Mehrotra and Rautava (2007) claim that business sentiment indicators are useful in forecasting developments in the Chinese economy because they tend to transmit useful information about the current and future state of affairs of economic activity in the country. Nilsson and Tapasanun (2009) support the idea that sentiment indicators play a big role in the foreign exchange market. They claim that the EUR/USD exchange rate rose as euro zone economic sentiment indicator increased for the first time since May 2007. As risk sentiment improved, the US dollar and the yen fell against their opposites. The sterling rose on expectations of a UK economic recovery by the end of the year. Likewise, positive feelings for a global economic recovery and higher commodity prices made the Canadian and Australian dollars rise again. Rodriguez (2009) states that several sentiment indicators have a significant role in the US dollar/Euro exchange rate. On a theoretical level, financial relationships have been suggested between foreign exchange markets and sentiment indicators.

Deans (2010) and Lawrence (2011) state that it is the traders' expectations in the foreign exchange market which cause the constant buying and selling of currencies (Koske and Stadtmann, 2009). Some of these expectations are in turn related to political and psychological factors. Political factors may include the monetary policy in place, government intervention or manipulation, a country's relative economic exposure and the political stability of a country (Forex Mansion, 2011; Online Forex, 2010). There is an implicit assumption among traders which states that even psychological factors exert an influence on market participants engaged in exchange rate transactions.

Psychological factors could include risk avoidance, market anticipation, greed, speculative pressures and future expectations (Hill, 2004).

Due to the vast array of external and internal forces encompassing foreign exchange markets, the possibility of making erroneous exchange rate forecasts is more possible than ever. Traders often try to predict exchange rates with a high degree of reliability, but most of the times those forecasts are far from being true. A high-quality forecast would allow traders and market participants to make more-informed decisions (Wang, 2008). Regrettably, in the financial world this is not the case. The next section will explain the difficulty in forecasting exchange rates.

1.2.2 Complexity of exchange rates

Exchange rates are highly volatile which makes them very difficult to predict over short to medium time horizons (Cheong, Kim & Yoon, 2011). Because of this volatility, an estimation of the future value assets and liabilities denominated in foreign currency is very hard to predict. Some researchers have proposed the idea that exchange rates and financial assets behave alike. This means that the price movements of a financial asset are determined by changes in expectations about future economic variables, rather than by changes in current ones (Wang, 2008). What this implies is that the real contribution of average exchange rate models is not their capacity to forecast currency values, but their ability to forecast economic fundamentals such as trade balances, money supply, national income and other key variables. Other researchers challenge the idea that economic fundamentals help predict currency values and attribute changes in exchange rates to random luck (Meese and Rogoff, 1983). They claim that the performance of a random walk model is just as good as the performance of a model based on economic fundamental variables. Figure 1.2 shows a typical representation of a random walk model.

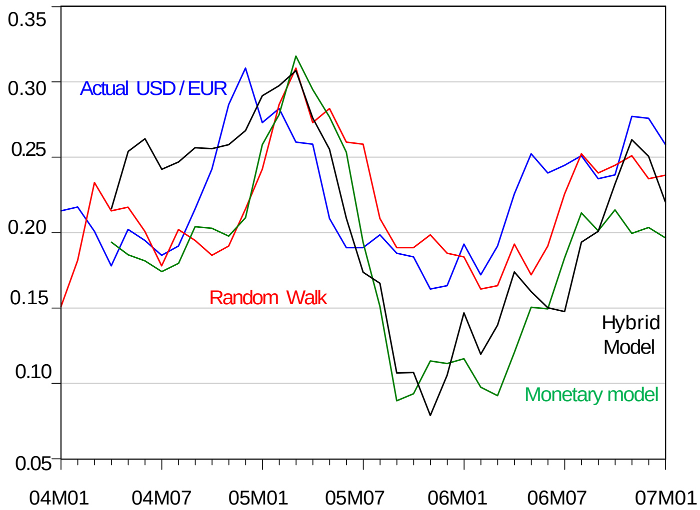


Figure 1.2: Log USD/EUR exchange rate (blue) and forecasts from random walk (red), Monetary (green), Hybrid (black). Source: Chinn and Moore (2008)

Another reason why economic models find it so difficult to predict exchange rates is that there is no apparent connection between exchange rates and economic fundamentals (Wang, 2008). This could be attributed to the intrinsic limitations of the economic models themselves or to a model's misspecifications. The coefficients of an economic model try to specify the relationship between exchange rates and its fundamentals. However, these parameters are estimated based on historical data while the predictive power of these models is based on their ability to forecast currency values from new data. Meese and Rogoff (1983) claim these parameters may be different over time. This doesn't mean that economic fundamentals per se need to be discarded as predictors of exchange rates, but rather that other combinations of economic fundamentals and forecasting methods (econometric and time series models) have to be taken into account when predicting exchange rates.

1.2.3 Modelling exchange rates

The are two well-known approaches to forecast foreign exchange rates. The first one is known as the fundamental approach and the second one is known as the technical approach (Tsay, 2005). Table 1.1 on next page shows tha main principles of each approach.

The Fundamental Analysis	The Technical Analysis
Belief in economics	**Broad economic data only**
Macro and micro economics	**Price charts hold all the information**
Analysis of financial reports	**Analysis of price patterns**
Belief in management accounts	**Interpretation of indicators**

Table 1.1: Comparison between fundamental and technical analysis

The fundamental approach is based on fundamental economic variables which influence currency predictions. The following fundamental economic variables, most of which are taken from economic models, are of importance in foreign exchange markets: trade balance, inflation rates, unemployment, interest rates, GNP, productivity index and comsumption, among others (Johnston & Scott, 1997). Structural (equilibrium) models dominate fundamental forecasts. These models are then modified to incorporate the statistical characteristics of the data, and the knowledge and skill of the forecasters. The structural models are used to equilibrate exchange rates. Once the exchange rates are equilibrated, projections or trading signals can be produced. Bjørnland and Hungnes (2006) do a comparative study of the forecasting performance of a structural exchange rate model which unites the PPP condition with the interest rate differential in the long run against some alternative exchange rate models. They are able to show that the interest rate differential is very important in the long run when predicting exchange rate behavior.

A forecasting model with its respective forecasting equation is the first product of the fundamental approach (Tsay, 2005). This model is built on a single theory, for example the PPP, a combination of theories or on the specialized knowledge and skills of a forecaster. The very first thing this forecaster does is to collect the data needed to estimate the forecasting equation. This forecasting equation is then evaluated using statistical technqiues or some other measures. Once the model has been statistically approved, the next step will be the generation of forecasts. These forecasts will be finally evaluated to determine the reliability and accuracy of the model. One important thing to mention is that once the financial data is collected, the forecaster will divide it in 2 sets. The first set is commonly known as the training or estimation period. The second set is known as the validation period. The training period, as its name implies, is used for training your model and selecting its parameters. The validation period is used to test your model for future generation of forecasts. At this last stage, the forecaster decides if the model's forecasting performance is deemed acceptable for out-of-sample forecasting. Out-of-sample forecasting means using today's information to forecast the future path of exchange rates. On the other hand, in-sample forecasting means using today's information to forecast today's spot rate. The fitted values estimated in a model are all in-sample forecasts.

Going back to the second approach in exchange rate forecasting, the technical approach is mostly built on price information (Tsay, 2005). The word 'technical' means that the financial reasoning employed in the model does not make use of fundamental economic variables, but of extrapolations of past price trends. A technical trader looks for repetitive price patterns, trends or turning points. Buy or sell signals are produced from these turning points. The most often used technical models are based on filters, momentum indicators or moving averages. A filter model produces buy signals when an exchange rate rises a specified number of percentage points above its most recent trough, and sell signals when an exchange rate falls a specified number of percentage points below the previous peak. Momentum models measure the healthiness of an asset by looking at the change in velocity with which the asset's price rises or falls. If the price rises very quickly, a buy signal is produced. A moving average model is a specified average of past prices. The trader specifies the number of days he wants the moving average to be. Moving averages smooth-out the noise and price variations of financial data, thus allowing traders to identify trends present in the data and make financial gains out of them.

Moving averages are of importance in foreign exchange markets (Rosenberg, 2003). Neely and Weller (2011) sustain that more complex forms of moving averages, which are responsible for excess returns, are more present than ever. Harris and Yilmaz (2008) analyze moving average rules and momentum trading strategies in order to determine which one produces higher returns and higher Sharpe ratios for exchange rates. Lento (2008) examines the ability of moving averages to forecast security returns of exchange rates. The results are quite mixed suggesting that moving averages are able to outperform the random walk model at some instances only and that moving averages provide valuable information for predicitng the holding period returns ten days after a buy or sell signal is generated. Neely, Weller and Dittmar (1997) show that technical trading rules provide excess returns for six exchange rates studied, and that technical trading rules are able to identify patterns in the data which are not detected by standard statistical techniques. For their ability in detecting price trends in foreign exchange data, this thesis makes use of moving averages as inputs to the forecasting technique selected.

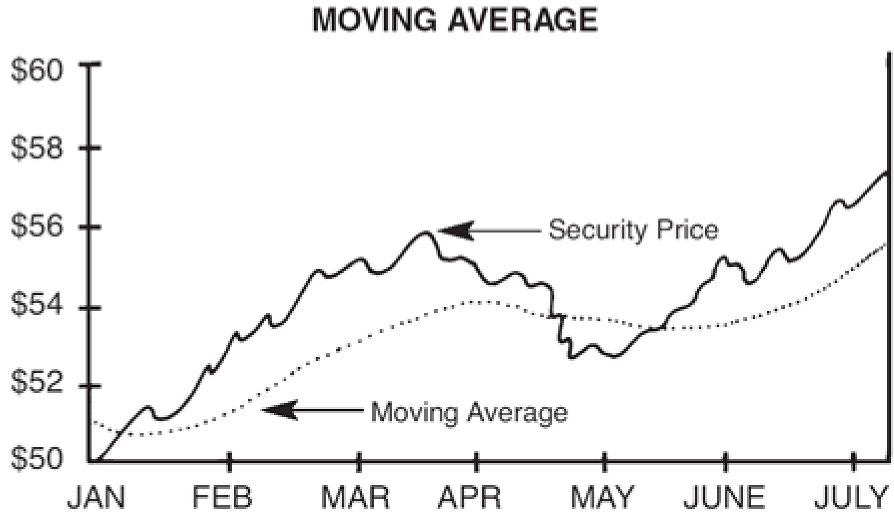


Figure 1.3: A 7-month moving average for a security price
Source: Microsoft Research

Figure 1.3 above shows an example of a 7-month moving average for any particular security price. Technical and fundamental economic variables are used extensively in foreign exchange markets. This thesis makes use of both variables as inputs to the forecasting models employed. In the next section, a brief review of selected forecasting techniques, which fall under the fundamental and technical approach, will be presented.

1.3 Forecasting techniques in foreign exchange markets

A number of linear and non-linear techniques have been used extensively by researchers who want to approximate currency predictions with the utmost degree of reliability. Some of the most often used techniques are: random walk, single exponential smoothing, autoregressive moving average models, generalized autoregressive conditional heteroskedasticity models (GARCH), self-exciting threshold autoregressive models (SETAR), bilinear and treshold models, artificial neural networks (ANNs) and support vector machines (SVMs), among others. Table 1.2 on next page shows the main characteristics of some of these forecasting models.

Linear models	Non-linear models
$Y = b_0 + b_1X_1 + b_2X_2 + ... + b_kX_k$	$y = F(x_1, x_2, ... , x_n)$
Linear relationship between a dependent variable Y and a set of predictor's variables, the X's	It's up to the researcher to determine the relationship between a set of independent variables and a dependent variable
Simple regression, multiple regression models, ANOVA/MANOVA	Common nonlinear models are probit, logit, exponential growth, breakpoint regression, and machine learning techniques

Table 1.2: Characteristics of forecasting models

Table 1.3 below shows the major non-linear techniques used in forecasting data which is non-linear in nature. A special enphasis will be given to neural newtorks and support vector machines.

Machine Learning	
Neural Networks	**Support Vector Machines**
Capable of modeling extremely complex functions and of handling dimensionality problems	SVM: Capable of performing regression and classification tasks by constructing nonlinear decision boundaries.
Common models: feedforward, multilayer perceptrons, backpropagation	Based on the concept of decision planes that define decision boundaries. A decision plane is one that separates between a set of objects having different class memberships
There are two types of training: supervised and unsupervised; suffer from over-fitting, network size; Empirical error minimization: Try to reduce the training pattern misclassification error	Supervised training; are well-suited for sparse data; a reduced set of data is enough to obtain good estimations Structural risk minimization: Balances the model complexity against the training error

Table 1.3: Predicting models for non-linear data

1.3.1 Comparing non-linear models

Brooks (1997) shows that the improvements in performance obtained from using linear and non-linear univariate time-series models are very small over forecasts generated by a random walk model. Gradojevic and Yang (2006) claim that ANNs outperform random walk and linear models based on a number of recursive out-of-sample forecasts. The authors prove that ANNs perform better than other linear models in terms of percentage of correctly predicted exchange rate changes. Boero and Marrocu (2002) do a comparative study of the forecasting performance of different models of three traded exchange rates (the French franc, the German mark and the Japanese yen) against the US dollar. Three non-linear models, mainly a two-regime SETAR, a three regime-SETAR and a GARCH-M model were compared and contrasted against two linear models, primarily AR and random walk processes. The results show that the advantages of non-linear models over linear ones lie in the criteria used to assess forecast accuracy . The authors conclude by stating that in their analysis non-linear models generate more forecasting gains than linear ones.

Tay and Cao (2001) do a comparative study of the forecasting performance of SVM against that of a multi-layer back-propagation (BP) neural network in financial time series forecasting. Using five real future contracts from the Chicago Mercantile Market, the authors are able to show the superiority of SVM over BP neural networks based on diverse statistical criteria such as normalised mean square error and mean absolute errors, among others. Kim (2003) studies the predictive potential of SVM in the stock price index, and also does a comparative study of SVM against BP neural networks and case-based reasoning. The results show SVM's dominance over BP neural networks and case-based reasoning when forecasting the daily Korea composite stick price index. Shin, Lee and Kim (2005) show that SVM outperforms BP neural networks when applied to corporate bankruptcy prediction.

Given the fact that linear models are unable to capture the non-linearities found in exchange rate data, SVMs and ANNs dare each other to be one of the best forecasting tools in foreign exchange markets. However, SVMs exhibit certain attributes which give them an advantage over ANNs. There are no over fitting problems in SVMs. ANNs reach a local optimal solution, while SVMs may reach a global optimum solution. SVMs can select a model automatically, while ANNs require a selection of a large number of parameters which is a very complicated task to do (Cao, Pang & Bai, 2005). For these reasons, SVM has been selected as the sole forecasting technique in this dissertation.

1.3.2 SVM: Brief overview

SVM is a supervised learning method initially used for classification, but soon extended for regression and other learning problems. It is firmly grounded in the framework of Statistical Learning Theory, developed mainly by Vapnik and Chevornenkis over the last decades (Vapnik, 1998). Models established by SVM algorithms are characterised by their excellent generalization capability. This is due to SVM's ability to minimize the structural risk, specifically the upper bound of the generalization error instead of minimizing the empirical error, thus resulting in better generalization than other conventional forecasting techniques. SVM produce a nonlinear regression in a low-dimensional space. The input data is nonlinearly mapped in a high dimensional feature, and then a linear regression is run in this altered space. The basic ideas of the SVM theory for regression are presented below.

Suppose we are given training data $\{(\mathbf{x_1}, y_1), (\mathbf{x_2}, y_2), \ldots (\mathbf{x_N}, y_N)\} \subset X \times R$, where X denotes the space of the input patterns. In ε-SV regression, the goal is to find a function *f(x)* that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time is as flat as possible (See Figure 1.4). In the linear case, if X= R^d, this function takes the form:

$$f(\mathbf{x}) = \langle \mathbf{w}, \mathbf{x} \rangle + b \qquad \text{with } \mathbf{w} \in R^d, b \in R$$

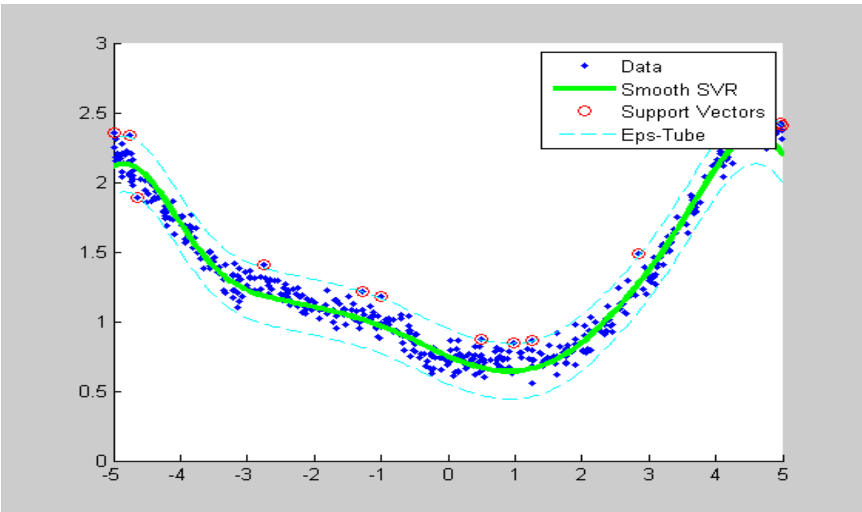


Figure 1.4: Training kernel (rbf) support vector regression machine.
Source: di.ens.fr.

The parameters **w** and b can be determined through the constraint optimization problem:

$$\text{minimize} \quad \frac{1}{2}\|\mathbf{w}\|^2 + C\sum_{i=1}^{N}\left(\xi_i + \xi_i^*\right)$$

$$\text{subject to} \begin{cases} y_i - \langle \mathbf{w}, \mathbf{x}_i \rangle - b \le \varepsilon + \xi_i \\ \langle \mathbf{w}, \mathbf{x}_i \rangle + b - y_i \le \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \qquad \ge 0 \end{cases}$$

where slack variables ξ and ξ^* are introduced to cope with infeasible constraints of the optimization problem and the constant C>0 determines the trade-off between the flatness of *f* and the amount up to which deviations larger than ε are tolerated.

This optimization problem can be solved easier in its dual formulation. Moreover, the dual formulation provides the key for extending the algorithm to nonlinear functions. The nonlinear case is tackled by mapping the input patterns into a high dimensional feature F space by means of a non-linear function ϕ: $X \rightarrow F$. This mapping is performed indirectly through a kernel function K: $X \times X \rightarrow R$ that can be considered as a dot product in the feature space. A common choice for kernel is the Gaussian radial basis function:

$$K(\mathbf{x}_i, \mathbf{x}_j) = e^{-\frac{\|\mathbf{x}_i - \mathbf{x}_j\|}{2\sigma^2}}$$

This kernel results an infinite dimension feature space. However, the infinite dimension does not spoil the results. Figure 1.5 below shows the basic idea behind Support Vector Machines. Here we see the original objects (left side of the schematic) mapped, i.e., rearranged, using a set of mathematical functions, known as kernels. The process of rearranging the objects is known as mapping (transformation). Note that in this new setting, the mapped objects (right side of the schematic) is linearly separable and, thus, instead of constructing the complex curve (left schematic), all we have to do is to find an optimal hyperplane that can separate the circles from the diamonds.

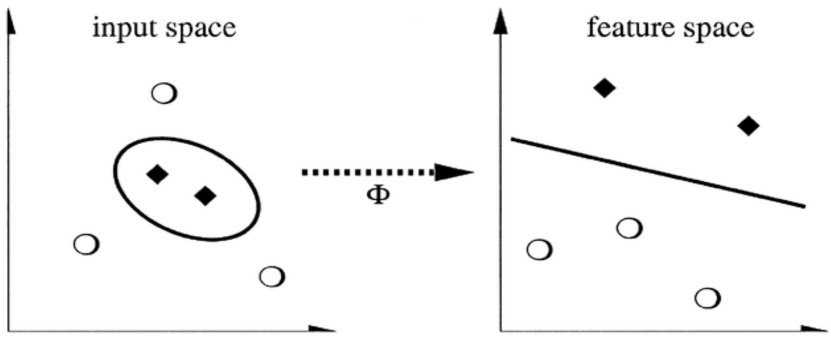


Figure 1.5: SVM's input and feature space. Source: Microsoft Research

1.4 Focus of Research

1.4.1 Problem Statement

Foreign exchange markets are filled with uncertainty (Canova & Marrinan, 1993). International traders are constantly looking for ways to protect themselves against these uncertainties and unwanted fluctuations because of the impact they may have on the economic outlook of a country (Galí & Monacelli, 2005). Unexpected exchange rate fluctuations have an effect on a number of fundamental macroeconomic variables such as the international account balance position (Dell'Ariccia, 1999). Exchange rate stability contributes to the development of a safe macroeconomic environment which leads to growth and investment (Ames, Brown, Devarajan & Izquierdo, 2001). However, looks like achieving this stability has become a difficult task to do. Countless forecasting techniques have been developed and still the desire tranquillity in the foreign exchange markets has not been attained (Tudela, 2004). It would be of a great importance to understand how the exchange rate mechanism works and what contributions can be made to any forecasting model so as to reach the desired level of confidence and trust the market requires (Grauwe & Schnabl, 2008).

1.4.2 Purpose of Research

The overall purpose of this research work is to examine the effect different variables have on exchange rate predictions through the use of automatic machine-learning techniques. The impact that fundamental economic variables, technical indicators and business and consumer survey variables have on exchange rates is examined carefully. The selected fundamental economic variables are: GDP, productivity, inflation, CAB and interest rates. As for the technical indicators, simple moving averages and exponential moving averages were also selected as predictors in the SVM models. The business and consumer survey variable chosen was ESI. In some cases, these variables were tested on the exchange rate predictions of 7 currencies, namely, US dollar, European euro, Japanese yen, Indian rupee, British pound, Chinese yuan, and the Canadian dollar.

The paper presented in chapter 2 has the objective of examining fundamental economic variables and a forecasting model's parameters in an effort to understand the possible advantages or disadvantages these variables may bring to the exchange rate predictions in terms of forecasting performance and accuracy. The paper presented in chapter 3 analyses how the combination of moving averages, business and consumer surveys and a forecasting model's parameters improves exchange rate predictions. Compared to the paper presented in chapter 2, this second paper adds moving averages and business and consumer surveys variables as inputs to the forecasting model, and disregards the use of fundamental economic variables. One of the goals of this paper is to determine the possible effects of business and consumer surveys on exchange rates.

The paper presented in chapter 4 has the same objectives as the paper in chapter 3, but its analysis is expanded by taking into account the exchange rates of 7 countries. The paper presented in chapter 5 takes a similar approach as chapters 3 and 4, but makes use of a single technical indicator. As it will be read, the objectives of this dissertation are constantly evolving just like a natural selection process does. 'Survival of the fittest' in the sense that the best combination of variables is persistently sought, and once a model's forecasting performance has been measured and verified, new exchange rates are added to the picture in an effort to verify the in-sample results. Next, a chapter by chapter flow diagram (Figures 1.6-1.9) will be shown for illustrative purposes.

Figure 1.6: Chapter's 2 Flow Diagram

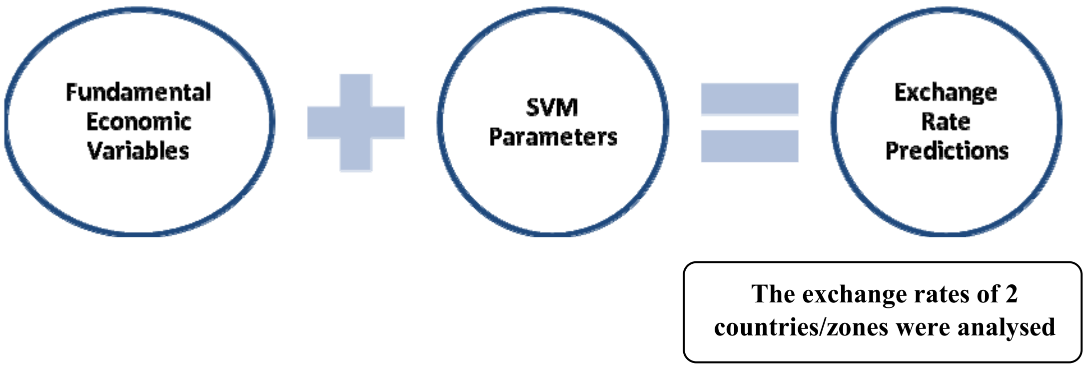


Figure 1.7: Chapter's 3 Flow Diagram

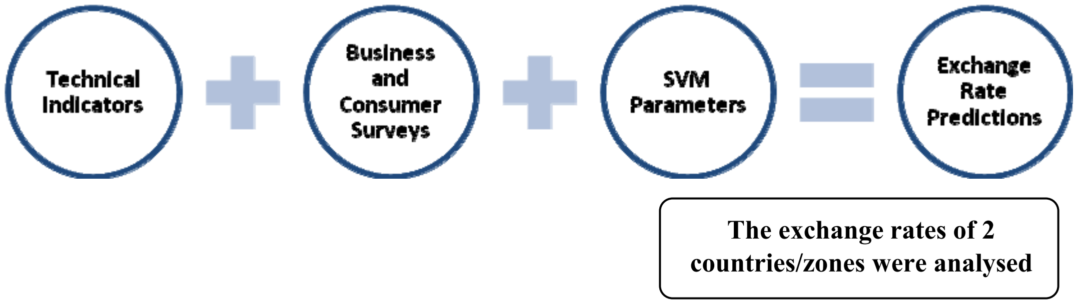
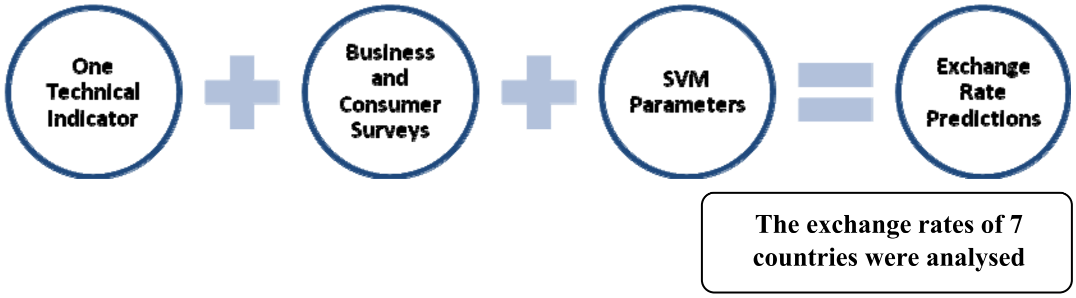


Figure 1.8: Chapter's 4 Flow Diagram

Figure 1.9: Chapter's 5 Flow Diagram



1.4.3 Expected contributions of this research

The proposed research will aid in the understanding of the exchange rate dilemma by clarifying the roles different variables have on the forecasting process. For example, it can be determined if qualitative variables have any impact on a forecasting model's power and accuracy. Also, it will help to understand what combination of technical indicators (SMA and/or EMA) and/or macroeconomic variables is appropriate for a forecasting model. In addition to this, the free-parameters selection issue will contribute to a further understanding of the dynamics involved with a prediction technique. It is the hope of this research that the role qualitative variables may have on predictions is understood and that at the end this will contribute somehow to the predicting chaos of the financial world nowadays.

1.4.4 Thesis structure

This thesis is organised in seven chapters. The present chapter 1 presents the basic theoretical background that constitutes this dissertation. The general concepts which were dealt with in this research project are shown in a clear, concise and understandable manner. Further, the problem statement, the purpose of research and the contributions of this dissertation are briefly stipulated. Chapter 2 contains the first research paper of this dissertation - *A Support Vector Machine Approach to Foreign Exchange Rate Forecasting*. The paper presented in chapter 2 is the result of collaboration with Professor Núria Agell, Professor Francisco Ruiz and Professor Josep Sayeras. This paper was accepted at the 28th Annual International Symposium on Forecasting held in Nice, France.

Chapter 3 encloses the paper - *A boost in exchange rate forecasting: qualitative variables, technical indicators and parameters selection*. The paper presented in chapter 3 is the result of collaboration with Professor Núria Agell and doctoral student Germán Sánchez. This paper was published in the conference proceedings of the 12th International Congress of the Catalan Association of Artificial Intelligence which was held in Cardona, Barcelona, Spain. On chapter 4, the paper - *An application of SVMs to predict financial exchange rate by using sentiment indicators* – is presented. This research work has been published in the conference proceedings of the Congreso Español de Informática (CEDI 2010) held in Valencia, Spain. The paper presented in chapter 4 is the result of collaboration with Professor Núria Agell, Professor Josep Sayeras and doctoral student Germán Sánchez.

Chapter 5 brings the final empirical piece of this dissertation - *Analyzing the use of business and consumer surveys in forecasting exchange rates: A cross-country comparison*. This paper has been submitted for review to the Emerging Market Finance and Trade journal. The paper presented in chapter 5 is the result of collaboration with Professor Núria Agell, Professor Josep Sayeras and doctoral student Germán Sánchez. The aim of each of the four research papers of this dissertation is the one of contributing to advance our knowledge on the effects and means by which the use of fundamental economic variables, technical indicators, business and consumer surveys, and a model's free-parameters selection is capable of improving exchange rate predictions. Through the use of a non-linear forecasting technique, one research paper examines the effect of fundamental economic variables and a model's parameters selection on exchange rate forecasts, whereas the other three articles concentrate on the effect of technical indicators, a model's parameters selection and business and consumer surveys variables on exchange rate forecasting. Chapter 6 concludes and outlines questions for future research. Finally, chapter 7 brings together all references used in the introduction and conclusion of this dissertation.

1.4.5 Contributions to scientific knowledge

The aim of this section is to summarise the peer-review processes undergone by the research comprised in this thesis. All four papers presented in this dissertation have been submitted to peer-review processes and/or have been presented in academic conferences /research seminars. The information depicted in Table 1.4 relates the specific article with its respective presentation and publication.

Title	Journal/ Conference/ Seminar
A Support Vector Machine Approach to Foreign Exchange Rate Forecasting	28th Annual International Symposium on Forecasting, Nice, France. June 2008.
A boost in exchange rate forecasting: qualitative variables, technical indicators and parameters selection	Proceedings of the 12th International Congress of the Catalan Association of Artificial Intelligence, Cardona, Barcelona, Spain. October 2009.
An application of SVMs to predict financial exchange rate by using sentiment indicators	Proceedings of the Congreso Español de Informática (CEDI 2010), Valencia, Spain. September 2010.
Analyzing the use of business and consumer surveys in forecasting exchange rates: A cross-country comparison	Submitted for review to the *Emerging Markets Finance and Trade Journal*. May 2011.

Table 1.4: Table of academic contributions

Chapter 2: A Support Vector Machine Approach to Foreign Exchange Rate Forecasting

Introduction to chapter 2

The second chapter of this thesis addresses the use of a new model of Support Vector Machines as a forecasting tool in order to improve the predictions of exchange rates. The model's new parameters along with several macroeconomic variables intend to obtain better forecasts than other forecasting techniques. This paper has been presented in some research seminars and conferences. This thesis brings the version presented at the *28th Annual International Symposium on Forecasting* held in Nice, France. Co-authors to this paper are: Professor Núria Agell (ESADE-URL), Professor Francisco Ruiz (UPC) and Professor Josep Sayeras (ESADE-URL).

Abstract

This paper presents a new approach based on the use of Support Vector Machines as a forecasting tool for the prediction of the currency exchange rate between the US dollar and the euro. The results obtained show Support Vector Machine's forecasting power as a sound alternative to other conventional forecasting tools such as Artificial Neural Networks and Autoregressive Integrated Moving Average models in the international finance area.

2.1 Introduction

Due to the different economical circumstances affecting the countries involved in a bilateral trade agreement, the foreign exchange rate agreed to in a settlement can fluctuate considerably. These economical uncertainties can have undesirable consequences on the value of a country's currency, thus possibly hurting the negotiable terms of any economical agreement. These exchange rate fluctuations could have an impact on the economic outlook of a country by causing an increase (decrease) in its international account balance position (Dell'Ariccia, 1999). According to Rose (2000), exchange rate uncertainty can hurt international trade, and its elimination should bring an improvement on and boost bilateral trade by 3-4 percent. Exchange rate stability contributes to the development of a safe macroeconomic environment that could lead to growth and investment. An unstable exchange rate may affect negatively growth prospects and could cause a decrease in the confidence of the market (Kontolemis, 2003).

The volatility of the exchange rate of a country is a subject which has drawn the attention of researchers across many disciplines. According to Walczak (2001), trying to model foreign exchange rates in unpredictable environments is a difficult task. Artificial Neural Networks (ANN) and Support Vector Machines (SVM) have shown to be useful tools as forecasting techniques in many financial and economic dilemmas. Genetic Algorithms (GA) have also proven their capabilities as predictors and forecasters of the still unresolved issues left by ANN and SVM models and other non-linear time series techniques. Some researchers have proposed that a hybrid combination of these models could make significant improvements in their predictive capacity (Giles, Lawrence & Chung, 1997). Much has been written about the evident advantages of using ANN techniques in the forecasting of foreign currency exchange rates (Giles et al., 1997; Nag & Mitra, 2002). Research has also shown the potential contributions genetic algorithms can provide to the prediction of exchange rates (Nag & Mitra, 2002). Lately, SVM have emerged as one of the most accurate techniques, compared to neural networks and other parametric models, when it comes to foreign exchange rate forecasting.

Due to the non-linearity behavior exhibited by foreign exchange rates, the forecasting ability of some linear models is highly constrained and hindered since they cannot model these irregular and unpredictable patterns. ANNs and genetic algorithms have demonstrated their ability in modeling these types of unpredictable patterns and irregular behaviors. Even though their capacity is evident, there is still some room for improvement regarding their accuracy. SVMs have outperformed ANNs and other linear models in terms of predictive power and forecasting accuracy. For these reasons, the goal is to come up with a model able to improve predictions about the future value of a country's currency in terms of another. This in turn will help develop a safer economic environment, thus encouraging growth and investment. Our purpose is to present a new approach based on the use of Support Vector Machines as a forecasting tool for the prediction of the currency exchange rate between the U.S. dollar and the euro.

The paper is organised as follows. Section 2.2 presents a theoretical background about foreign exchange rates and the tools available to model them. Section 2.3 gives an overview of previous research done on the subject through the use of ANN models. In section 2.4, the theory of SVM is presented. Section 2.5 discusses recent research done on the field about the linear, non-linear, parametric and non-parametric forecasting techniques used in financial time series forecasting. In Section 2.6, the macroeconomic variables and the dataset employed are explained along with graphical descriptions of the experiment and of its results. Finally, section 2.7 discusses the work and outlines several conclusions and lines for future research.

2.2 Modeling foreign exchange

Exchange rates are related to the price levels present in two countries. In turn, these price levels depend on the demand and supply for money within each country. Whenever there is a need to buy products and services, individuals demand money. Without it, they will lack the power to buy any kind of product. In order to acquire this power, they need some financial instrument or mean which will allow them to conduct the transaction required in order to acquire the sought product or service. If for a particular transaction, a barter agreement can be reached without the need of having money present, then it could be said that money was replaced as the principal financial instrument. Excellent examples of barter agreements were seen in the conquered countries of the Old World around the 17th or 18th centuries between the Mexican Indians and the Spaniards. Two centuries have passed and the barter agreements, which can still be seen today, have been replaced by the buying power of each country's currency.

Most of these currencies trade in the worldwide foreign exchange market using one convention, the US dollar. Almost all currencies are still quoted against the US dollar with exceptions in Asia and Europe where the yen and euro are used respectively. Financially speaking, the exchange rate between two countries means how much the currency of one country is worth in terms of the other country's currency. The exchange rate mechanism is seen as a useful tool in the establishment and creation of a common market between countries. According to Kontolemis (2003), the exchange rate stability is desirable for the smooth functioning and deepening of a single common market. Most of the time, exchange rate stability is associated with a stable macroeconomic environment which leads to investment from abroad and consequently growth. A stable exchange rate system limits the exchange risk and promotes foreign borrowing by domestic residents, thus encouraging faster growth and convergence with other countries.

Two characteristics of foreign exchange rates are their significant non-stationarity and very high noise (Giles et al., 1997). Most researchers will agree with the claim that the exchange rates behave according to the efficient market hypothesis (Balassa, 1964; Chinn, 2003; Floyd, 2007; Frenkel, 1976; Murfin & Ormerod, 1984; Samuelson, 1964). In its conception, this hypothesis states that at any given time, security prices reflect all available information (Fama, 1965). The price movements of an asset will not follow any pattern or trend, thus making its future unpredictable. Hence, the future price of an asset cannot be forecasted. Consequently, there is no better way to forecast the price of an asset than the current price of the asset. Applied to foreign exchange rates, there is no information in past percentage changes which could be applied for the prediction of future percentage changes (White & Racine, 2001). Its actual price will follow what is known as a random walk.

The theory of random walk was popularized in 1973 by the work of Burton Malkiel, "A Random Walk Down Wall Street", a piece of literature known in the financial arena as an investment classic. The theory of random walk is a stock market theory which states that the past movement or direction of the price of a stock or overall market cannot be used to predict its future movement. Originally examined by Maurice Kendall in 1953, the theory states that stock price fluctuations are independent of each other and have the same probability distribution, but that over a period of time, prices maintain an upward trend (Hughes, 1996). Summarizing, random walk states that a stock’s price takes a random and unpredictable path. The probability of having a stock's future price going up is the same as the one we could have if the case were otherwise. By following the random walk strategy, it is impossible to do better than the market without assuming additional risk. Malkiel alleges that statistical, technical and fundamental analyses are worthless and are still unproven in outperforming the markets.

Hsieh (1989) alleges that foreign exchange rates and other financial time series “follow a random walk and should therefore not be predictable much past 50 percent (the average performance of random walk models for foreign exchange markets)”. Random walk models have outperformed other statistical and econometric models when it comes to foreign exchange rate determination (Meese & Rogoff, 1983). Nag and Mitra (2002) reach the same conclusion based on the work done by other researchers who state that through the use of time-varying parameters models similar results are reached. Nag and

Mitra (2002) also conjecture that the linear unpredictability of the exchange rate models is due to the linear limitations of the models themselves. Nevertheless, the development of non-linear models significantly outperforming the performance of the random walk model was scarce.

2.2.1 Neural Networks

Recent research has suggested that ANNs have proven to be more accurate in its forecasting ability than any other forecasting statistical tool such as linear time series techniques, exponential smoothing and autoregressive integrated moving average models. Nag and Mitra (2002) claim that ANNs are considered to be a valuable tool for building nonlinear models of data such as the ones found in foreign exchange rates. One of the many advantages of ANNs is that its models are data-driven and self-adaptive. Hornik (1991) advocates for the approximation capabilities of neural networks by stating that they can estimate any continuous function to any desired accuracy. The non-linearity of ANN's models gives them the advantage of not having to specify the functional relationship between input and output variables (Nag & Mitra, 2002).

ANNs are much better than other existing statistical methods when it comes to out-of-sample forecasting ability. Nag and Mitra (2002) argue that genetically engineered ANN models are much better than non-linear time series models and fixed-geometry ANN models when it comes to prediction, power and accuracy. These genetically engineered ANN models make use of an iterative algorithm in which ANNs are tested in order to determine their fitness in solving a problem. The best networks are selected and are genetically modified until an optimum network architecture is reached. "Through this process, the better networks survive and their features are carried forward into future generations and are combined with others to find better networks for the particular application. This genetic search method is much more effective than random searching, as the genetic process of recombining features vastly improves the speed of identifying highly fit networks" (Nag & Mitra, 2002).

The development of a high-quality neural network model is a difficult task (Walczak, 2001). Most financial traders desiring to use ANNs face two dilemmas: the selection of appropriate variables and the quantity of information needed (training examples) so that the neural network can adequately model the financial time series. Recent research has shown that too much information can seriously decrease and harm the quality of the neural network architecture. Walczak claims that smaller training set sizes outperform larger training set sizes, thus contradicting the work done by Box, Jenkins and Reinsel (1994) which claimed to have proven otherwise. These smaller-than-expected training sizes led to the formulation of the Time Series Recency Effect. This theory states that building a model with data which is closer in time to the data that is supposed to be forecasted will produce a higher-quality model. The advantages of this model are the following: it paves the way to rule out the models making use of huge quantities of data; it produces higher-quality models; it reduces the development costs of neural network time series models since less information is required; and it contributes to a net reduction in development time (Walczak, 2001).

Velásquez and González (2006) model the effect of the Colombian real exchange rate index using neural networks. They develop a univariate model based on neural networks of the real exchange rate index of the Colombian currency against the currencies of eighteen member countries of the International Monetary Fund. They find that the series of the Colombian currency does not follow a linear trend, thus making it apt for the use of neural networks. The neural network developed in their research is able to capture the non-linear deterministic relationships of the real exchange rate value for the Colombian currency in the current and previous month. The residuals obtained from the non-linear model are smaller in magnitude and size than the ones obtained if a linear model were used with the same parameters. They conclude that the model developed is a better predictor of the series dynamics than a linear model.

Improvements in the forecasting capacity of neural networks through the use of genetic algorithms or a hybrid between a fixed-neural network model and a genetic algorithm have been sought for some time. The purpose is to construct an ANN exchange rate model that does not suffer from the limitations of the traditional fixed-geometry ANN models and performs significantly better. In order to do this, a genetic algorithm search procedure is employed in order to optimize the ANN architectural parameters. Andreou and Zombanakis (2006) study the predictive forecasting power of neural network methodology on the Euro exchange rate versus the U.S. Dollar and the Japanese Yen. Their analysis is based on the research done by Andreou, Georgopoulos and Likothanassis (2002) which succeeded in forecasting the developments of the Greek Drachma versus the U.S. Dollar, the Deutsche Mark, the French Frank and the British Pound with nearly 99% accuracy by using neural networks trained with Kalman filtering and evolved by a dedicated genetic algorithm in terms of typology and size. In their paper, they attempt to do a forecast of the U.S. Dollar and the Japanese Yen rates versus the Euro making use of the same technique employed by Andreou et al. (2002), but applying it to a series of five-minutes observations covering the last three months of 2004.

They analyze the cyclical behavior showed by their series through the use of various forms of Rescaled Range Statistics analysis (R/S analysis). One of the aims of this R/S analysis is to trace long-term memory in a time series. According to their analysis, the U.S. Dollar / Euro series shows no specific long time pattern while the Yen / Euro series shows a misleading pattern. Their main conclusion is that the neural networks they used are able to learn the underlying dynamics of the exchange-rate developments and yields successful results of above 98% accuracy.

2.2.2 Support Vector Machines

Cristianini and Shawe-Taylor (2000) allege that SVMs are able to improve the generalisation property of neural networks. This is done through the use a hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. Originally introduced by Vapnik and his colleagues, SVMs have become a new powerful tool for learning from data and for outperforming other models when it comes to classification and regression problems. Compared to the empirical risk minimization of NN, an SVM is able to minimize the structural risk, specifically the upper bound of the generalization error instead of minimizing the empirical error, thus resulting in better generalization than other conventional forecasting techniques. SVM produce a nonlinear regression in a low-dimensional space. The input data is nonlinearly mapped in a high dimensional feature space by using a kernel function, and then a linear regression is run in this altered space.

The objective is to determine a function f which approximates the unknown function $d(x)$ obtained from the data set $D= \{(x_1, y_1),\ldots.,(x_i, y_i),\ldots(x_N, y_N)\}$, where x_i represents the input vector and y_i the predicted value. The dataset is assumed to have the following linear function:

$$f(x) = \sum_{i=1}^{N} w_i \phi_i(x) + b \qquad (1)$$

where $\phi_i(x)$ represents the feature which is nonlinearly mapped from the input space *x*. The constants w_i and *b* are obtained from the minimization of the regularized risk function:

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \frac{1}{2}\|w\|^2 \quad (2)$$

$$L_\varepsilon(d, y) = \begin{cases} |d-y|-\varepsilon & |d-y| \geq \varepsilon, \\ 0 & otherwise, \end{cases} \quad (3)$$

where both *C* and *ε* are prescribed parameters. The regularized constant *C* estimates the tradeoff between the empirical error and model flatness. The first term $L_\varepsilon(d, y)$ describes the ε-insensitive loss function where errors below ε are not penalized, knowing ε beforehand. The term $\frac{1}{2}\|w\|^2$ measures function flatness. By using the slack variables ζ and ζ^* which represent the distance from the actual values to their respective boundary values of ε-tube, equation (2) becomes:

Minimize:

$$R(w, \zeta, \zeta^*) = \frac{1}{2}\|w\|^2 + C^*(\sum_{i=1}^{N} \zeta_i + \zeta_i^*) \quad (4)$$

Subjected to:

$$w\phi(x_i) + b_i - d_i \leq \varepsilon + \zeta_i^*, \quad (5)$$

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \zeta_i, \quad (6)$$

$$\zeta \ , \zeta \ \geq 0 \quad (7)$$

$i = 1, 2, ..., N.$

Afterwards, equation (1) becomes:

$$f(x, a_i, a_i^*) = \sum_{i=1}^{N} (a_i - a_i^*) K(x, x_i) + b \quad (8)$$

where a_i, a_i^* represent the Lagrange multipliers introduced. The equality $a_i * a_i^* = 0, a_i \geq 0, \ a_i^* \geq 0, i = 1, ..., N,$ is satisfied by the Lagrange multipliers and these are obtained by maximizing the dual form of equation (4) which takes the following form:

$$\phi(a_i, a_i^*) = \sum_{i=1}^{N} d_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^{N} (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i - a_i^*)(a_j - a_j^*) K(x_i, x_j) \quad (9)$$

with the constraints:

$$\sum_{i=1}^{N} (a_i - a_i^*) = 0$$
$$0 \le a_i \le C, i = 1, 2, ..., N$$
$$0 \le a_j \le C, i = 1, 2, ..., N$$

In equation (8), $K(x\ ,x_i\ )$ is called the kernel function. Its value is equal to the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$ such that Mercer's condition is satisfied, $K(x_i, x_j) = \phi(x_i) * \phi(x_j)$. The kernel function used in this study is the Gaussian kernel function:

$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / (2\sigma^2))$. The Gaussian kernel function was used to determine the nonlinear behavior of the exchange rates because they perform well under general smoothness assumptions.

2.2.3 Comparing Methodologies

Research done on the subject has focused on making comparisons between the predictive capacity of SVM models and that of back-propagation (BPNNs) neural network models. BPNNs have proven to be effective, efficient and profitable tools in forecasting financial time series. Tenti (1996) claims that since BPNNs architectures are model-free estimators, they are considered to be universal function approximators able to detect nonlinearities with a remarkable certainty. For this reason, BPNNS are great at prediction and classification problems. Cao and Tay (2003) compare the feasibility of SVM in financial forecasting to the ones of multilayer BPNN and regularized radial basis function (RBF) neural network.

Among the findings, they claim that SVM are an excellent alternative to BPNNs for financial time series forecasting. They find that the RBF neural network and the SVM model perform alike, significantly better than the BP neural network. They also allege that the selection of free parameters plays an important role in the forecasting accuracy of the model. A SVM model with adaptive parameters achieves higher generalization performance and makes use of fewer support vectors than standard SVM in financial forecasting. Cao and Tay (2001) study the predictive performance of SVM compared to the one obtained from BP neural networks. They conclude that it is advantageous to use

SVMs in financial time series forecasting due to its superior forecasting ability based on the results of five performance metrics: NMSE, MAE, DS, CP and CD. The smaller values obtained for the NMSE and MAE, and the larger values obtained for the DS, CP, and CD argue for the use of SVMs instead of BP neural networks.

Comparisons have also been made between SVMs and ARIMA models. Hansen, McDonald and Nelson (2006) compare the predictive potential of SVMs for time series forecasting with three widely accepted ARIMA models, namely, the Forecast Pro, EGB2 and GT. They make use of nine problem domains each representing a single real time series having uniquely characteristics. They find that SVM outperforms the other models and achieves the best results in 8 of the domains. They also conclude that SVM and Forecast Pro's results are robust under a variety of time series complexities, and that the EGB2 model appears to perform well in certain problems only. The GT model performance is insufficient compared to the one obtained from the other three models.

Pai and Lin (2005) try to come up with a hybrid model capable of improving the forecasting accuracy of its individual models for stock prices. This hybrid model has ARIMA and SVM components. They argue that the ARIMA model serves as a preprocessor to filter the linear pattern of data sets. Afterwards, the error terms obtained from the ARIMA model are fed into the SVMs in the hybrid models. The purpose of running the SVMs is to reduce the error function from the ARIMA. The regularization parameters of the SVMs are adjusted. The results indicate that the hybrid model outperforms the other models based on the MAE, MSE, MAPE, and the RMSE. The proposed hybrid model yields better forecasting results than the random walk models. Pai, Hong, Chang and Chen (2006) try to present a hybrid model, having genetic algorithms (GAs) and support vector machine components, in order to forecast tourist arrivals in the island of Barbados. GAs are used in order to determine the values of the three free parameters of the SVM model. The GAs are used to yield a smaller MAPE by searching for better combinations of the three parameters in the SVM model. The forecasting performance of the SVM genetically modified models outperforms those of the other ARIMA models. The SVMGA model with the smallest MAPE value is chosen as the best model.

Ince and Trafalis (2006) propose a hybrid forecasting model which incorporates parametric and nonparametric techniques. Among the parametric techniques proposed, the ARIMA, the VAR and other co-integration techniques are used. The SVR and ANN (MLP) are used as nonparametric ones. The parametric techniques are used to model an input selection process, and after the number of inputs is determined, the techniques of ANN and SVR are applied to the dataset. Specifically, they try to identify the most important factors influencing the daily value of exchange rates by making use of ARIMA and VAR techniques. After the number of inputs is determined, SVR and MLP networks are applied to the dataset. The performance of SVR against MLP networks (and vice versa) is evaluated by making use of MSE and MAE metrics. Moreover, the performance of the input selection method, namely ARIMA vs. VAR, is also compared. The results show that the SVR methodology does perform better than MLP networks for each input selection algorithm. Regarding the input selection process, the authors argue that the best selection procedure is dependent upon the training algorithms. For a MLP network, it is better to use a VAR technique to determine the inputs. But if a SVR method is used, then the ARIMA input selection technique will give the best results.

Ince and Trafalis (2007) try to determine the most influential inputs for a forecasting model in order to better predict stock prices. By making use of five technical indicators along with two heuristic models and of nonparametric techniques, they are able to conclude that heuristic input selection models based on personal experience are better than kPCA and factor analysis. Their results show that it would be unwise to choose the explanatory variables by using some statistical techniques because of the dependency of these techniques on the experience of the market. They conclude by stating that the right inputs vary with the learning algorithm. Kamruzzaman (2003) analyzes the prediction of the foreign currency exchange rates of six countries against the Australian dollar. He tries to determine the performance of SVM for Australian forex forecasting in terms of kernel type and sensitivity of free parameters selection. Specifically, he tries to determine the effect of a single kernel function on prediction accuracy, and the effect of free parameter selection on prediction error. He finds that no single kernel function dominates all currency prediction.

Instead, the kernel function should be chosen based on the pattern of the individual currency rate. Different values of the regularization parameters hardly have any impact on the variation of the prediction error. The support vectors remain the same and the performance is not affected at all. Hock and Cao (2001) propose a two-stage neural network architecture by combining SVM with self-organizing feature maps (SOM). Specifically, they use what is known as a mixture of experts architecture (ME). In the first stage, the SOM divides the input space into several disjoint regions. Then a tree-structured architecture is used for partition, which divides the large input space into two regions until a specified partition condition is not satisfied. In the second stage, different SVM experts, using different kernel functions and learning parameters, are constructed to deal with the different input regions. The prediction performance of the proposed model is evaluated using the NMSE, MAE, DS and WDS metrics. The author concludes that the proposed method performs better and faster than a single SVM model.

2.3 Presentation of the experiment and results

2.3.1 Variables justification

What are the determinants of exchange rate movements? No one knows for sure, but recent research suggests that some key macroeconomic variables play a significant role in exchange rate determination. These macroeconomic variables are all related to the trading relationship between two countries. As for example, a country that has a lower inflation rate will exhibit a rising currency value since its purchasing power has increased compared to the currency of another country with a higher inflation rate. Those countries having a higher inflation rate will experience depreciation in their currencies compared to the currencies with a lower inflation rate. Often, this goes hand to hand with higher interest rates. Higher interest rates offer lenders an opportunity to receive a higher return from their investment relative to other countries. Consequently, higher interest rates will attract foreign capital and will cause a rise in the exchange rate. Chinn (2003) conducts a survey among foreign exchange traders in the United States and finds that all of them agreed with the fact that news about macroeconomic variables is incorporated rapidly into exchange rates, even though the relative importance of individual macroeconomic variables shifts over time.

The author finds that interest rates predict quite well the foreign exchange rate at long-time horizons. Balassa (1964) and Samuelson (1964) suggest that productivity, growth domestic product and exchange rates are linked, at least, in a theoretical level. Chinn (2003) finds that productivity levels affect the dollar exchange rate in the long run and also found a strong correlation for the US dollar/ Euro exchange rate. Theoretically, the current account balance of a country (CAB) is written as a function 'X' of the real exchange rate, the domestic GDP and the foreign GDP. The CAB should increase if the real exchange rate increases (domestic currency depreciation), domestic GDP decreases or foreign GDP increases. Floyd (2007) argues that occasionally the real exchange rate and the current account balance will be positively related, negatively related or with no apparent relationship. It will depend on the magnitudes of the underlying shocks to saving and investment in comparison to the magnitudes of the shocks to desired exports and imports.

According to an August 2007 poll by Consensus Economics, one of the world's leading international economic survey organizations, the principal macroeconomic indicators affecting exchange rates movements against the US dollar are: the relative growth, inflation differential, trade/current account balance, interest rate differentials and equity flows. In this August 2007 special survey of factors affecting exchange rates, their panelists are asked to rank the current importance of a range of different factors or economic indicators in determining exchange rate movements (against the US dollar, unless otherwise noted). Scores are assigned to each of the factors shown in the table below on a scale of 0 (no influence) to 10 (very strong influence). The consensus results are the averages of individual panelists' scores for each factor or economic indicator. Given that different currencies are influenced by a wide range of factors, the following common list of five (relative growth, inflation differential, trade/current account balance, interest rate differentials and equity flows) are considered, and for which panelists are asked to assess for every currency (See Table 2.1 shown below). Scores are assigned to each of the factors shown in the table below on a scale of 0 (no influence) to 10 (very strong influence).

Table 2.1: Consensus ranking of exchange rate determinants						
Exchange Rates per US$, unless Otherwise Stated	**Relative Growth**	**Inflation Differential**	**Trade / Current Account**	**Interest Rate Differentials Short (Long)**	**Equity Flows**	**Other Factors (Score)**
G-7 & Western Europe						
Euro	5.0	5.3	5.9	9.0 (5.5)	4.3	
Japanese Yen	6.5	5.7	5.0	8.8 (7.0)	5.8	*Market Volatility (9.0) Structural Flows (9.0)*
UK Pound	6.0	6.3	3.5	9.0 (6.1)	6.0	*M&A Flows (5.9)*

Table 2.1: Consensus ranking of exchange rate determinants

2.3.2 Data set description

For purposes of this paper, the variables considered to determine exchange rate movements are: the inflation differential, the interest rate differential, the GDP, productivity, and the current account balance (CAB). Since data is collected for both zones, there are 10 economic variables under scrutiny. The data for these variables is collected monthly from January 1999, which is the year of the introduction of the euro, until December 2007. Monthly data for the variables inflation and interest rate differential is gathered from the bulletins published by the US Federal Reserve Board, the US Bureau of Labor Statistics and the European Central Bank statistical warehouse. On the other hand, quarterly data from the US Bureau of Economic Analysis, US Bureau of Labor Statistics and European Central Bank statistical warehouse is gathered for the variables productivity, GDP and CAB since these indicators are only published on a quarterly basis rather than a monthly basis.

Knowing that monthly data is needed in order to run the experiment, the quarterly values are assumed to be constant during their respective three month period (each month is assigned its respective quarterly value). For the exchange rate variable, the data set comes from the Pacific Exchange Rate Service database (2008). For the CAB indicator, the values for the first three months of 1999 are missing. In order to compensate for this shortcoming, the first three months for each one of the five indicators are not counted when performing the experiment. A total of 105 observations are collected in all from January 1999 until December 2007.

2.3.3 Experiments and Results

With the data collected, four different experiments are run using the statistical software package known as R Project for Statistical Computing (R, 2006). Each experiment produces an SVM model with a Gaussian kernel component. Using the function in R known as ‘tune.svm’, different values are assigned to the prescribed parameter C, which is the regularized constant determining the tradeoff between the empirical error and the model flatness, and the variable sigma σ, which is present in the denominator of the kernel component of the Gaussian function. The values for the parameter C are: 1, 10, 100, and 1000. The values assigned to the variable σ go from 0,1 to 2, each time increasing the range by 0,1 margin. There are 20 possible values for σ and 4 for C, thus having 80 possible combinations in every single experiment.

The sampling method employed to produce all these combinations is a 10-fold cross validation method. This method gives the result that minimizes the validation process. All four experiments have as inputs the following: the percentage change in GDP, Productivity, CAB, Inflation, and the interest rate differential. The output for all experiments is the exchange rate (ER) of the dollar against the euro ($/€). The forecasting horizon is one month time. The performance metric used to evaluate our results is the mean squared error (MSE). Next, the four experiments will be explained in detail in ascending order.

In the first experiment, all ten macroeconomic variables are used as inputs and the ER is used as output. The R command used for purposes of this experiment is:

```
obj<-tune.svm(ER~., data= datos, gamma=seq(0.1,2,by=0.1),cost=c(1,10,100,1000))
obj.
```

With a σ of 0,1 and a C of 100, the best performance obtained has an MSE of 0,00990.

In the second experiment, only five variables are used as inputs which consist of the difference between the US and EU variables. The R command used in this experiment is:

```
datos2<-data.frame(datos[1]-datos[2]);
for (i in 2:5) datos2<-cbind(datos2,datos[2*i-1]-datos[2*i]) datos2<-cbind(datos2,datos[11])
names(datos2)<-c("dif_Inf","dif_Pro", "dif_GDP", "dif_CAB", "dif_IRD", "ER")
obj2<-tune.svm(ER~., data=datos2, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj2$best.performance
```

With a σ of 0,5 and a C of 10, the best performance obtained has an MSE of 0,00850. In the third experiment, the quotients for the two zones ($\frac{\$}{€}$) are used as inputs, and the ER as output. The R command used is:

```
datos3<-data.frame(datos[1]/datos[2]);
for ( i in 2:5) datos3<-cbind(datos3,datos[2*i-1]/datos[2*i]) datos3<-cbind(datos3,datos[11])
names(datos3)<-c("Inf", "Pro", "GDP", "CAB", "IRD","ER")
obj3<-tune.svm(ER~., data=datos3, gamma= seq(0.1,2,by=0.1),cost=c(1,10,100,1000))
obj3$best.performance
```

With a σ of 1,2 and a C of 1000, the best performance obtained has an MSE of 0,00420.

In the last experiment, six variables are used as inputs. These consist of the five variables of the previous experiment plus the ER of the previous period. The ER is used as output. The R command used is:

```
datos4<-data.frame( datos [1:104,11]
datos4<-cbind(datos4,datos3[2:105,1:6])
names(datos4)<-c("ER_ant", "Inf", "Pro", "GDP", "CAB", "IRD","ER")
obj4<-tune.svm(ER~., data=datos4, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj4$best.performance
```

With a σ of 0,1 and a C of 10, the best performance obtained has an MSE of 0,00130. Once all four models are trained with the input data, these models are tested in order to measure their forecasting power and predictive accuracy. In order to accomplish this, 20 data points are used as a training set along with graphical representations of each model's prediction. The graphs shown below will illustrate this point better (Figure 2.1). The first graph on the upper left belongs to the first experiment, followed by the second experiment which is the graph on the upper right side of the page. The third and four experiments are shown below following the same placement order. The blue points represent the data points. The red lines show each model's prediction. The numbers above each graph show the error obtained from the models' predictions.

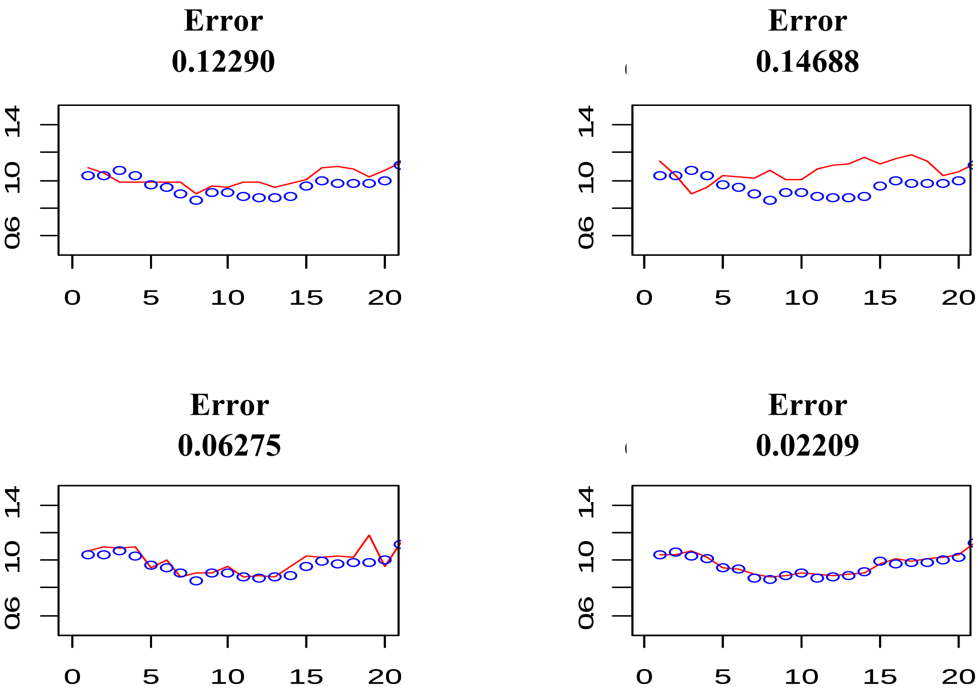


Figure 2.1: Models' predictions

2.4 Interpretation of the Results

By taking a closer look at the graphs, it can be seen that the first model follows more or less the path left by the training set points (blue points), but fails to provide an accurate forecast (was the third lowest with a 12,29% of error). The second model misses almost entirely the trace left behind by the training set points, thus making it the model with the worst forecasting accuracy among them all (14,69%). The third model produces the second highest and more accurate forecast with a 6,28% of error. It can be seen that in the beginning and along the middle, the third model follows strictly the blue points, but unfortunately rises a little bit at the end. Finally, the best prediction is achieved with the fourth model which has the lowest MSE, 2,21%. The fourth model is able to generalize better than the rest, thus producing a high quality forecast. Ideally, an SVM model which minimizes prediction errors would be the most attractive method. However, in practice other considerations need to be taken into account before any single kernel method is chosen.

2.4.1 Conclusions and Future Research

This paper investigates the performance of an SVM model for American forex forecasting in terms of sensitivity of free parameters selection. In reducing total prediction error, experiment four comes out as producing the best result. Over a wide range of values for regularization parameters C and σ, the results show that a C=10 and a gamma of 0.1 produce the best performance. Further improvements needs to be made on the proper selection of variables as inputs, suitable kernel functions, more variables, more performance metrics and more comparisons of linear and non linear forecasting models. Future research could explore the possibility of coming up with a hybrid model having an SVM and any other non-linear component such as NNs or GAs. Recent research done on this field has shown the potential advantages and applications that could be obtained for exchange rate forecasting by employing these powerful predictive tools. Another research possibility could be to examine the impact of external variables, such as political events, on the exchange rate mechanism. Recent political situations have shown that the governmental instability experienced by one country could have irreversible consequences on the economical development of neighboring countries, and thus affect or inhibit any advantageous agreement fostered by neutral parties.

2.5 References

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APPENDIX TO CHAPTER 2

R Commands

```
library("class");library("e1071")
setwd("C:/Documents and Settings/Jaime/Desktop/")
datos<-read.table('josean1.csv',sep=";")
names(datos)<-c("Inf_US", "Inf_EU", "Pro_US", "Pro_EU", "GDP_US", "GDP_EU", "CAB_US",
"CAB_EU", "IRD_US", "IRD_EU", "ER")
```

INPUTS:

Inf_US, Inf_EU: Inflation
Pro_US, Pro_EU: Productivity
GDP_US, GDP_EU: Gross Domestic Product
CAB_US, CAB_EU: Current Account Balance
IRD_US, IRD_EU: Intr.rate diff.

OUTPUT:

ER: Exchange Rate

EXPERIMENT 1

```
obj<-tune.svm(ER~., data=datos, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj
```

EXPERIMENT 2:

```
datos2<-data.frame(datos[1]-datos[2]);
for (i in 2:5) datos2<-cbind(datos2,datos[2*i-1]-datos[2*i])
datos2<-cbind(datos2,datos[11])
names(datos2)<-c("dif_Inf", "dif_Pro", "dif_GDP", "dif_CAB", "dif_IRD", "ER")
obj2<-tune.svm(ER~., data=datos2, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj2$best.performance
```

EXPERIMENT 3:

```
datos3<-data.frame(datos[1]/datos[2]);
for (i in 2:5) datos3<-cbind(datos3,datos[2*i-1]/datos[2*i])
datos3<-cbind(datos3,datos[11])
names(datos3)<-c("Inf", "Pro", "GDP", "CAB", "IRD","ER")
obj3<-tune.svm(ER~., data=datos3, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj3$best.performance
```

EXPERIMENT 4:

```
datos4<-data.frame(datos[1:104,11])
datos4<-cbind(datos4,datos3[2:105,1:6])
names(datos4)<-c("ER_ant", "Inf", "Pro", "GDP", "CAB", "IRD","ER")
obj4<-tune.svm(ER~., data=datos4, gamma= seq(0.1,2,by=0.1), cost=c(1,10,100,1000))
obj4$best.performance
```

TRAINING PHASE EXPERIMENTS 1 THROUGH 4:

```
split.screen(c(2,2))
indtra<-sample(104,75)
```

```
screen(1)
model<- svm(ER~., data=datos, subset=indtra,gamma=obj$best.parameters$gamma,
cost=obj$best.parameters$cost)
pred<-predict(model,datos[-indtra,1:10])
plot(pred, col="red", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="", type='l')
par(new=T)
plot(datos[-indtra,11], col="blue", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="")
#error cuadrático medio
title(main=c("error",sqrt(sum((pred-datos[-indtra,11])^2)/length(pred))))
```

```
screen(2)
model<- svm(ER~., data=datos2, subset=indtra,gamma=obj2$best.parameters$gamma,
cost=obj2$best.parameters$cost)
pred<-predict(model,datos2[-indtra,1:5])
plot(pred, col="red", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="", type='l')
par(new=T)
plot(datos2[-indtra,6], col="blue", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="")
#error cuadrático medio
title(main=c("error",sqrt(sum((pred-datos2[-indtra,6])^2)/length(pred))))
```

```
screen(3)
model<- svm(ER~., data=datos3, subset=indtra,gamma=obj3$best.parameters$gamma,
cost=obj3$best.parameters$cost)
pred<-predict(model,datos3[-indtra,1:5])
plot(pred, col="red", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="", type='l')
par(new=T)
plot(datos3[-indtra,6], col="blue", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="")
#error cuadrático medio
title(main=c("error",sqrt(sum((pred-datos3[-indtra,6])^2)/length(pred))))
```

```
screen(4)
model<- svm(ER~., data=datos4, subset=indtra,gamma=obj4$best.parameters$gamma,
cost=obj4$best.parameters$cost)
pred<-predict(model,datos4[-indtra,1:6])
plot(pred, col="red", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="", type='l')
par(new=T)
plot(datos4[-indtra,7], col="blue", xlim=c(0,20), ylim=c(0.5,1.5),xlab="", ylab="")
#error cuadrático medio
title(main=c("error",sqrt(sum((pred-datos4[-indtra,7])^2)/length(pred))))
```

Table I: Monthly percentage changes of macroeconomic variables

		Inflation		Productivity		GDP		Cur.Acc.Bal		Intr.rate diff.		E R
		US	EU	US	EU	US	EU	US	EU	US	EU	
1999	**January**	0.20000	0.03300	3.60000	0.09000	3.40000	2.18000	4.01500	n/a	4.63000	3.13800	1.16100
	February	0.00000	0.06000	3.60000	0.09000	3.40000	2.18000	4.01500	n/a	4.76000	3.11800	1.12100
	March	0.10000	0.17500	3.60000	0.09000	3.40000	2.18000	4.01500	n/a	4.81000	2.92500	1.08800
	April	0.70000	0.25400	0.90000	0.52000	3.40000	2.36000	13.96300	-138.18500	4.74000	2.70900	1.07000
	May	0.10000	0.04500	0.90000	0.52000	3.40000	2.36000	13.96300	-138.18500	4.74000	2.55100	1.06300
	June	0.00000	0.06000	0.90000	0.52000	3.40000	2.36000	13.96300	-138.18500	4.76000	2.56300	1.03800
	July	0.40000	0.25000	2.80000	1.19000	4.80000	3.08000	11.93800	-414.80800	4.99000	2.52100	1.03500
	August	0.20000	0.14700	2.80000	1.19000	4.80000	3.08000	11.93800	-414.80800	5.07000	2.44300	1.06000
	September	0.40000	0.12700	2.80000	1.19000	4.80000	3.08000	11.93800	-414.80800	5.22000	2.43400	1.05000
	October	0.20000	0.11500	7.00000	2.08000	7.30000	4.07000	6.00100	74.342000	5.20000	2.50200	1.07100
	November	0.20000	0.17800	7.00000	2.08000	7.30000	4.07000	6.00100	74.34200	5.42000	2.93500	1.03400
	December	0.20000	0.20900	7.00000	2.08000	7.30000	4.07000	6.00100	74.34200	5.30000	3.04200	1.01100
2000	**January**	0.30000	0.26600	-1.80000	2.01000	1.00000	4.23000	15.51400	15.19500	5.45000	3.04300	1.01400
	February	0.40000	0.14000	-1.80000	2.01000	1.00000	4.23000	15.51400	15.19500	5.73000	3.27600	0.98300
	March	0.60000	0.16500	-1.80000	2.01000	1.00000	4.23000	15.51400	15.19500	5.85000	3.51000	0.96400
	April	-0.10000	-0.03900	7.50000	2.01000	6.40000	4.62000	0.82500	4.00500	6.02000	3.68500	0.94700
	May	0.20000	0.14000	7.50000	2.01000	6.40000	4.62000	0.82500	4.00500	6.27000	3.92000	0.90600
	June	0.60000	0.38800	7.50000	2.01000	6.40000	4.62000	0.82500	4.00500	6.53000	4.29500	0.94900
	July	0.30000	0.24400	-0.90000	1.31000	-0.50000	3.80000	8.55000	38.29800	6.54000	4.30900	0.94000
	August	0.00000	0.14000	-0.90000	1.31000	-0.50000	3.80000	8.55000	38.29800	6.50000	4.41900	0.90400
	September	0.50000	0.45000	-0.90000	1.31000	-0.50000	3.80000	8.55000	38.29800	6.52000	4.59000	0.87200
	October	0.20000	0.03900	3.90000	0.82000	2.10000	3.33000	2.45900	0.06400	6.51000	4.76300	0.85500
	November	0.20000	0.27200	3.90000	0.82000	2.10000	3.33000	2.45900	0.06400	6.51000	4.82900	0.85600
	December	0.20000	0.17300	3.90000	0.82000	2.10000	3.33000	2.45900	0.06400	6.40000	4.82700	0.89700
2001	**January**	0.60000	-0.09900	-0.50000	0.82000	-0.50000	2.96000	-2.98500	-45.40800	5.98000	4.75600	0.93800
	February	0.20000	0.17900	-0.50000	0.82000	-0.50000	2.96000	-2.98500	-45.40800	5.49000	4.99300	0.92200
	March	0.10000	0.30600	-0.50000	0.82000	-0.50000	2.96000	-2.98500	-45.40800	5.31000	4.78100	0.91000
	April	0.20000	0.40600	5.70000	0.39000	1.20000	2.03000	-9.27200	-28.98100	4.80000	5.06400	0.89200
	May	0.50000	0.49000	5.70000	0.39000	1.20000	2.03000	-9.27200	-28.98100	4.21000	4.65400	0.87400
	June	0.20000	0.17800	5.70000	0.39000	1.20000	2.03000	-9.27200	-28.98100	3.97000	4.54000	0.85300
	July	-0.20000	-0.02400	1.80000	0.27000	-1.40000	1.66000	-6.18800	-87.43400	3.77000	4.50500	0.86100
	August	0.00000	-0.01300	1.80000	0.27000	-1.40000	1.66000	-6.18800	-87.43400	3.65000	4.49100	0.90100
	September	0.40000	0.28000	1.80000	0.27000	-1.40000	1.66000	-6.18800	-87.43400	3.07000	3.98700	0.91100
	October	-0.30000	0.06100	6.00000	0.03000	1.60000	1.02000	-3.67400	-624.81100	2.49000	3.97100	0.90600
	November	-0.10000	0.01700	6.00000	0.03000	1.60000	1.02000	-3.67400	-624.81100	2.09000	3.50700	0.88800
	December	-0.10000	0.18700	6.00000	0.03000	1.60000	1.02000	-3.67400	-624.81100	1.82000	3.33900	0.89200
2002	**January**	0.20000	0.56900	7.20000	-0.52000	2.70000	0.51000	18.51400	58.76100	1.73000	3.29400	0.88300
	February	0.20000	0.04900	7.20000	-0.52000	2.70000	0.51000	18.51400	58.76100	1.74000	3.28300	0.87000
	March	0.30000	0.28400	7.20000	-0.52000	2.70000	0.51000	18.51400	58.76100	1.73000	3.26400	0.87600
	April	0.40000	0.21200	0.70000	0.09000	2.20000	0.88000	10.79800	-17.57800	1.75000	3.31600	0.88600
	May	0.10000	0.20100	0.70000	0.09000	2.20000	0.88000	10.79800	-17.57800	1.75000	3.31000	0.91700
	June	0.10000	0.00600	0.70000	0.09000	2.20000	0.88000	10.79800	-17.57800	1.75000	3.34900	0.95500
	July	0.20000	0.15900	4.30000	0.56000	2.40000	1.17000	0.28200	119.12500	1.73000	3.30200	0.99200
	August	0.30000	0.16900	4.30000	0.56000	2.40000	1.17000	0.28200	119.12500	1.74000	3.29300	0.97800
	September	0.20000	0.20400	4.30000	0.56000	2.40000	1.17000	0.28200	119.12500	1.75000	3.31900	0.98100
	October	0.20000	0.18200	-0.30000	0.67000	0.20000	1.11000	6.28500	-37.83100	1.75000	3.30000	0.98100
	November	0.20000	0.03200	-0.30000	0.67000	0.20000	1.11000	6.28500	-37.83100	1.34000	3.30400	1.00100
	December	0.20000	0.18900	-0.30000	0.67000	0.20000	1.11000	6.28500	-37.83100	1.24000	3.09800	1.01800
2003	**January**	0.40000	0.43100	3.40000	0.74000	1.20000	0.91000	9.52200	-69.83500	1.24000	2.78700	1.06200
	February	0.50000	0.29700	3.40000	0.74000	1.20000	0.91000	9.52200	-69.83500	1.26000	2.76400	1.07700
	March	0.20000	0.26900	3.40000	0.74000	1.20000	0.91000	9.52200	-69.83500	1.25000	2.74900	1.08100
	April	-0.40000	-0.12400	5.90000	0.12000	3.50000	0.48000	-3.70200	23.16100	1.26000	2.56100	1.08500
	May	-0.20000	-0.04800	5.90000	0.12000	3.50000	0.48000	-3.70200	23.16100	1.26000	2.55700	1.15800
	June	0.10000	0.18200	5.90000	0.12000	3.50000	0.48000	-3.70200	23.16100	1.22000	2.21300	1.16600
	July	0.30000	0.15600	10.20000	0.13000	7.50000	0.64000	0.32000	129.58300	1.01000	2.07800	1.13700

	August	0.40000	0.26200	10.20000	0.13000	7.50000	0.64000	0.32000	129.58300	1.03000	2.09800	1.11400
	September	0.30000	0.25800	10.20000	0.13000	7.50000	0.64000	0.32000	129.58300	1.01000	2.02100	1.12200
	October	-0.10000	0.08700	-0.40000	0.39000	2.70000	1.18000	-3.18300	14.09100	1.01000	2.01500	1.16900
	November	0.10000	0.13000	-0.40000	0.39000	2.70000	1.18000	-3.18300	14.09100	1.00000	1.97300	1.17000
	December	0.30000	0.042	-0.40000	0.39000	2.70000	1.18000	-3.18300	14.09100	0.98000	2.05700	1.22900
2004	**January**	0.40000	0.31700	0.80000	1.00000	3.00000	1.69000	10.74100	54.15200	1.00000	2.02100	1.26100
	February	0.30000	0.14300	0.80000	1.00000	3.00000	1.69000	10.74100	54.15200	1.01000	2.03200	1.26500
	March	0.20000	0.29100	0.80000	1.00000	3.00000	1.69000	10.74100	54.15200	1.00000	2.00600	1.22600
	April	0.20000	0.21700	4.80000	1.44000	3.50000	2.15000	13.39600	-20.34900	1.00000	2.07600	1.19900
	May	0.40000	0.32300	4.80000	1.44000	3.50000	2.15000	13.39600	-20.34900	1.00000	2.01500	1.20100
	June	0.40000	0.13000	4.80000	1.44000	3.50000	2.15000	13.39600	-20.34900	1.03000	2.02800	1.21400
	July	0.10000	0.13300	0.90000	1.16000	3.60000	1.94000	-0.38700	-40.67900	1.26000	2.06800	1.22700
	August	0.20000	0.24900	0.90000	1.16000	3.60000	1.94000	-0.38700	-40.67900	1.43000	2.04000	1.21800
	September	0.20000	0.04000	0.90000	1.16000	3.60000	1.94000	-0.38700	-40.67900	1.61000	2.05200	1.22200
	October	0.50000	0.31300	0.50000	0.84000	2.50000	1.66000	16.05500	30.90800	1.76000	2.11100	1.24900
	November	0.40000	-0.00300	0.50000	0.84000	2.50000	1.66000	16.05500	30.90800	1.93000	2.08500	1.29900
	December	0.10000	0.09500	0.50000	0.84000	2.50000	1.66000	16.05500	30.90800	2.16000	2.04600	1.34100
2005	**January**	0.00000	0.03500	3.40000	0.44000	3.10000	1.40000	-0.57800	-65.65300	2.28000	2.07700	1.31200
	February	0.30000	0.23100	3.40000	0.44000	3.10000	1.40000	-0.57800	-65.65300	2.50000	2.05900	1.30100
	March	0.30000	0.38900	3.40000	0.44000	3.10000	1.40000	-0.57800	-65.65300	2.63000	2.05700	1.32000
	April	0.50000	0.12400	0.70000	0.63000	2.80000	1.55000	0.46400	97.30300	2.79000	2.07600	1.29400
	May	-0.20000	0.19700	0.70000	0.63000	2.80000	1.55000	0.46400	97.30300	3.00000	2.07000	1.26900
	June	0.10000	0.18400	0.70000	0.63000	2.80000	1.55000	0.46400	97.30300	3.04000	2.06200	1.21700
	July	0.70000	0.30800	4.30000	0.95000	4.50000	1.84000	-5.36600	-80.10300	3.26000	2.07300	1.20400
	August	0.70000	0.27000	4.30000	0.95000	4.50000	1.84000	-5.36600	-80.10300	3.50000	2.06100	1.22900
	September	1.30000	0.41900	4.30000	0.95000	4.50000	1.84000	-5.36600	-80.10300	3.62000	2.09400	1.22600
	October	0.20000	0.13500	-1.40000	1.05000	1.20000	2.00000	24.45300	-117.55700	3.78000	2.06700	1.20200
	November	-0.50000	-0.16300	-1.40000	1.05000	1.20000	2.00000	24.45300	-117.55700	4.00000	2.08600	1.17900
	December	-0.10000	0.07600	-1.40000	1.05000	1.20000	2.00000	24.45300	-117.55700	4.16000	2.27900	1.18600
2006	**January**	0.60000	0.24700	2.10000	1.19000	4.80000	2.52000	-7.04200	267.22400	4.29000	2.32500	1.21000
	February	-0.10000	0.15900	2.10000	1.19000	4.80000	2.52000	-7.04200	267.22400	4.49000	2.35000	1.19400
	March	0.20000	0.18400	2.10000	1.19000	4.80000	2.52000	-7.04200	267.22400	4.59000	2.52000	1.20200
	April	0.50000	0.36800	1.30000	1.17000	2.40000	2.92000	2.48400	102.64100	4.79000	2.62800	1.22700
	May	0.30000	0.25700	1.30000	1.17000	2.40000	2.92000	2.48400	102.64100	4.94000	2.57700	1.27700
	June	0.30000	0.16100	1.30000	1.17000	2.40000	2.92000	2.48400	102.64100	4.99000	2.69800	1.26500
	July	0.50000	0.31500	-1.50000	1.20000	1.10000	2.85000	5.71000	131.64000	5.24000	2.81400	1.26800
	August	0.40000	0.13100	-1.50000	1.20000	1.10000	2.85000	5.71000	131.64000	5.25000	2.96800	1.28100
	September	-0.40000	-0.12000	-1.50000	1.20000	1.10000	2.85000	5.71000	131.64000	5.25000	3.04100	1.27300
	October	-0.50000	-0.03000	1.60000	1.56000	2.10000	3.23000	-13.52600	-176.95000	5.25000	3.27800	1.26100
	November	0.10000	0.08200	1.60000	1.56000	2.10000	3.23000	-13.52600	-176.95000	5.25000	3.32800	1.28800
	December	0.60000	0.12400	1.60000	1.56000	2.10000	3.23000	-13.52600	-176.95000	5.24000	3.50100	1.32100
2007	**January**	0.10000	0.20100	1.00000	1.36000	0.60000	3.16000	5.46100	142.71300	5.25000	3.56300	1.30000
	February	0.30000	0.15800	1.00000	1.36000	0.60000	3.16000	5.46100	142.71300	5.26000	3.57000	1.30700
	March	0.50000	0.26000	1.00000	1.36000	0.60000	3.16000	5.46100	142.71300	5.26000	3.69100	1.32400
	April	0.30000	0.35000	2.60000	0.79000	3.80000	2.47000	-4.10800	2.34800	5.25000	3.81900	1.35200
	May	0.50000	0.22400	2.60000	0.79000	3.80000	2.47000	-4.10800	2.34800	5.25000	3.79000	1.35110
	June	0.30000	0.19600	2.60000	0.79000	3.80000	2.47000	-4.10800	2.34800	5.25000	3.95600	1.34190
	July	0.20000	0.19600	6.30000	0.75000	4.90000	2.66000	-6.63700	-3.84700	5.26000	4.06300	1.37160
	August	0.00000	0.10900	6.30000	0.75000	4.90000	2.66000	-6.63700	-3.84700	5.02000	4.04700	1.36220
	September	0.40000	0.24800	6.30000	0.75000	4.90000	2.66000	-6.63700	-3.84700	4.94000	4.02900	1.38960
	October	0.30000	0.36500	1.90000	0.46000	0.60000	2.17000	-2.54100	-127.33000	4.76000	3.94100	1.42270
	November	0.90000	0.57500	1.90000	0.46000	0.60000	2.17000	-2.54100	-127.33000	4.49000	4.02200	1.46840
	December	0.40000	0.15000	1.90000	0.46000	0.60000	2.17000	-2.54100	-127.33000	4.24000	3.87900	1.45700

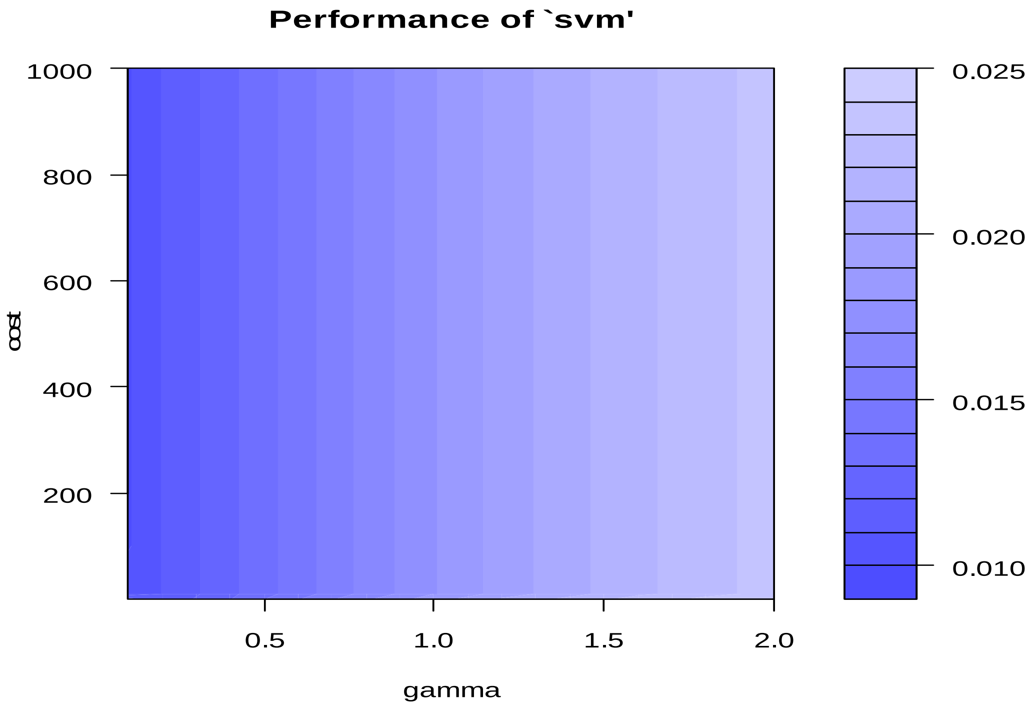
Detailed results: Experiment 1									
Trial	**Gamma**	**Cost**	**Error**	**Dispersion**	**Trial**	**Gamma**	**Cost**	**Error**	**Dispersion**
1	0.1	1	0.01243	0.01334	**43**	0.3	100	0.01187	0.00983
2	0.2	1	0.01130	0.01214	**44**	0.4	100	0.01275	0.00938
3	0.3	1	0.01206	0.01120	**45**	0.5	100	0.01363	0.00899
4	0.4	1	0.01297	0.01024	**46**	0.6	100	0.01452	0.00878
5	0.5	1	0.01398	0.00956	**47**	0.7	100	0.01542	0.00871
6	0.6	1	0.01495	0.00913	**48**	0.8	100	0.01630	0.00870
7	0.7	1	0.01592	0.00891	**49**	0.9	100	0.01713	0.00872
8	0.8	1	0.01684	0.00880	**50**	1	100	0.01793	0.00876
9	0.9	1	0.01771	0.00875	**51**	1.1	100	0.01868	0.00882
10	1	1	0.01853	0.00876	**52**	1.2	100	0.01939	0.00888
11	1.1	1	0.01932	0.00879	**53**	1.3	100	0.02004	0.00894
12	1.2	1	0.02004	0.00883	**54**	1.4	100	0.02065	0.00899
13	1.3	1	0.02071	0.00889	**55**	1.5	100	0.02120	0.00904
14	1.4	1	0.02131	0.00895	**56**	1.6	100	0.02171	0.00909
15	1.5	1	0.02187	0.00901	**57**	1.7	100	0.02219	0.00913
16	1.6	1	0.02237	0.00906	**58**	1.8	100	0.02262	0.00917
17	1.7	1	0.02284	0.00911	**59**	1.9	100	0.02302	0.00920
18	1.8	1	0.02326	0.00916	**60**	2	100	0.02339	0.00923
19	1.9	1	0.02365	0.00921	**61**	0.1	1000	0.00992	0.00898
20	2	1	0.02401	0.00924	**62**	0.2	1000	0.01100	0.00999
21	0.1	10	0.10547	0.01064	**63**	0.3	1000	0.01187	0.00983
22	0.2	10	0.01100	0.00999	**64**	0.4	1000	0.01275	0.00938
23	0.3	10	0.01187	0.00983	**65**	0.5	1000	0.01363	0.00899
24	0.4	10	0.01275	0.00938	**66**	0.6	1000	0.01452	0.00878
25	0.5	10	0.01363	0.00899	**67**	0.7	1000	0.01542	0.00871
26	0.6	10	0.01452	0.00878	**68**	0.8	1000	0.01630	0.00870
27	0.7	10	0.01542	0.00871	**69**	0.9	1000	0.01713	0.00872
28	0.8	10	0.01630	0.00870	**70**	1	1000	0.01793	0.00876
29	0.9	10	0.01713	0.00872	**71**	1.1	1000	0.01868	0.00882
30	1	10	0.01793	0.00876	**72**	1.2	1000	0.01939	0.00888
31	1.1	10	0.01868	0.00882	**73**	1.3	1000	0.02004	0.00894
32	1.2	10	0.01939	0.00888	**74**	1.4	1000	0.02065	0.00899
33	1.3	10	0.02004	0.00894	**75**	1.5	1000	0.02120	0.00904
34	1.4	10	0.02065	0.00899	**76**	1.6	1000	0.02171	0.00909
35	1.5	10	0.02120	0.00904	**77**	1.7	1000	0.02219	0.00913
36	1.6	10	0.02171	0.00909	**78**	1.8	1000	0.02262	0.00917
37	1.7	10	0.02219	0.00913	**79**	1.9	1000	0.02302	0.00920
38	1.8	10	0.02262	0.00917	**80**	2	1000	0.02339	0.00923
39	1.9	10	0.02302	0.00920					
40	2	10	0.02339	0.00923					
41	**0.1**	**100**	**0.00992**	**0.00898**					
42	0.2	100	0.01100	0.00999					

Detailed results: Experiment 2									
Trial	**Gamma**	**Cost**	**Error**	**Dispersion**	**Trial**	**Gamma**	**Cost**	**Error**	**Dispersion**
1	0.1	1	0.01679	0.00988	**43**	0.3	100	0.00929	0.00464
2	0.2	1	0.01486	0.01016	**44**	0.4	100	0.00889	0.00496
3	0.3	1	0.01377	0.00997	**45**	0.5	100	0.00874	0.00526
4	0.4	1	0.01351	0.00979	**46**	0.6	100	0.00868	0.00562
5	0.5	1	0.01335	0.00945	**47**	0.7	100	0.00882	0.00587
6	0.6	1	0.01311	0.00920	**48**	0.8	100	0.00902	0.00602
7	0.7	1	0.01286	0.00888	**49**	0.9	100	0.00924	0.00612
8	0.8	1	0.01261	0.00862	**50**	1	100	0.00949	0.00623
9	0.9	1	0.01243	0.00840	**51**	1.1	100	0.00973	0.00663
10	1	1	0.01232	0.00821	**52**	1.2	100	0.00998	0.00637
11	1.1	1	0.01229	0.00810	**53**	1.3	100	0.01025	0.00643
12	1.2	1	0.01235	0.00799	**54**	1.4	100	0.01055	0.00647
13	1.3	1	0.01247	0.00787	**55**	1.5	100	0.01084	0.00650
14	1.4	1	0.01261	0.00775	**56**	1.6	100	0.01113	0.00652
15	1.5	1	0.01277	0.00767	**57**	1.7	100	0.01142	0.00654
16	1.6	1	0.01298	0.00760	**58**	1.8	100	0.01172	0.00655
17	1.7	1	0.01322	0.00754	**59**	1.9	100	0.01202	0.00656
18	1.8	1	0.01348	0.00749	**60**	2	100	0.01232	0.00657
19	1.9	1	0.01375	0.00744	**61**	0.1	1000	0.00996	0.00506
20	2	1	0.01402	0.00740	**62**	0.2	1000	0.01075	0.00486
21	0.1	10	0.01139	0.00873	**63**	0.3	1000	0.00946	0.00431
22	0.2	10	0.00936	0.00614	**64**	0.4	1000	0.00886	0.00482
23	0.3	10	0.00890	0.00573	**65**	0.5	1000	0.00872	0.00526
24	0.4	10	0.00867	0.00554	**66**	0.6	1000	0.00868	0.00562
25	**0.5**	**10**	**0.00853**	**0.00561**	**67**	0.7	1000	0.00882	0.00587
26	0.6	10	0.00855	0.00569	**68**	0.8	1000	0.00902	0.00602
27	0.7	10	0.00875	0.00587	**69**	0.9	1000	0.00924	0.00612
28	0.8	10	0.00900	0.00608	**70**	1	1000	0.00949	0.00623
29	0.9	10	0.00919	0.00618	**71**	1.1	1000	0.00973	0.00631
30	1	10	0.00946	0.00626	**72**	1.2	1000	0.00998	0.00637
31	1.1	10	0.00972	0.00632	**73**	1.3	1000	0.01025	0.00643
32	1.2	10	0.00998	0.00637	**74**	1.4	1000	0.01055	0.00647
33	1.3	10	0.01025	0.00643	**75**	1.5	1000	0.01084	0.00650
34	1.4	10	0.01055	0.00647	**76**	1.6	1000	0.01113	0.00652
35	1.5	10	0.01084	0.00650	**77**	1.7	1000	0.01142	0.00654
36	1.6	10	0.01113	0.00652	**78**	1.8	1000	0.01172	0.00655
37	1.7	10	0.01142	0.00654	**79**	1.9	1000	0.01202	0.00656
38	1.8	10	0.01172	0.00655	**80**	2	1000	0.01232	0.00657
39	1.9	10	0.01202	0.00656					
40	2	10	0.01232	0.00657					
41	0.1	100	0.00950	0.00711					
42	0.2	100	0.00927	0.00496					

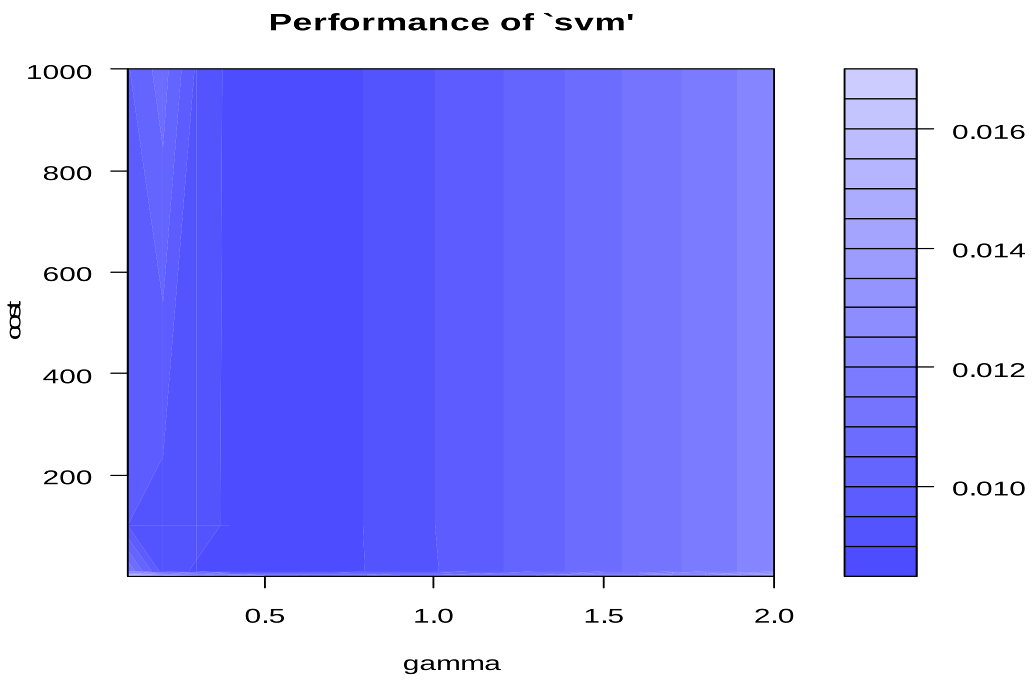
Detailed results: Experiment 3									
Trial	**Gamma**	**Cost**	**Error**	**Dispersion**	**Trial**	**Gamma**	**Cost**	**Error**	**Dispersion**
1	0.1	1	0.02495	0.00589	**42**	0.2	100	0.02125	0.01161
2	0.2	1	0.02249	0.00740	**43**	0.3	100	0.02069	0.01232
3	0.3	1	0.01929	0.00847	**44**	0.4	100	0.01771	0.01092
4	0.4	1	0.01901	0.00893	**45**	0.5	100	0.01551	0.00980
5	0.5	1	0.01894	0.00952	**46**	0.6	100	0.01187	0.00825
6	0.6	1	0.01925	0.01005	**47**	0.7	100	0.01041	0.00828
7	0.7	1	0.01947	0.01053	**48**	0.8	100	0.00928	0.00658
8	0.8	1	0.01954	0.01099	**49**	0.9	100	0.00801	0.00552
9	0.9	1	0.01960	0.01156	**50**	1	100	0.00710	0.00482
10	1	1	0.01954	0.01203	**51**	1.1	100	0.00657	0.00434
11	1.1	1	0.01962	0.01258	**52**	1.2	100	0.00611	0.00394
12	1.2	1	0.01964	0.01338	**53**	1.3	100	0.00588	0.00368
13	1.3	1	0.01954	0.01410	**54**	1.4	100	0.00556	0.00359
14	1.4	1	0.01924	0.01393	**55**	1.5	100	0.00531	0.00358
15	1.5	1	0.01895	0.01375	**56**	1.6	100	0.00519	0.00363
16	1.6	1	0.01866	0.01361	**57**	1.7	100	0.00517	0.00367
17	1.7	1	0.01842	0.01354	**58**	1.8	100	0.00505	0.00371
18	1.8	1	0.01813	0.01338	**59**	1.9	100	0.00499	0.00378
19	1.9	1	0.01786	0.01323	**60**	2	100	0.00503	0.00388
20	2	1	0.01754	0.01309	**61**	0.1	1000	0.02159	0.01241
21	0.1	10	0.02048	0.00925	**62**	0.2	1000	0.01788	0.01065
22	0.2	10	0.01962	0.00918	**63**	0.3	1000	0.01183	0.01019
23	0.3	10	0.01932	0.01004	**64**	0.4	1000	0.01076	0.00778
24	0.4	10	0.01927	0.01134	**65**	0.5	1000	0.00806	0.00594
25	0.5	10	0.01946	0.01236	**66**	0.6	1000	0.00722	0.00528
26	0.6	10	0.01911	0.01239	**67**	0.7	1000	0.00684	0.00626
27	0.7	10	0.01819	0.01186	**68**	0.8	1000	0.00544	0.00490
28	0.8	10	0.01680	0.01078	**69**	0.9	1000	0.00491	0.00447
29	0.9	10	0.01541	0.00998	**70**	1	1000	0.00457	0.00414
30	1	10	0.01411	0.00941	**71**	1.1	1000	0.00432	0.00387
31	1.1	10	0.01267	0.00847	**72**	**1.2**	**1000**	**0.00416**	**0.00373**
32	1.2	10	0.01165	0.00799	**73**	1.3	1000	0.00419	0.00369
33	1.3	10	0.01088	0.00786	**74**	1.4	1000	0.00423	0.00370
34	1.4	10	0.01038	0.00760	**75**	1.5	1000	0.00432	0.00372
35	1.5	10	0.00971	0.00711	**76**	1.6	1000	0.00446	0.00374
36	1.6	10	0.00924	0.00669	**77**	1.7	1000	0.00459	0.00376
37	1.7	10	0.00885	0.00634	**78**	1.8	1000	0.00470	0.00377
38	1.8	10	0.00837	0.00581	**79**	1.9	1000	0.00479	0.00378
39	1.9	10	0.00788	0.00540	**80**	2	1000	0.00489	0.00384
40	2	10	0.00753	0.00518					
41	0.1	100	0.02161	0.01130					

Detailed results: Experiment 4									
Trial	**Gamma**	**Cost**	**Error**	**Dispersion**	**Trial**	**Gamma**	**Cost**	**Error**	**Dispersion**
1	0.1	1	0.00149	0.00228	**42**	0.2	100	0.00140	0.00203
2	0.2	1	0.00161	0.00233	**43**	0.3	100	0.00165	0.00258
3	0.3	1	0.00160	0.00256	**44**	0.4	100	0.00163	0.00285
4	0.4	1	0.00165	0.00277	**45**	0.5	100	0.00164	0.00307
5	0.5	1	0.00175	0.00295	**46**	0.6	100	0.00170	0.00323
6	0.6	1	0.00185	0.00312	**47**	0.7	100	0.00177	0.00336
7	0.7	1	0.00195	0.00325	**48**	0.8	100	0.00185	0.00346
8	0.8	1	0.00207	0.00337	**49**	0.9	100	0.00194	0.00353
9	0.9	1	0.00218	0.00346	**50**	1	100	0.00202	0.00359
10	1	1	0.00228	0.00354	**51**	1.1	100	0.00209	0.00364
11	1.1	1	0.00237	0.00362	**52**	1.2	100	0.00216	0.00369
12	1.2	1	0.00246	0.00368	**53**	1.3	100	0.00223	0.00373
13	1.3	1	0.00255	0.00374	**54**	1.4	100	0.00230	0.00377
14	1.4	1	0.00263	0.00379	**55**	1.5	100	0.00236	0.00382
15	1.5	1	0.00270	0.00383	**56**	1.6	100	0.00242	0.00385
16	1.6	1	0.00276	0.00387	**57**	1.7	100	0.00248	0.00389
17	1.7	1	0.00283	0.00390	**58**	1.8	100	0.00253	0.00393
18	1.8	1	0.00290	0.00394	**59**	1.9	100	0.00259	0.00397
19	1.9	1	0.00297	0.00397	**60**	2	100	0.00265	0.00401
20	2	1	0.00304	0.00401	**61**	0.1	1000	0.00172	0.00150
21	**0.1**	**10**	**0.00132**	**0.00221**	**62**	0.2	1000	0.00202	0.00234
22	0.2	10	0.00144	0.00240	**63**	0.3	1000	0.00172	0.00258
23	0.3	10	0.00152	0.00259	**64**	0.4	1000	0.00163	0.00285
24	0.4	10	0.00156	0.00282	**65**	0.5	1000	0.00164	0.00307
25	0.5	10	0.00161	0.00303	**66**	0.6	1000	0.00170	0.00323
26	0.6	10	0.00170	0.00320	**67**	0.7	1000	0.00177	0.00336
27	0.7	10	0.00179	0.00334	**68**	0.8	1000	0.00185	0.00346
28	0.8	10	0.00187	0.00345	**69**	0.9	1000	0.00194	0.00353
29	0.9	10	0.00196	0.00352	**70**	1	1000	0.00202	0.00359
30	1	10	0.00204	0.00359	**71**	1.1	1000	0.00209	0.00364
31	1.1	10	0.00211	0.00364	**72**	1.2	1000	0.00216	0.00369
32	1.2	10	0.00217	0.00369	**73**	1.3	1000	0.00223	0.00373
33	1.3	10	0.00223	0.00373	**74**	1.4	1000	0.00230	0.00377
34	1.4	10	0.00229	0.00377	**75**	1.5	1000	0.00236	0.00382
35	1.5	10	0.00235	0.00382	**76**	1.6	1000	0.00242	0.00385
36	1.6	10	0.00242	0.00386	**77**	1.7	1000	0.00248	0.00389
37	1.7	10	0.00248	0.00389	**78**	1.8	1000	0.00253	0.00393
38	1.8	10	0.00253	0.00393	**79**	1.9	1000	0.00259	0.00397
39	1.9	10	0.00259	0.00397	**80**	2	1000	0.00265	0.00401
40	2	10	0.00265	0.00401					
41	0.1	100	0.00135	0.00209					

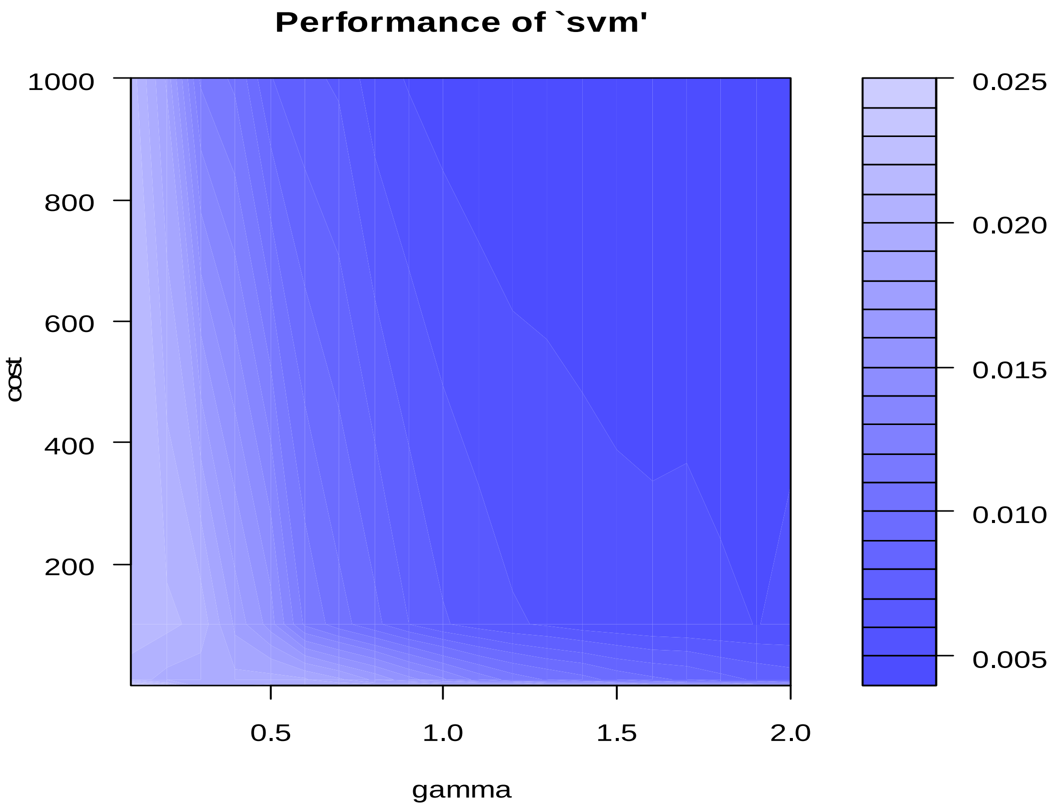
Experiment # 1: Performance of SVM



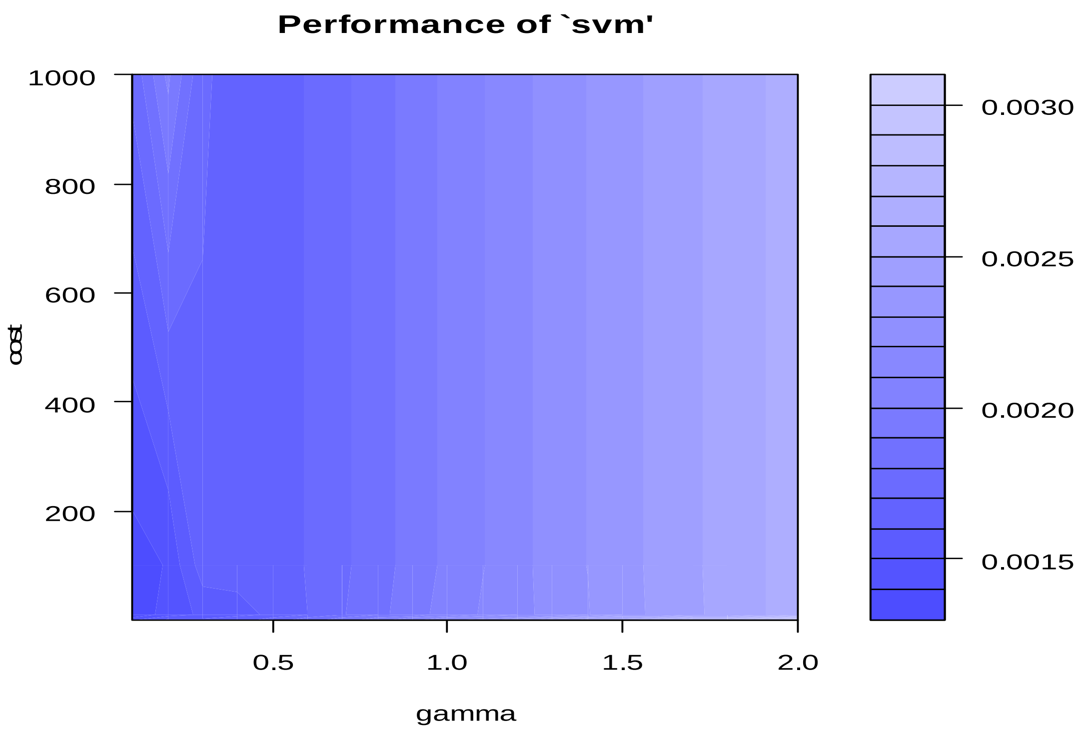
Experiment # 2: Performance of SVM



Experiment # 3: Performance of SVM



Experiment # 4: Performance of SVM



Chapter 3: A boost in exchange rate forecasting: qualitative variables, technical indicators and parameters selection

Introduction to chapter 3

The third chapter of this thesis addresses the use of moving averages, a model's free parameters selection, and a business and consumer survey variable as means of improving exchange rate predictions. Moving averages and the consumer survey variable are used as inputs to the SVM model with the aim of obtaining greater forecasting performance and accuracy. This paper has been presented in some research seminars and conferences. This thesis brings the version presented at *Frontiers in Artificial Intelligence and Applications, Proceedings of the 12th International Congress of the Catalan Association of Artificial Intelligence* held in Cardona, Barcelona, Spain. Co-authors to this paper are: Professor Núria Agell (ESADE-URL) and doctoral student Germán Sánchez (ESAII-UPC, ESADE-URL).

Abstract

This paper tries to determine, through the use of Support Vector Machines, the impact that technical indicators, a business and consumer variable (mostly based on qualitative information) and the choice of free parameters selection have on a model's forecasting performance, power and accuracy applied to currency exchange rate prediction. This approach was applied to the weekly currency exchange rate between the European euro and the US dollar. The results obtained show that the proposed factors can significantly impact the model's forecasting performance compared to traditional models where no business and consumer information is incorporated.

3.1 Introduction

Most of the major world currencies trade in the worldwide foreign exchange market using one convention, the US dollar. Almost all currencies are still quoted against the US dollar with exceptions in Asia and Europe where the yen and euro are used respectively. Financially speaking, the exchange rate between two countries means how much the currency of one country is worth in terms of the other country's currency. The exchange rate mechanism is seen as a useful tool in the establishment and creation of a common market between countries. According to Kontolemis (2003), the exchange rate stability is desirable for the smooth functioning and deepening of a single common market. Exchange rate stability is associated with a stable macroeconomic environment which leads to investment from abroad and consequently growth. A stable exchange rate system limits the exchange risk and promotes foreign borrowing by domestic residents, thus encouraging faster growth and convergence with other countries.

Two characteristics of foreign exchange rates are their significant non-stationarity and very high noise (Giles, Lawrence & Chung, 1997). Most researchers will agree with the claim that the exchange rates behave according to the efficient market hypothesis (Balassa, 1964; Chinn, 2003; Floyd, 2007; Frenkel, 1976; Murfin & Ormerod, 1984; Samuelson, 1964). In its conception, this hypothesis states that at any given time, security prices reflect all available information (Fama, 1965). The price movements of an asset will not follow any pattern or trend, thus making its future unpredictable. Hence, the future price of an asset cannot be forecasted. Consequently, there is no better way to forecast the price of an asset than the current price of the asset. Applied to foreign exchange rates, there is no information in past percentage changes which could be applied for the prediction of future percentage changes (White & Racine, 2001). Its actual price will follow what is known as a random walk.

The theory of random walk was popularized in 1973 by the work of Burton Malkiel, "A Random Walk Down Wall Street", a piece of literature known in the financial arena as an investment classic. The theory of random walk is a stock market theory which states that the past movement or direction of the price of a stock or overall market cannot be used to predict its future movement. Originally examined by Maurice Kendall in 1953, the theory states that stock price fluctuations are independent of each other and have the same probability distribution, but that over a period of time, prices maintain an upward trend (Hughes, 1996). Summarizing, random walk states that a stock's price takes a random and unpredictable path. The probability of having a stock's future price going up is the same as the one we could have if the case were otherwise. By following the random walk strategy, it is impossible to do better than the market without assuming additional risk. Malkiel alleges that statistical, technical and fundamental analyses are worthless and are still unproven in outperforming the markets.

Hsieh (1989) alleges that foreign exchange rates and other financial time series "follow a random walk and should therefore not be predictable much past 50 percent (the average performance of random walk models for foreign exchange markets)". Random walk models have outperformed other statistical and econometric models when it comes to foreign exchange rate determination (Meese & Rogoff, 1983). Nag and Mitra (2002) reach the same conclusion based on the work done by other researchers who state that through the use of time-varying parameters models similar results are reached. Nag and Mitra (2002) also conjecture that the linear unpredictability of the exchange rate models is due to the linear limitations of the models themselves. Nevertheless, the development of non-linear models significantly outperforming the performance of the random walk model was scarce.

Because of the high volatility and non-linear behavior found in exchange rates, this paper makes use of a non-linear forecasting technique to predict exchange rates. One of the purposes of this paper is to try to determine, through the use of Support Vector Machines (SVM), the impact that a business and consumer survey variable, which is mostly based on qualitative information, may have on the prediction of the currency exchange rate between the European euro and the U.S dollar. Secondly, a quest for the right combination of the model's free parameters selection and technical indicators is conducted in an attempt to improve the model's prediction and accuracy. Compared to previous research done on the field where only quantitative variables have been used as inputs, this research employs a variable based on qualitative information as one of the inputs of the proposed models. Previous literature suggests that quantitative variables are all that matters when predicting exchange rates. The models used in this paper will evidence the opposite indicating the significance that qualitative variables have on the exchange rate dilemma.

This paper has been organised in the following way. Section 3.2 presents basic information about moving averages. In section 3.3, the forecasting ability of neural networks is shown. In Section 3.4, the fundamentals tenets of the SVM theory are presented. In Section 3.5, a comparison of different forecasting methodologies is shown. In section 3.6, the variables and the dataset employed are explained along with graphical descriptions of the experiment and its results. Finally, section 3.7 concludes and outlines lines of future research related to the subject under study.

3.2 Moving Averages

Traders and investors often use technical indicators such as moving averages in order to smooth time series data and detect spot trends. Moving averages smooth-out the noise and price variations of financial data, thus allowing traders to identify trends present in the data and make financial gains out of them. Even though moving averages are sound alternatives for identifying trends, decisions should not be made based on their results. Since they are seen as trend following indicators (lagging), they will always be a step behind. Why? Because past price data is used to form moving averages, they are considered lagging indicators (StockCharts, 2009). It is better to incorporate these moving averages into some other forecasting models such as support vector machines or neural network models which can complement their prediction. The two most often used types of moving averages are the simple moving average (SMA) and the exponential moving average (EMA). The former one is calculated by taking the arithmetic mean of a given set of values. The latter one, which is also called an exponentially weighted moving average, applies weighting factors to any given set of values. These weighting factors which decrease exponentially apply more weight to most recent observations while giving less weight to older observations.

A simple moving average calculates the average of a given number of observations. For example, let's say that we have the currency closing prices of the Euro/Yen exchange rate for the past 10 days. If the closing prices are, $p_b, p_{b-1}, p_{b-2}, ..., p_{b-9}$, then the SMA is computed as follows:

$$SMA = \frac{p_b + p_{b-1} + ... + p_{b-9}}{10}$$

If instead of a 10-day moving average, a 50-day moving average is required, then the closing prices for the past 50 days will be added and divided by 50. As new values are added to your dataset, older values are left out and not taken into account for moving average purposes. This will guarantee that moving averages take into consideration recent values only. Another tool which keeps track of recent data by giving more weight to recent observations is the exponential moving average. This weight-factor depends on the specified period of the moving average, let it be a 12-day EMA or a 26-day EMA. There are 2 ways of calculating this EMA: as a percent-based EMA or as a period-based

EMA. As the name implies, the parameter of a percent-based EMA is a percentage while the parameter of a period-based EMA is the duration of the EMA. For purposes of this paper, the EMA has been computed as follows:

$$EMA_t = EMA_{t-1} + \alpha \times \left(\Pr ice_{t-1} - EMA_{t-1}\right)$$

where EMA_t is today's EMA, EMA_{t-1} is yesterday's EMA, $\Pr ice_{t-1}$ is yesterday's closing price and α equals the smoothing factor, a number between 0 and 1. This smoothing factor is calculated as follows: $\frac{2}{N+1}$, where N equals the number of time periods. Going back to the Euro/Yen example, this α would be equal to: $\frac{2}{10+1} = 0.1818$.

3.2.1 Which one is better?

Traders argue that one of the advantages of using EMA lies in its ability to follow data more closely than SMA. Since SMAs are lagging indicators, EMA can keep a better track of observations by assigning more weight to recent values. Critics argue that SMAs are limited in their tracking abilities due to the fact that each observation in the dataset has the same weight. It doesn't matter if the value occurred at the beginning of the period or at the end of it, it gets the same weight. Because of this limitation, analysts began to develop new tracking tools, such as EMA, which were able to put more emphasis on recent values. By being more responsive to new information, EMA are able to follow any trend with a better precision and accuracy. The moving average chosen will depend on the analyst's strategy and preferences. Shorter moving averages will be able to respond better and quicker to the data. Longer moving averages will respond slower to the data and may not be able to detect any trend or signal. EMA will follow the data more closely than simple SMA, thus detecting trends and generating more signals. For purposes of this paper, SMA and EMA of the €/$ exchange rate will be used as inputs to the forecasting models.

He and Shen (2007) make use of an ensemble technique to predict the currency exchange rate among six currency pairs. Through the use of moving averages and neural network models, they are able to conclude that an ensemble of learning algorithms can provide better results and improve forecasting performance compared to traditional single learning algorithms. Yu (2002) compares the forecasting power and accuracy of nine univariate models for predicting stock price volatility using daily New Zealand data. Among the models used, three incorporated moving averages: a five-year and a ten-year moving average and an exponentially-weighted moving average. He finds that the moving average models underperform the other six models chosen, giving contradictory evidence to the one found in other markets. Taylor (2004) makes use of an innovative exponential smoothing technique to predict the volatility in financial returns. Compared to a variety of other models, the new method gives promising results and paves the way for the use of this technique as an adaptive smoothing parameter.

3.3 Neural Networks

Recent research has suggested that artificial neural networks (ANNs) have proven to be more accurate in its forecasting ability than any other forecasting statistical tool such as linear time series techniques, exponential smoothing and autoregressive integrated moving average models. Nag and Mitra (2002) claim that ANNs are considered to be a valuable tool for building nonlinear models of data such as the ones found in foreign exchange rates. One of the many advantages of ANNs is that its models are data-driven and self-adaptive. Hornik (1991) advocates for the approximation capabilities of neural networks by stating that they can estimate any continuous function to any desired accuracy. The non-linearity of ANN's models gives them the advantage of not having to specify the functional relationship between input and output variables (Nag & Mitra, 2002).

Research has shown that ANNs are much better than other existing statistical methods when it comes to out-of-sample forecasting ability. Nag and Mitra (2002) argue that genetically engineered ANN models are much better than non-linear time series models and fixed-geometry ANN models when it comes to prediction, power and accuracy. These genetically engineered ANN models make use of an iterative algorithm in which ANNs are tested in order to determine their fitness in solving a problem. The best networks are selected and are genetically modified until an optimum network architecture is reached. "Through this process, the better networks survive and their features are carried forward into future generations and are combined with others to find better networks for the particular application. This genetic search method is much more effective than random searching, as the genetic process of recombining features vastly improves the speed of identifying highly fit networks" (Nag & Mitra, 2002).

Walczak (2001) claims that the development of a high-quality neural network model is a difficult task. Most financial traders desiring to use ANNs face two dilemmas: the selection of appropriate variables and the quantity of information needed (training examples) so that the neural network can adequately model the financial time series. Recent research has shown that too much information can seriously decrease and harm the quality of the neural network architecture. Walczak claims that smaller training set sizes outperform larger training set sizes thus contradicting the work done by Box, Jenkins and Reinsel (1994) which claimed to have proven otherwise. These smaller-than-expected training sizes led to the formulation of the Time Series Recency Effect. This theory states that building a model with data which is closer in time to the data that is supposed to be forecasted will produce a higher-quality model. The advantages of this model are the following: it paves the way to rule out the models making use of huge quantities of data; it produces higher-quality models; it reduces the development costs of neural network time series models since less information is required; and it contributes to a net reduction in development time (Walczak, 2001).

Velásquez and González (2006) model the effect of the Colombian real exchange rate index using neural networks. They develop a univariate model based on neural networks of the real exchange rate index of the Colombian currency against the currencies of eighteen member countries of the International Monetary Fund. They find that the series of the Colombian currency does not follow a linear trend, thus making it apt for the use of neural networks. The neural network developed in their research is able to capture the non-linear deterministic relationships of the real exchange rate value for the Colombian currency in the current and previous month. The residuals obtained from the non-linear model are smaller in magnitude and size than the ones obtained if a linear model were used with the same parameters. They conclude that the model developed is a better predictor of the series dynamics than a linear model.

Improvements in the forecasting capacity of neural networks through the use of genetic algorithms or a hybrid between a fixed-neural network model and a genetic algorithm have been sought for some time. The purpose is to construct an ANN exchange rate model that does not suffer from the limitations of the traditional fixed-geometry ANN models and performs significantly better. In order to do this, a genetic algorithm search procedure is employed in order to optimize the ANN architectural parameters. Andreou and Zombanakis (2006) study the predictive forecasting power of neural network methodology on the Euro exchange rate versus the U.S. Dollar and Japanese Yen. Their analysis is based on the research done by Andreou, Georgopoulos and Likothanassis (2002) which succeeded in forecasting the developments of the Greek Drachma versus the U.S. Dollar, the Deutsche Mark, the French Frank and the British Pound with nearly 99% accuracy by using neural networks trained with Kalman filtering and evolved by a dedicated genetic algorithm in terms of typology and size. The authors attempt to do a forecast of the U.S. Dollar and Japanese Yen rates versus the Euro making use of the same technique employed by Andreou et al. (2002), but applying it to a series of five-minute observations covering the last three months of 2004.

They analyze the cyclical behavior showed by their series through the use of various forms of Rescaled Range Statistics analysis (R/S analysis). One of the aims of this R/S analysis is to trace long-term memory in a time series. According to their analysis, the U.S. Dollar / Euro series shows no specific long time pattern while the Yen / Euro series shows a misleading pattern. Their main conclusion is that the neural networks used are able to learn the underlying dynamics of the exchange-rate developments and yields successful results of above 98% accuracy.

3.4 Support Vector Machines

Cristianini and Shawe-Taylor (2000) allege that SVMs are able to improve the generalisation property of neural networks. This is done through the use a hypothesis space of linear functions in a high dimensional feature space, trained with a learning algorithm from optimization theory that implements a learning bias derived from statistical learning theory. Originally introduced by Vapnik and his colleagues, SVMs have become a new powerful tool for learning from data and for outperforming other models when it comes to classification and regression problems. Compared to the empirical risk minimization of NN, an SVM is able to minimize the structural risk, specifically the upper bound of the generalization error instead of minimizing the empirical error, thus resulting in better generalization than other conventional forecasting techniques. SVM produce a nonlinear regression in a low-dimensional space. The input data is nonlinearly mapped in a high dimensional feature space by using a kernel function, and then a linear regression is run in this altered space.

The objective is to determine a function f which approximates the unknown function $d(x)$ obtained from the data set $D= \{(x_1, y_1),\ldots.,(x_i, y_i),\ldots(x_N, y_N)\}$, where x_i represents the input vector and y_i the predicted value. The dataset is assumed to have the following linear function:

$$f(x) = \sum_{i=1}^{N} w_i \phi_i(x) + b \qquad (1)$$

where $\phi_i(x)$ represents the feature which is nonlinearly mapped from the input space x. The constants w_i and b are obtained from the minimization of the regularized risk function:

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \frac{1}{2}\|w\|^2 \qquad (2)$$

$$L_\varepsilon(d, y) = \begin{cases} |d-y|-\varepsilon & |d-y| \geq \varepsilon, \\ 0 & otherwise, \end{cases} \qquad (3)$$

where both C and ε are prescribed parameters. The regularized constant C estimates the tradeoff between the empirical error and model flatness. The first term $L_\varepsilon(d, y)$ describes the ε-insensitive loss function where errors below ε are not penalized, knowing ε beforehand. The term $\frac{1}{2}\|w\|^2$ measures function flatness. By using the slack variables ζ and ζ^* which represent the distance from the actual values to their respective boundary values of ε-tube, equation (2) becomes:

Minimize:

$$R(w, \zeta, \zeta^*) = \frac{1}{2}\|w\|^2 + C^*(\sum_{i=1}^{N} \zeta_i + \zeta_i^*) \qquad (4)$$

Subjected to:

$$w\phi(x_i) + b_i - d_i \leq \varepsilon + \zeta_i^*, \qquad (5)$$

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \zeta_i, \qquad (6)$$

$$\zeta_i, \zeta_i^* \geq 0 \qquad (7)$$

$i = 1, 2, ..., N.$

Afterwards, equation (1) becomes:

$$f(x, a_i, a_i^*) = \sum_{i=1}^{N} (a_i - a_i^*) K(x, x_i) + b \qquad (8)$$

where a_i, a_i^* represent the Lagrange multipliers introduced. The equality $a_i * a_i^* = 0, a_i \geq 0, a_i^* \geq 0, i = 1, ..., N,$ is satisfied by the Lagrange multipliers and these are obtained by maximizing the dual form of equation (4) which takes the following form:

$$\phi(a_i, a_i^*) = \sum_{i=1}^{N} d_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^{N} (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i - a_i^*)(a_j - a_j^*) K(x_i, x_j) \quad (9)$$

with the constraints:

$$\sum_{i=1}^{N} (a_i - a_i^*) = 0$$
$$0 \le a_i \le C, i = 1, 2, ..., N$$
$$0 \le a_j \le C, i = 1, 2, ..., N$$

In equation (8), $K(x ,x_i)$ is called the kernel function. Its value is equal to the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$ such that Mercer's condition is satisfied, $K(x_i, x_j) = \phi(x_i) * \phi(x_j)$. The kernel function used in this study is the Gaussian kernel function:

$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / (2\sigma^2))$. The Gaussian kernel function was used to determine the nonlinear behavior of the exchange rates because they perform well under general smoothness assumptions.

3.5 Comparing Methodologies

Research done on the subject has focused on making comparisons between the predictive capacity of SVM models and that of back-propagation (BPNNs) neural network models. BPNNs have proven to be effective, efficient and profitable tools in forecasting financial time series. Tenti (1996) claims that since BPNNs architectures are model-free estimators, they are considered to be universal function approximators able to detect nonlinearities with a remarkable certainty. For this reason, BPNNS are great at prediction and classification problems. Cao and Tai (2003) compare the feasibility of SVM in financial forecasting to the ones of multilayer BPNN and regularized radial basis function (RBF) neural network.

Among the findings, they claim that SVM are an excellent alternative to BPNNs for financial time series forecasting. They find that the RBF neural network and the SVM model perform alike, significantly better than the BP neural network. They also allege that the selection of free parameters plays an important role in the forecasting accuracy of the model. A SVM model with adaptive parameters achieves higher generalization performance and makes use of fewer support vectors than standard SVM in financial forecasting. In previous research done on the same subject, Cao and Tay (2001) study the predictive performance of SVM compared to the one obtained from BP neural networks. They conclude that it is advantageous to use SVMs in financial time series forecasting due to its superior forecasting ability based on the results of five performance metrics: NMSE, MAE, DS, CP and CD. The smaller values obtained for the NMSE and MAE, and the larger values obtained for the DS, CP, and CD argue for the use of SVMs instead of BP neural networks.

Comparisons have also been made between SVMs and Autoregressive Integrated Moving Average models (ARIMA). Hansen, McDonald and Nelson (2006) compare the predictive potential of SVMs for time series forecasting with three widely accepted ARIMA models, namely, the Forecast Pro, EGB2 and GT. They use nine problem domains each representing a single real time series having uniquely characteristics. They find that SVM outperforms the other models and achieves the best results in 8 of the domains. They also conclude that SVM and Forecast Pro's results are robust under a variety of time series complexities, and that the EGB2 model appears to perform well in certain problems only. The GT model performance is insufficient compared to the one obtained from the other three models.

Pai and Lin (2005) try to come up with a hybrid model capable of improving the forecasting accuracy of its individual models for stock prices. This hybrid model has ARIMA and SVM components. They argue that the ARIMA model serves as a preprocessor to filter the linear pattern of data sets. Afterwards, the error terms obtained from the ARIMA model are fed into the SVMs in the hybrid models. The purpose of running the SVMs is to reduce the error function from the ARIMA. The regularization parameters of the SVMs are adjusted. The results indicate that the hybrid model outperforms the other models based on the MAE, MSE, MAPE, and the RMSE. The proposed hybrid model yields better forecasting results than the random walk models.

Pai, Hong, Chang and Chen (2006) try to present a hybrid model, having genetic algorithms (GAs) and support vector machine components, in order to forecast tourist arrivals in the island of Barbados. GAs are used in order to determine the values of the three free parameters of the SVM model. The GAs are used to yield a smaller MAPE by searching for better combinations of the three parameters in the SVM model. The forecasting performance of the SVM genetically modified models outperforms those of the other ARIMA models. The SVMGA model with the smallest MAPE value is chosen as the best model.

Ince and Trafalis (2006) propose a hybrid forecasting model which incorporates parametric and nonparametric techniques. Among the parametric techniques proposed, the ARIMA, the VAR and other co-integration techniques are used. The SVR and ANN (MLP) are used as nonparametric ones. The parametric techniques are used to model an input selection process, and after the number of inputs is determined, the techniques of ANN and SVR are applied to the dataset. Specifically, they try to identify the most important factors influencing the daily value of exchange rates by making use of ARIMA and VAR techniques. After the number of inputs is determined, SVR and MLP networks are applied to the dataset. The performance of SVR against MLP networks (and vice versa) is evaluated by making use of MSE and MAE metrics. Moreover, the performance of the input selection method, namely ARIMA vs. VAR, is also compared. The results show that the SVR methodology does perform better than MLP networks for each input selection algorithm. Regarding the input selection process, the authors argue that the best selection procedure is dependent upon the training algorithms. For a MLP network, it is better to use a VAR technique to determine the inputs. But if a SVR method is used, then the ARIMA input selection technique will give the best results.

Ince and Trafalis (2007) try to determine the most influential inputs for a forecasting model in order to better predict stock prices. By making use of five technical indicators along with two heuristic models and of nonparametric techniques, they are able to conclude that heuristic input selection models based on personal experience are better than kPCA and factor analysis. Their results show that it would be unwise to choose the explanatory variables by using some statistical techniques because of the dependency of these techniques on the experience of the market. They conclude by stating that the right inputs vary with the learning algorithm. Kamruzzaman (2003) analyzes the prediction of the foreign currency exchange rates of six countries against the Australian dollar. He tries to determine the performance of SVM for Australian forex forecasting in terms of kernel type and sensitivity of free parameters selection. Specifically, he tries to determine the effect of a single kernel function on prediction accuracy, and the effect of free parameter selection on prediction error. He finds that no single kernel function dominates all currency prediction.

Instead, the kernel function should be chosen based on the pattern of the individual currency rate. Different values of the regularization parameters hardly have any impact on the variation of the prediction error. The support vectors remain the same and the performance is not affected at all. Hock and Cao (2001) propose a two-stage neural network architecture by combining SVM with self-organizing feature maps (SOM). Specifically, they use what is known as a mixture of experts architecture (ME). In the first stage, the SOM divides the input space into several disjoint regions. Then a tree-structured architecture is used for partition, which divides the large input space into two regions until a specified partition condition is not satisfied. In the second stage, different SVM experts, using different kernel functions and learning parameters, are constructed to deal with the different input regions. The prediction performance of the proposed model is evaluated using the NMSE, MAE, DS and WDS metrics. The author concludes that the proposed method performs better and faster than a single SVM model.

3.6 Presentation of the experiment and results

3.6.1 Variables justification

3.6.1.1 Economic Sentiment Indicator

The European Commission Directorate-General for Economic and Financial Affairs (European Commission DG ECFIN, 2009) publishes on a monthly basis business and consumer surveys which provide important quantitative and qualitative information about the economic health, short-term forecasts and economic research for the euro-area. Business and consumer surveys reveal the opinion and expectations of financial and economic experts in the area about the current trend of the different sectors of the economy: industry, services, construction and retail trade, as well as consumers. These surveys are carried out by professional organizations such as governmental agencies, banks, consulting companies and research institutes, among others. These organizations work with and share a common methodology consisting of harmonized questionnaires and a common timetable. These business surveys (construction, services, consumers, industry and retail trade) are all integrated into a broader one-dimensional index called the Economic Sentiment Indicator (ESI) which summarizes all positive and negative developments in the surveyed sectors of each EU member country.

On a monthly basis, an average of 40.000 consumers and 125.000 companies across the European Union participate in these surveys. The answers to the surveys are summed up in the form of balances. These balances are the result of the difference between the percentages of interviewees giving positive and negative responses. Once these balances are calculated, they are used in the financial building of composite confidence indicators. These confidence indicators are computed as the arithmetic means of answers to a set of questions related to the particular surveyed sector. One of these composite indicators is the ESI whose goal is to track GDP growth at Member State, EU and euro-area level. The harmonised surveys making up the composite ESI consist of answers to qualitative questions covering a broad range of issues such as expectations about production, selling prices and employment, short-term developments in the construction sector, intentions on major purchases, and assessments of current business conditions, among others. All these qualitative surveys make use of a similar answer scheme with the following three-option ordinal scale: “too large” (+), “adequate” (=), “too small” (-); or “more than sufficient” (+), “sufficient” (=), “not sufficient” (-); or “increase” (+), “remain unchanged” (=), “decrease” (-). In the end, these indicators will give a clearer picture of the state of the economy in different sectors.

What precisely does this leading indicator predict? There is a widespread belief that these expectations themselves influence public opinion and economic policy makers through the media. Mehrotra and Rautava (2007) claim that business sentiment indicators are useful in forecasting developments in the Chinese economy because they tend to transmit useful information about the current and future state of affairs of the economic activity in the country. Others claim that ESI indicators play an insignificant role in business policy, thus having no relation at all with any of the main macro-economic variables of a country. What about exchange rates? Opinions vary. While some may argue that ESI indicators hardly have an impact on the exchange rate dilemma, recent evidence suggests otherwise. In a recent report published by CMS Forex, Nilsson and Tapasanun (2009) claim that the EUR/USD exchange rate rose as eurozone economic sentiment indicator increased for the first time since May 2007. According to the report, as risk sentiment improved, the US dollar and the yen fell against their opposites. The sterling rose on expectations of a UK economic recovery by the end of the year. Likewise, positive feelings for a global economic recovery and higher commodity prices made the Canadian and Australian dollars rise again.

In a recent article written for Daily FX, Rodríguez (2009) claims that several sentiment indicators have a significant role in the US dollar/Euro exchange rate. These sentiment indicators suggest that the US dollar may be reaching its steepest decline in months against some major currencies. Through an innovative FX indicator called Speculative Sentiment Index data (SSI), Rodriguez is able to predict a future weakness of the US dollar into the current week of trading. This indicator, which is based on private customer flow information, will be able to track price trends and identify breaks and reversals in the top four currency pairs. Another leading qualitative indicator called the World Economic Survey (WES) assesses a country's general economic situation, main economic problems, as well as expectations about important economic indexes such as foreign trade volume, trade balance, inflation rate, and interest rates. Through a team of economic experts, the WES evaluates the value of some of the major currencies (US dollar, European euro, British pound and Japanese yen), and the prospects of each currency's appreciation/depreciation against the US dollar.

While exchange rates may be predicted based on a number of quantitative information and technical analyses, recent evidence advocates for the incorporation of qualitative information into FX models. Enough has been said and done about the universe of quantitative variables which when incorporated into forecasting models account for improvements in the model's forecasting power and accuracy. Nonetheless, the vast array of literature dealing with exchange rates lacks research related to the possible impact of qualitative information on a model's predictive power. Will there be an impact on the model's accuracy if a qualitative variable is added? If a significant impact is expected, will the model improve? Will the model be able to generalize? Does an improvement in a model's forecasting power due to the addition of some qualitative variable mean that the volatility of foreign exchange rates is simply due to qualitative information? For purposes of this paper, the composite confidence indicator ESI will be used for analysis.

3.6.2 Data set description

In this research, the most recently available foreign currency exchange rate data is used for analysis. The data set comes from the Pacific Exchange Rate Service database (2009). The period under consideration is from January 1, 1999 until March 19, 2009. The data set of the world's top two currencies is used, specifically European Euros (EUR) and US Dollar (USD). European Euros (EUR) is selected as the base currency. Weekly analysis is performed in this research using every Wednesday's closing price as the target price. The training period is from December 15, 1999 (Wednesday) until November 22, 2000 (Wednesday). This corresponds to 50 points for the training period and 434 points for the testing period. The training period is about 1/8 of the testing period.

The qualitative confidence indicator ESI and moving-averages are used as inputs to the SVM models. Two types of moving-averages are used: simple moving-average (SMA) and exponential moving averages (EMA). Since weekly analysis is performed, the input feature vector is:

$$F = \{F1,\ F2,\ F3,\ F4,\ F5\} = \{X(T),\ SMA12,\ SMA26,\ SMA34,\ SMA50\}$$

where $X(T)$ is the current Wednesday closing price, $SMA12$, $SMA26$, $SMA34$ and $SMA50$ is the simple moving average for a 12, 26, 34 and 50-days period, respectively. Since one of the purposes of this experiment is to test the impact of the qualitative variable ESI on the forecasting power and accuracy of the model, the variable ESI is added to the feature vectors used in the first model. So instead of having 5 input vectors, the new model has 6 input feature vectors. Firstly, the model is run with the moving averages variables and a prediction is attempted. Secondly, the ESI indicator is added as an input feature vector, and the resulting model with 6 input feature vectors is run again and a new prediction is attempted. The same procedure is adopted for EMA values.

Since weekly analysis is performed, the input feature vector $F = \{F1, F2, F3, F4, F5\} = \{X(T), EMA12, EMA26, EMA34, EMA50\}$, where $X(T)$ is the current Wednesday closing price, $EMA12$, $EMA26$, $EMA34$ and $EMA50$ is the exponential moving average for a 12, 26, 34 and 50-days period, respectively. Since one of the purposes of this experiment is to test the impact of the qualitative variable ESI on the forecasting power and accuracy of the model, the variable ESI is added to the previous feature vectors used in the first model. So instead of having 5 input vectors, the new model has 6 input feature vectors. Firstly, the model is run with the moving averages variables and a prediction is attempted. Secondly, the ESI indicator is added as an input feature vector, and the resulting model with 6 input feature vectors is run again and a new prediction is attempted.

Knowing that weekly data is needed in order to run the experiment, the monthly values for the ESI indicator are assumed to be constant during their respective four week period (each week was assigned its respective monthly value). Since the target forecast is the next Wednesday's exchange rate and due to limitations of availability of information, the ESI value of the previous month is used to forecast the exchange rate of the current month.

3.6.3 Experiments and Results

With the data collected, four different experiments are run using the statistical software package known as R Project for Statistical Computing (R, 2006). Each experiment produces an SVM model with a Gaussian kernel component. Using the function in R known as 'tune.svm', different values are assigned to the prescribed parameter C, which is the regularized constant determining the tradeoff between the empirical error and the model flatness, and the variable sigma σ, which is present in the denominator of the kernel component of the Gaussian function. The values for the parameter C are: 0.1, 1, 10, 100, 1000 and 10000. The values assigned to the variable σ are: 0.1, 1, 2, 4, 8, 16, 32. There are 7 possible values for σ and 6 for C, thus having 42 possible combinations in every single experiment.

For each one of these 42 combinations, a 10-fold cross validation method is used. This method gives the result that minimizes the validation process. The output for all experiments is the weekly exchange rate (ER) of the euro against the dollar (€/$). The forecasting horizon is the next Wednesday's exchange rate. The performance metric used to evaluate our results is the normalized mean squared error (NMSE). Next, the four experiments will be explained in detail.

In the first experiment, the 5 EMA variables are used as inputs and the ER is used as output. The R command used for purposes of this experiment is:

```
X1 <- datos_EMA[,1:5]
obj1 <- tune(svm,
 train.x=X1,
 train.y=Y,
kernel=kernel,
tunecontrol = tune.control(sampling="cross", cross=nfolds),
ranges = list(gamma = gamma, cost = cost)
#parameters1 <- obj1$best.parameters
bestperformance1 <- obj1$best.performance
#performances1 <- obj1$performances
modelo1 <- obj1$best.model
#summary(obj1)
# Obtenemos los valores predecidos:
pred1 <- predict(modelo1, X1)
```

With a σ of 0,1 and a C of 1000, the best performance has a NMSE of 0.00447.

In the second experiment, the 5 EMA variables along with the ESI indicator are used as inputs and the ER as output.

The R command used in this experiment is:

```
X2 <- datos_EMA[,1:6]
obj2 <- tune(svm,
train.x=X2,
```

```
train.y=Y,
kernel=kernel,
tunecontrol = tune.control(sampling="cross", cross=nfolds),
ranges = list(gamma = gamma, cost = cost)
modelo2 <- obj2$best.model
bestperformance2 <- obj2$best.performance
# Obtenemos los valores predecidos:
pred2 <- predict(modelo2, X2)
```

With a σ of 0,1 and a C of 10, the best performance obtained has a NMSE of 0.00412. In the third experiment, the 5 SMA variables are used as inputs and the ER as output. The R command used is:

```
X3 <- datos_SMA[,1:5]
obj3 <- tune(svm,
train.x=X3,
train.y=Y,
kernel=kernel,
tunecontrol = tune.control(sampling="cross", cross=nfolds),
ranges = list(gamma = gamma, cost = cost)
modelo3 <- obj3$best.model
bestperformance3 <- obj3$best.performance
# Obtenemos los valores predecidos:
pred3 <- predict(modelo3, X3)
```

With a σ of 0,1 and a C of 10, the best performance has a NMSE of 0.00455. In the last experiment, the 5 SMA variables along with the ESI indicator are used as inputs and the ER as output. The R command used is:

```
X4 <- datos_SMA[,1:6]
obj4 <- tune(svm,
train.x=X4,
train.y=Y,
kernel=kernel,
tunecontrol = tune.control(sampling="cross", cross=nfolds),
ranges = list(gamma = gamma, cost = cost)
modelo4 <- obj4$best.model
bestperformance4 <- obj4$best.performance
# Obtenemos los valores predecidos:
pred4 <- predict(modelo4, X4)
```

With a σ of 0,1 and a C of 10, the best performance has a NMSE of 0.00410. The tables shown in the next page summarize these results. Once all four models are trained with the input data, these models are tested in order to measure their forecasting power and predictive accuracy. In order to accomplish this, 50 data points are used as a training set along with graphical representations of each model's prediction. The figures shown on the next pages will illustrate this point better. The first figure shows the weekly exchange rate using EMA variables (with and without ESI values). The second figure shows the weekly exchange rate with EMA and SMA variables (without ESI values). The third figure shows the weekly exchange rate with ESI values for EMA and SMA variables. The fourth figure shows the weekly exchange rate for SMA variables (with and without ESI values).

Table 3.1: Final Results

	Gamma	Cost	NMSE
1: EMA (-ESI)	0.1	1000	0.00447
2: EMA (+ESI)	0.1	10	0.00412
3: SMA (-ESI)	0.1	10	0.00455
4: SMA (+ESI)	0.1	10	0.00410
5: X(t)=X(t)-1	-	-	0.00483*

*Represents maximum error as a result of trying to forecast next week's exchange rate with its previous value.

Table 3.2: NMSE

-ESI	**0.00455**	**0.00447**
+ESI	**0.00410**	**0.00412**
	SMA	**EMA**

Table 3.3: Error Reduction Rate (%)*

-ESI	**6.5**	**8.3**
+ESI	**16.7**	**16.3**
	SMA	**EMA**

*Compared to maximum error

If the result of using SMA and -ESI is taken as a reference point, then the error reduction rates are the following:

Table 3.4: Error Reduction Rate (%)*

-ESI	**0.0**	**1.8**
+ESI	**10.3**	**9.9**
	SMA	**EMA**

*Compared to SMA and –ESI

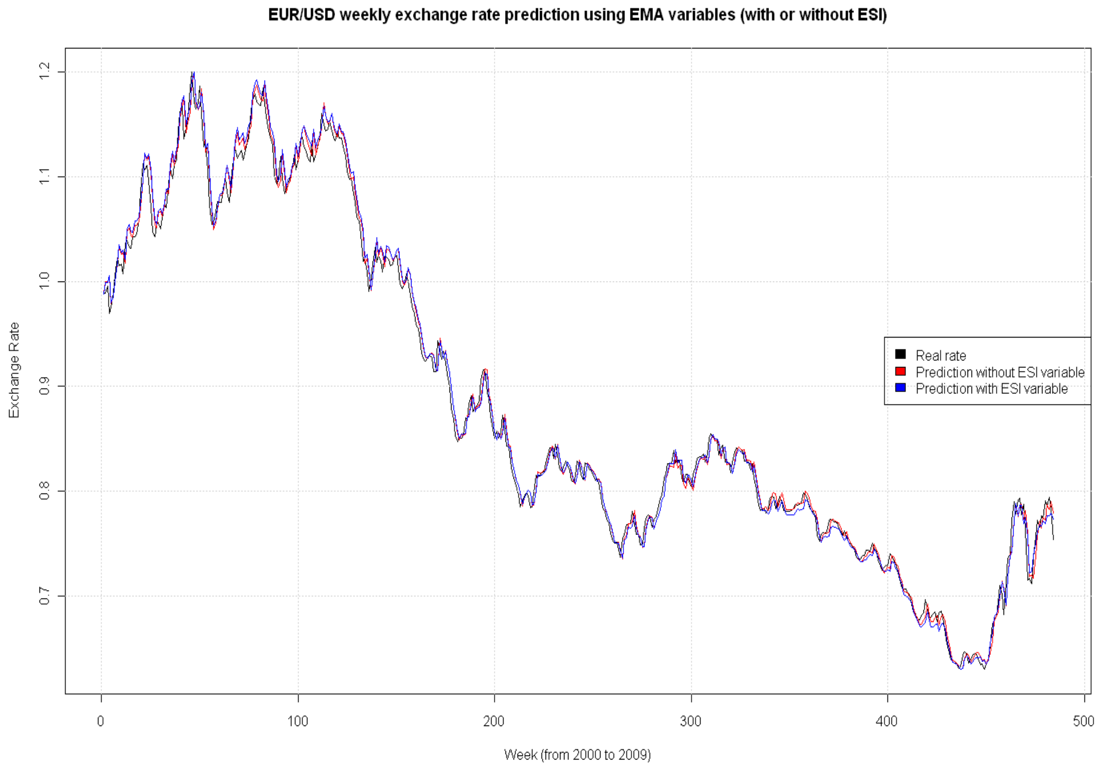


Figure 3.1: EUR/USD weekly exchange rate prediction using EMA (with or without ESI)

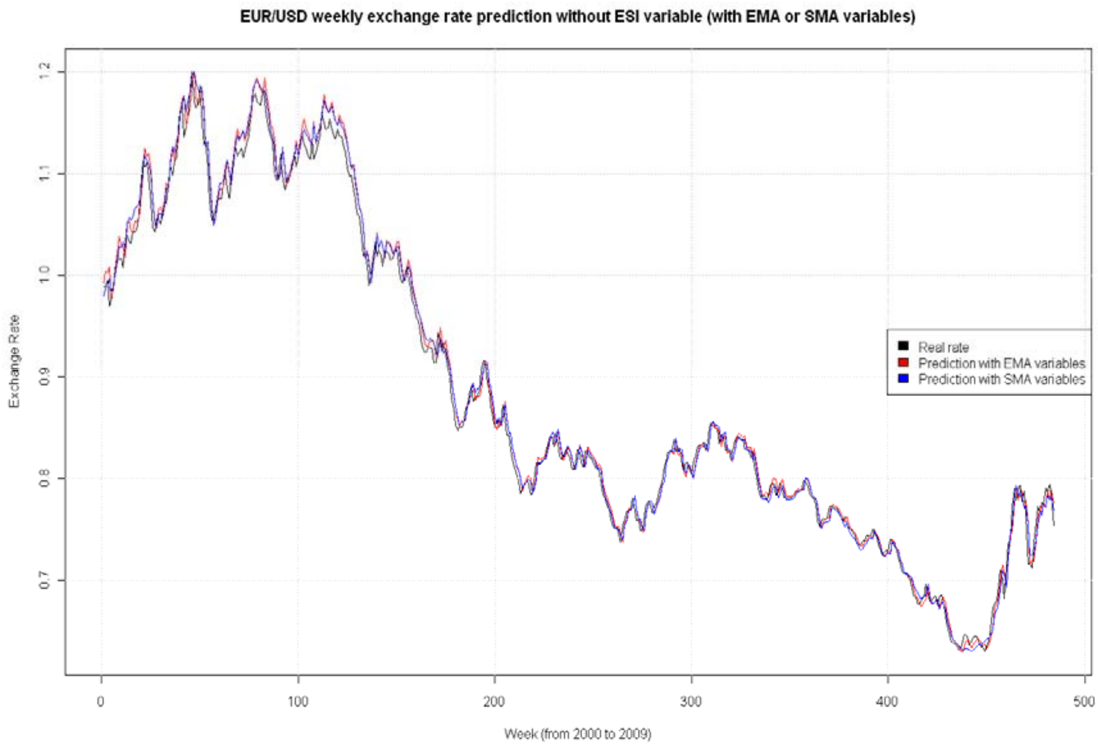


Figure 3.2: EUR/USD weekly exchange rate prediction without ESI (with EMA or SMA)

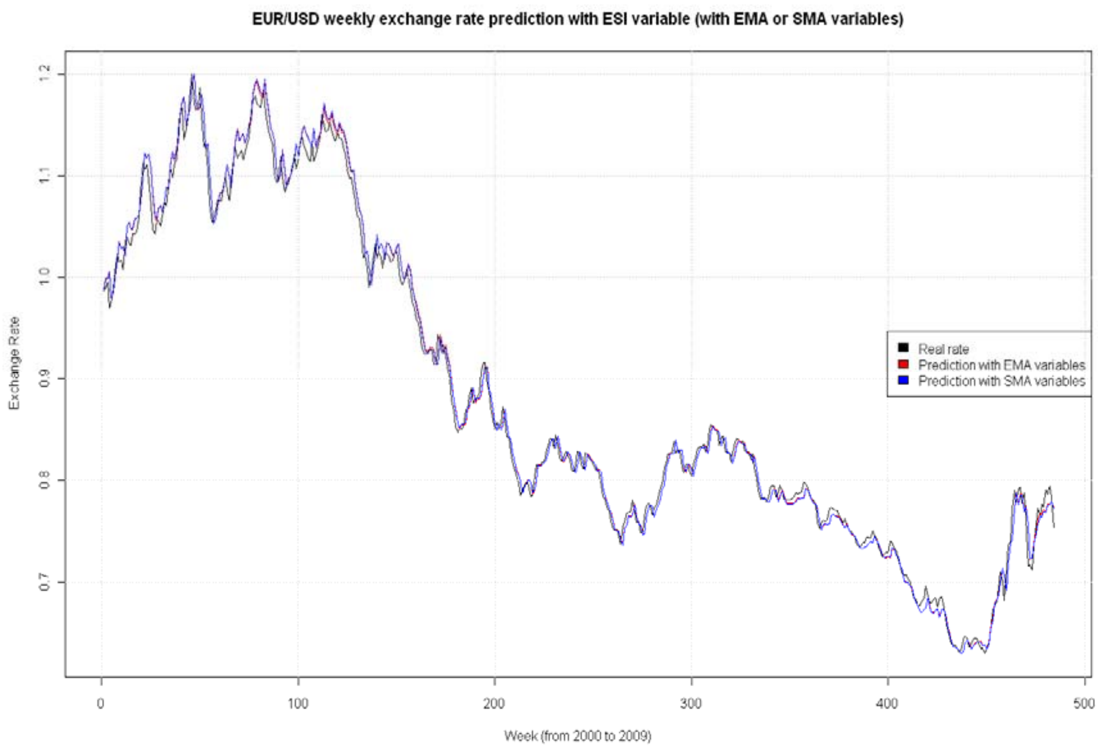


Figure 3.3: EUR/USD weekly exchange rate prediction with ESI (with EMA or SMA)

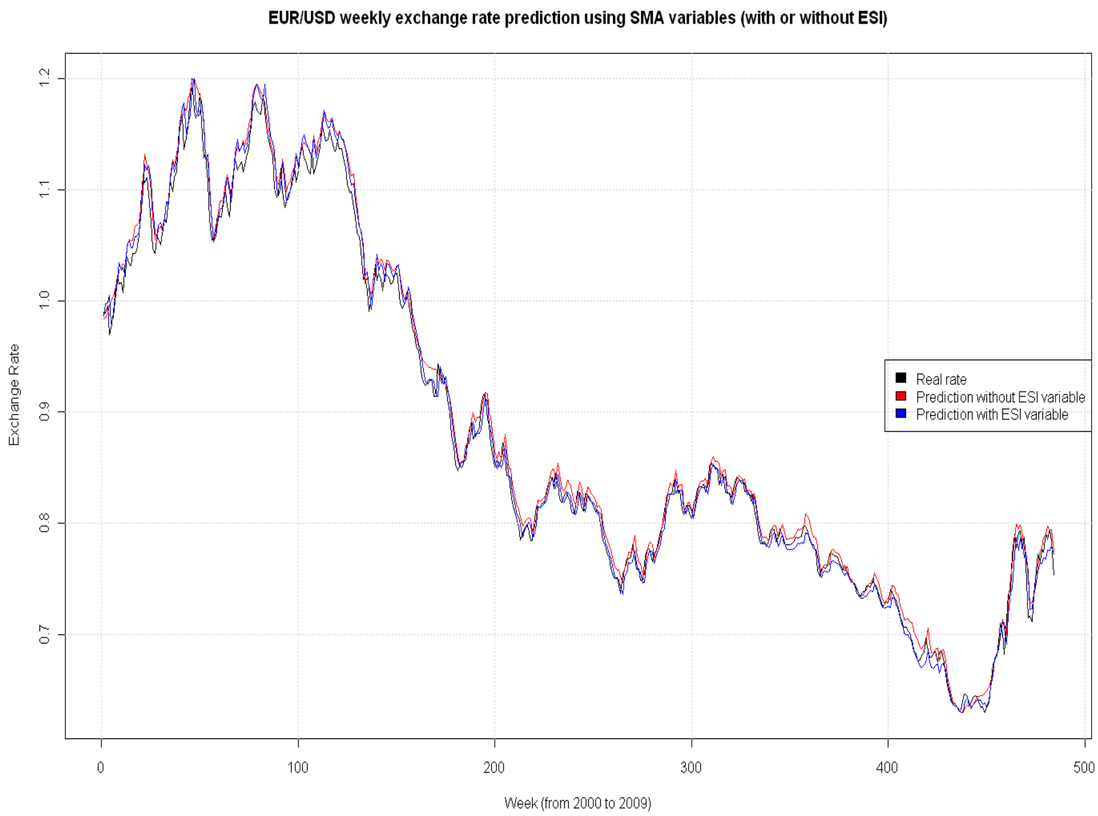


Figure 3.4: EUR/USD weekly exchange rate prediction using SMA variables (with or without ESI)

3.6.4 Interpretation of the Results

By taking a closer look at table 3.1, it could be seen that the model having SMA variables without an ESI indicator has the highest error (NMSE = 0.00455). After the ESI indicator is added, the error is lowered by 10.3% (Table 3.4). This indicates that the ESI variable has an important impact on the accuracy of the forecasting model. Figure 3.1 shows the weekly exchange rate prediction using EMA variables with or without ESI. By using EMA variables in our model without ESI variables, the error is lowered only by 1.8% (Table 3.4). The error reduction rate obtained in SMA and EMA models using ESI variables is approximately the same (10.3% and 9.9% respectively). These results indicate that the qualitative variable ESI does have an impact on the forecasting accuracy of the proposed models. Even though its inclusion makes predictions more accurate, there is still room for improvement regarding exchange rate predictability.

Is it possible to predict foreign exchange rates with great precision and accuracy? It can be worked on. So, what can we do about it? Is there any way we can control for these vast arrays of factors affecting exchange rates? There are a lot of variables which have been proven to have a significant influence on the exchange rate mechanism that to try to list and use them all will give for sure a financial headache to its forecasters. Among these factors, how can we know which ones are the most relevant ones to any exchange rate mechanism, and how can we make sure that they are the appropriate ones for any particular model selected? What guarantee do we have that the models we will try to develop will contribute significantly to the exchange rate dilemma? At the end, is this an implicit recognition of the theory of random walk? Can someone really argue that a decrease in the error reduction rate of an exchange rate model will bring undeniable improvements to the exchange rate arena? No one knows for sure, but it’s better to try than do nothing at all. If researchers lie on a sea of laziness without risking a failed attempt at change, their behaviors will testify against their inactions by failing to actively improve the mechanisms on which society stands today.

3.7 Conclusions and Future Research

This paper investigates the performance of an SVM model for European forex forecasting in terms of sensitivity of free parameters selection. Also, the right combination of technical indicators and a qualitative variable is pursued in order to determine which model has the lowest error. In addition, the impact of a qualitative variable on the model's forecasting power and accuracy is measured and evaluated. In reducing total prediction error, models having ESI values comes out as producing the best results. Thus, concluding that SMA and EMA models can be used interchangeably. In SMA and EMA models lacking ESI variables the preferred model of choice would be EMA models due to their lower forecasting error.

Over a wide range of values for regularization parameters C and σ, the results show that a $C = 10$ and a σ of 0.1 produce the best performance. Further improvements needs to be made on the proper selection of variables as inputs, suitable kernel functions, more variables, more performance metrics and more comparisons of linear and non linear forecasting models. Future research could explore the possibility of coming up with a hybrid model having an SVM and any other non-linear component such as NNs or GAs. Recent research done on this field has shown the potential advantages and applications that could be obtained for exchange rate forecasting by employing these powerful predictive tools. Another research possibility could be to examine the impact of external variables, such as political events, on the exchange rate mechanism. Recent political situations have shown that the governmental instability experienced by one country could have irreversible consequences on the economical development of neighboring countries, and thus affect or inhibit any advantageous agreement fostered by neutral parties.

3.7.1 Acknowledgements

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Chapter 4: An application of SVMs to predict financial exchange rate by using sentiment indicators

Introduction to chapter 4

The fourth chapter of this thesis addresses the impact of a model's free parameters selection, moving averages, and a business and consumer survey variable on the exchange rate predictions of 7 countries. This paper has been presented in some research seminars and conferences. This thesis brings the version presented at the Congreso Español de Informática (CEDI 2010) held in Valencia, Spain. Co-authors to this paper are: Professor Núria Agell (ESADE-URL), Professor Josep Sayeras (ESADE-URL) and doctoral student Germán Sánchez (ESAII-UPC, ESADE-URL).

Abstract

This paper analyses, through the use of Support Vector Machines, the impact that the economic sentiment indicator variable known as ESI has on a model's forecasting accuracy when it comes to currency exchange rate prediction. The study has been carried out either using exponential or simple moving averages. Weekly currency exchange rates between the European euro and some major currencies have been considered. The results obtained show that the proposed indicator can significantly impact the model's forecasting performance compared to traditional models where no qualitative information is incorporated.

4.1 Introduction

There are a lot of variables which have been proven to have a significant influence on the exchange rate mechanism that to try to list and use them all will give for sure a financial headache to its forecasters (Kontolemis, 2003). Among these factors, how can we know which ones are the most relevant ones to any exchange rate mechanism, and how can we make sure that they are the appropriate ones for any particular model selected? What guarantee do we have that the models we will try to develop will contribute significantly to the exchange rate dilemma? At the end, is this an implicit recognition of the theory of random walk? Can someone really argue that a decrease in the error reduction rate of an exchange rate model will bring undeniable improvements to the exchange rate arena? No one knows for sure, but it’s better to try than to do nothing at all.

Exchange rates exhibit two characteristics: significant non-stationarity and a high level of noise (Giles, Lawrence & Chung Tsoi, 1997). Most researchers will agree with the claim that the exchange rates behave according to the efficient market hypothesis (Balassa, 1964; Chinn, 2003; Floyd, 2007; Frenkel, 1976; Murfin & Ormerod, 1984; Samuelson, 1964). In its conception, this hypothesis states that at any given time, security prices such as the price of any particular stock will reflect all available information (Fama, 1965). The price movements of an asset will not follow any pattern or trend, thus making its future unpredictable. Hence, the future price of an asset cannot be forecasted. Consequently, there is no better way to forecast the price of an asset than the current price of the asset. Applied to foreign exchange rates, there is no information in past percentage changes which could be applied for the prediction of future percentage changes (White & Racine, 2001). Its actual price will follow what is known as a random walk.

Hsieh (1989) alleges that foreign exchange rates and other financial time series “follow a random walk and should therefore not be predictable much past 50 percent (the average performance of random walk models for foreign exchange markets)”. Random walk models have outperformed other statistical and econometric models when it comes to foreign exchange rate determination (Meese & Rogoff, 1983). Nag and Mitra (2002) reach the same conclusion based on the work done by other researchers who state that through the use of time-varying parameters models similar results are reached. Nag and Mitra (2002) also conjectured that the linear unpredictability of the exchange rate models was due to the linear limitations of the models themselves. Nevertheless, the development of non-linear models significantly outperforming the performance of the random walk model was scarce.

While exchange rates may be predicted based on a number of quantitative information and technical analyses, recent evidence advocates for the incorporation of qualitative information into Forex models. In a recent article written for Daily FX, Rodriguez (2009) claims that several sentiment indicators have a significant role in the US dollar/Euro exchange rate. These sentiment indicators suggest that the US dollar may be reaching its steepest decline in months against some major currencies. Through an innovative FX indicator called Speculative Sentiment Index data (SSI), Rodriguez is able to predict a future weakness of the US dollar into the current week of trading. This indicator, which is based on private customer flow information, will be able to track price trends and identify breaks and reversals in the top four currency pairs.

Another leading qualitative indicator called the World Economic Survey (WES) assesses a country's general economic situation, main economic problems, as well as expectations about important eco nomic indexes such as foreign trade volume, trade balance, inflation rate, and interest rates. Through a team of economic experts, the WES evaluates the value of some of the major currencies (US dollar, European euro, British pound and Japanese yen), and the prospects of each currency's appreciation/depreciation against the US dollar. In a recent report published by CMS Forex, Nilsson and Tapasanun (2009) claims that the EUR/USD exchange rate rose as eurozone eco nomic sentiment indicator increased for the first time since May 2007. According to the report, as risk sentiment improved, the US dollar and the yen fell against their opposites. The sterling rose on expectations of a UK economic recovery by the end of the year. Likewise, positive feelings for a global economic recovery and higher commodity prices made the Canadian and Australian dollars rise again.

Because of the high volatility and non-linear behaviour found in exchange rates, this paper makes use of a non-linear forecasting technique to predict them. Compared to previous research done on the field where only financial indicators have been used as inputs, this research employs a sentiment indicator as one of the inputs of the proposed models. Previous literature suggests that financial indicators are all that matters when predicting exchange rates (Balassa, 1964; Chinn, 2003; Floyd, 2007; Samuelson, 1964). The models used in this paper will evidence the opposite indicating the significance that sentiment variables have on the exchange rate dilemma. Secondly, a quest for the right combination of free parameters selection and technical indicators is conducted in an attempt to improve the model's prediction and accuracy.

This paper has been organised in the following way. In section 4.2 the Economic Sentiment Indicator is introduced. Section 4.3 presents the modelling approach by introducing Support Vector Machine techniques and moving averages indicators. In Section 4.4, the variables and the dataset employed are explained along with graphical descriptions of the experiment and its results. Finally, section 4.5 outlines conclusions and possible lines of future research related to the subject under study.

4.2 Economic Sentiment Indicator

The European Commission Directorate-General for Economic and Financial Affairs (European Commission DG ECFIN, 2009) publishes on a monthly basis business and consumer surveys which provide important quantitative and qualitative information about the economic health, short-term forecasts and economic research for the euro-area. Business and consumer surveys reveal the opinion and expectations of financial and economic experts in the area about the current trend of the different sectors of the economy: industry, services, construction and retail trade, as well as consumers. These surveys are carried out by professional organizations such as governmental agencies, banks, consulting companies and research institutes, among others. These organizations work with and share a common methodology consisting of harmonized questionnaires and a common timetable. These business surveys (construction, services, consumers, industry and retail trade) are all integrated into a broader one-dimensional index called the Economic Sentiment Indicator (ESI) which summarizes all positive and negative developments in the surveyed sectors of each EU member country.

There is a widespread belief that these expectations themselves influence public opinion and economic policy makers through the media. Mehrotra and Rautava (2007) claim that business sentiment indicators are useful in forecasting developments in the Chinese economy because they tend to transmit useful information about the current and future state of affairs of the economic activity in the country. Enough has been said and done about the universe of quantitative variables which when incorporated into forecasting models account for improvements in the model's forecasting power and accuracy. Nonetheless, the vast array of literature dealing with exchange rates lacks research related to the possible impact of qualitative information on a model's predictive power. Will there be an impact on the model's accuracy if a qualitative variable is added? If a significant impact is expected, will the model improve? Will the model be able to generalise? Does an improvement in a model's forecasting power due to the addition of some qualitative variable mean that the volatility of foreign exchange rates is simply due to qualitative information? For purposes of this paper, the composite confidence indicator ESI will be used for analysis.

4.3 Modelling Approach

In this paper Support Vector Machines (SVM) are used to build up an empirical model to obtain current exchange rates values from observed values given by past moving exchange ratios average and ESI.

4.3.1 Support Vector Machines

SVMs are supervised learning methods mainly used for classification and regression problems. Originally introduced by Vapnik, SVMs have become a new powerful tool for learning from data because they improve the generalisation capability of other conventional forecasting techniques (Cristianini & Shawe-Taylor, 2000). SVMs produce a nonlinear regression in a low-dimensional space. The input data is nonlinearly mapped in a high dimensional feature space by using a kernel function, and then a linear regression is run in this altered space. Compared to the empirical risk minimisation of NN, an SVM is able to minimise the structural risk, specifically the upper bound of the generalisation error.

4.3.2 Moving Averages

Traders and investors often use technical indicators such as moving averages in order to smooth time series data and detect spot trends (Stockcharts.com, 2009). The two most often used types of moving averages are the simple moving average (SMA) and the exponential moving average (EMA).

For purposes of this paper, the following EMA was used:

$$E_t = E_{t-1} + \alpha\left(P_{t-1} - E_{t-1}\right) \qquad (1)$$

where E_t is today's EMA, E_{t-1} is yesterday's EMA, P_{t-1} is yesterday's closing price and α equals the smoothing factor, a number between 0 and 1. This smoothing factor

is calculated as follows: $\frac{2}{N+1}$, where N equals the number of time periods.

4.3.3 Which one is better?

Traders argue that one of the advantages of using EMA lies in its ability to follow data more closely than SMA. Since SMAs are lagging indicators, EMA can keep a better track of observations by assigning more weight to recent values. Critics argue that SMAs are limited in their tracking abilities due to the fact that each observation in the dataset has the same weight. It doesn't matter if the value occurred at the beginning of the period or at the end of it, it gets the same weight. Because of this limitation, analysts began to develop new tracking tools, such as EMA, which were able to put more emphasis on recent values. By being more responsive to new information, EMA are able to follow any trend with a better precision and accuracy. The moving average chosen will depend on the analyst's strategy and preferences. Shorter moving averages will be able to respond better and quicker to the data. Longer moving averages will respond slower to the data and may not be able to detect any trend or signal. EMA will follow the data more closely than simple SMA, thus detecting trends and generating more signals. For purposes of this paper, SMAs and EMAs for six major currencies will be used as inputs in the forecasting models.

4.4 Experimental results

4.4.1 Data set description

In this research, the most recently available foreign currency exchange rate data is used for analysis. The dataset comes from the Pacific Exchange Rate Service available online at http://fx.sauder.ubc.ca/data.html (Pacific Exchange Rate Service, 2009). The period under consideration is from December 15, 1999 until March 19, 2009. The data set of six world's major currencies is used, specifically European Euros (EUR), US Dollar (USD), Great Britain Pound Sterling (GBP), Chinese Yuan (CNY), Canadian Dollar (CAD), Japanese Yen (JPY) and Indian Rupee (INR). European Euros (EUR) is selected as the base currency. Weekly analysis is performed in this research using every Wednesday's closing price as the target price. The qualitative confidence indicator ESI and moving-averages are used as inputs to the SVM models. Two types of moving-averages are used: simple moving-average (SMA) and exponential moving averages (EMA).

Since weekly analysis is performed, the input feature vector is:

F = {F 1, F 2, F 3, F 4, F 5}

= {X (T), SM_{A12}, SM_{A26}, SM_{A34}, SM_{A50}

where X (T) is the current Wednesday closing price, SM_{A12}, SM_{A26}, SM_{A34}, SM_{A50} are the simple moving average for a 12, 26, 34 and 50-days period, respectively. Since one of the purposes of this experiment is to test the impact of the qualitative variable ESI on the forecasting power and accuracy of the model, the variable ESI is added to the feature vectors used in the first model. So instead of having 5-input-features vectors, the new model has 6-input-features vectors. Firstly, the model is run with the moving averages variables and a prediction is attempted. Secondly, the ESI indicator is added as an input feature vector, and the resulting model with 6-input-features vectors is run again and a new prediction is attempted. The same procedure is adopted for EMA values.

Knowing that weekly data is needed in order to run the experiment, the monthly values for the ESI indicator were assumed to be constant during their respective four week period (each week was assigned its respective monthly value). Since the target forecast is the next Wednesday's exchange rate and due to limitations of availability of information, the ESI value of the previous month is used to forecast the exchange rate of the current month.

4.4.2 Results

With the data collected from 6 currencies exchange rate, four different experiments are run using the statistical software package known as R Project for Statistical Computing (The R Project, 2006). Each experiment produces an SVM model with a Gaussian kernel component. Using the function in R known as 'tune.svm', different values are assigned to the prescribed parameter C , which is the regularised constant determining the tradeoff between the empirical error and the model flatness, and the variable sigma σ, which is present in the denominator of the kernel component of the Gaussian function. The values for the parameter C are: 0,1, 1, 10, 100, 1000 and 10000. The values assigned to the variable σ are: 0,1, 1, 2, 4, 8, 16 and 32. There are 7 possible values for σ and 6 for C, thus having 42 possible combinations in every single experiment. For each one of these 42 combinations, a 10- fold cross validation method is used. This method comes up with the combination that minimises the validation process. The output for all experiments is the weekly exchange rate (ER) of the euro against the mentioned currencies. The forecasting horizon is the next Wednesday's exchange rate. The performance metric used to evaluate our results is the normalised mean squared error (NMSE). Four experiments are performed to analyse the improvement on the model accuracy when using the ESI indicator.

In the first experiment, the 5 EMA variables are used as inputs and the ER is used as output. A 10-fold cross validation method is used to select the optimum parameters. In the second experiment, the 5 EMA variables along with the ESI indicator are used as inputs. In the third experiment, the 5 SMA variables are used as inputs. Finally, in the last experiment the 5 SMA variables along with the ESI indicator are used as inputs.

Tables 4.1 and 4.2 summarise these results. Once all four models are trained with the corresponding input data, these models are tested in order to measure their forecasting power and predictive accuracy. Table 4.1 shows, for each of the experiments, the combination of σ and C which get the best NMSE, while table 4.2 shows the NMSE.

	USD		GBP		CNY		JPY		INR		CAD	
	σ	***C***	***σ***	***C***	***σ***	***C***	***σ***	***C***	***σ***	***C***	***σ***	***C***
EMA (without ESI)	0.1	1000	0.1	10000	0.1	100	0.1	10	0.1	10	0.1	1000
EMA with ESI	0.1	100	0.1	1000	0.1	10	0.1	10	0.1	10	0.1	1000
SMA (without ESI)	0.1	10	1	10	2	1	1	10	0.1	10	0.1	1
SMA with ESI	0.1	100	1	10	1	10	0.1	100	0.1	10	0.1	1000

Table 4.1: σ and C parameters with best NMSE

	USD	GBP	CNY	JPY	INR	CAD
EMA (without ESI)	0.00431	0.00721	0.00634	0.00821	0.00571	0.00255
EMA with ESI	0.00392	0.00681	0.00586	0.00751	0.00546	0.00208
SMA (without ESI)	0.00455	0.00697	0.00544	0.00579	0.00572	0.00294
SMA with ESI	0.00386	0.00582	0.00428	0.00638	0.00546	0.00186

Table 4.2: NMSE

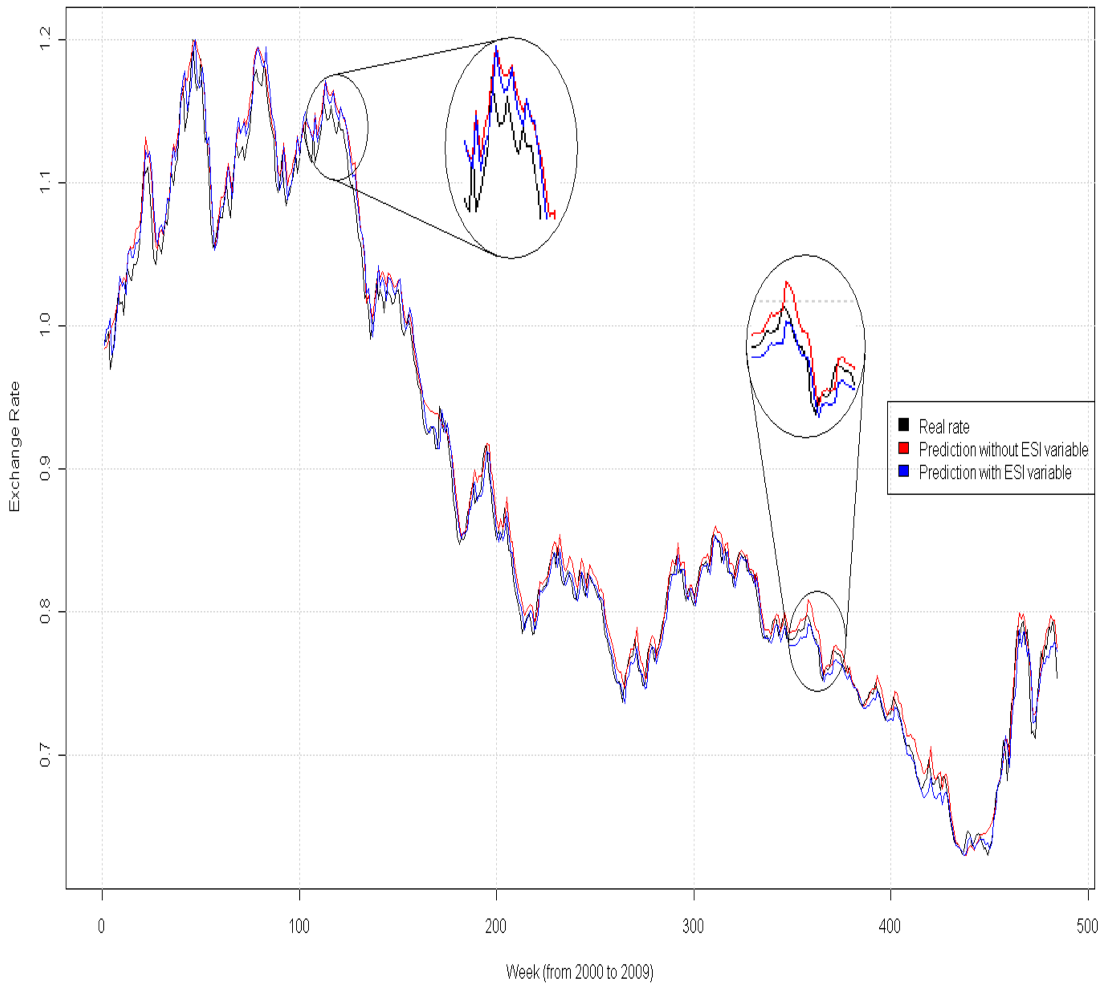

Figure 4.1: EUR/USD weekly exchange rate prediction: SMA variables (with or without ESI)

4.4.3 Interpretation

By taking a closer look at table 4.2, we can see that experiments that have been carried out by using the ESI indicator have always outperformed results compared to the same experiments run without it. In addition, the experiments allow us to conclude that in general predictions the tests using SMA variables are more accurate than those done using EMA as input variables. Note that the results obtained for CAD currency are significantly worse than the rest of currencies.

In figure 4.1, a general vision of the weekly exchange rate prediction using SMA variables with or without ESI can be seen and a better behavior of the models that use the ESI indicator is noticed.

4.5 Conclusions and Future Research

This paper investigates the performance of an SVM model for European forex forecasting in terms of sensitivity of free parameters selection. The right combination of technical indicators and a qualitative variable is pursued in order to determine which model has the lowest error. In addition, the impact of a qualitative variable on the model's forecasting power and accuracy is measured and evaluated. In reducing total prediction error, models having ESI values comes out as producing the best results. Further improvements needs to be made on the proper selection of variables as inputs, suitable kernel functions, more variables, more performance metrics and more comparisons of linear and non linear forecasting models. Future research could explore the possibility of coming up with non-Gaussian kernels. Another research possibility could be to examine the impact of external variables, such as political events, on the exchange rate mechanism. Recent political situations have shown that the governmental instability experienced by one country could have irreversible consequences on the economical development of neighbouring countries, and thus affect or inhibit any advantageous agreement fostered by neutral parties.

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Chapter 5: Analyzing the use of business and consumer surveys in forecasting exchange rates: A cross-country comparison

Introduction to chapter 5

The fifth chapter of this thesis addresses the impact of a model's free parameters selection, a moving average, and a business and consumer survey variable on the exchange rate predictions of 4 developed and 2 non-developed countries. This paper has been presented in some research seminars and conferences. This thesis brings the version submitted to the *Emerging Markets, Finance and Trade Journal* in Illinois, USA. Co-authors to this paper are: Professor Núria Agell (ESADE-URL), Professor Josep Sayeras (ESADE-URL) and doctoral student Germán Sánchez (ESADE-URL, ESAII-UPC).

Abstract

In this paper we analyze whether the use of the Economic Sentiment Indicator (ESI) is relevant in forecasting the exchange rates of 4 developed economies and 2 emerging market economies. Unlike previous studies where sentiment indicators have proven to be helpful forecasters, we show that ESI will have no significative impact on the exchange rates considered. Taking the European euro as the base currency, the data set of the exchange rates of 4 industrialized economies and 2 emerging markets was analyzed: US dollar, British pound, Chinese yuan, Canadian dollar, Japanese yen and Indian rupee. Support Vector Machines were used to obtain forecasts for the different currencies. Weekly forecasts were carried out using simple moving averages as input feature vectors. The results show that ESI provides limited information in all cases except for one of the emergent market economies where it appears to make a significant contribution.

5.1 Introduction

Over the last couple of decades, business and consumer surveys have received considerable attention from researchers and policy makers worldwide. They have become important tools for the analysis of economic scenarios by providing useful information about current and future macroeconomic conditions. The advantage of using survey data lies in their quick availability, low measurement errors and the variability of topics covered. The impact this information may have on macroeconomic forecasts has been studied extensively by analysts and researchers around the globe (Carroll, Fuhrer, & Wilcox, 1994; Chopin & Darrat, 2000; Cotsomitis & Kwan, 2006; Easaw & Heravi, 2004; Fan & Wong, 1998; Kwan & Cotsomitis, 2004; Kwan & Cotsomitis, 2006; Ludvigson, 2004; Mehrotra & Rautava, 2007; Mishkin, 1978). The majority of these forecasts try to measure growth or changes in macro variables such as household spending, retail sales, inflation and unemployment, among others. But recently, attention has shifted from household spending and retail sales to GDP (Growth Domestic Product) and other key factors driving the economy (Claveria, Pons & Ramos, 2007; Hansson, Jansson & Löf, 2005). In spite of this shift in attention, information about the impact that survey data has on the exchange rate has been scarce (Gormus & Gunes, 2010).

Attempts have been done at a theoretical level, but most of them fail to provide the empirical evidence needed as to the precise effects, if any, business and consumer surveys have on the exchange rate mechanism (Hopper, 1997; Menkhoff & Rebitzky, 2008; Simpson & Ramchander, 2004). Even though Simpson and Ramchander (2004) study the effectiveness of survey data in predicting the direction of change in the U.S. dollar exchange rate, the authors implicitly gave for granted the usefulness of business surveys in exchange rate forecasting. Hansson, Jansson & Löf (2003) study the usefulness of business survey data in the prediction of macroeconomic variables such as GDP, unemployment, interest rates, price and wage inflation and exchange-rate changes. Leaving aside GDP, the results are quite mixed suggesting that further research needed to be done on the impact of survey information on these other variables.

In a recent article written for CMS Forex, Nilsson and Tapasanun (2009) claim that the EUR USD exchange rate rose as the euro zone ESI increased for the first time since May 2007. It is alleged that as risk sentiment improved, the U.S. dollar and the yen fell against their opposites. Moreover, the sterling rose on expectations of a UK economic recovery by the end of the year. Likewise, positive feelings for a global economic recovery and higher commodity prices made the Canadian and Australian dollars rise again. Financial research has associated the stability of the British pound to the expectations of the UK consumer confidence indicator (Deans, 2010; Lawrence, 2011). At a theoretical level, links have been made between business surveys and exchange rates, but almost no empirical evidence has been given to attest this relationship. Since a dearth of data exists on this issue, the objective of this paper is to try to determine the impact of ESI on exchange rates, if any. Precisely, the aim is to see if by adding this indicator, exchange rate predictions show any improvement in their forecasting horizons.

During the last decades, early attempts were made to model financial time series (Boothe & Glassman, 1987; Wolff, 1988). Some of these attempts focused on using linear time series techniques for exchange rate forecasting. These efforts proved futile due to the non-linear characteristics found in exchange rates (Hsieh, 1989; Meese & Rose, 1991). The failure of these techniques meant the prevalence of the random walk model over its competing predictive options. Nevertheless, this apparent drawback was nothing short of the motivation researchers needed in their quest of finding other modelling alternatives. Since non-linear behavior was a certain attribute of exchange rates, non-parametric models such as artificial neural networks (ANN) were used as a sound option for modelling this attribute (Giles, Lawrence & Ah Chung, 1997; Velásquez & González, 2006; White & Racine, 2001). ANN models had three characteristics which gave them an edge over its competing linear alternatives: they were data-driven, self-adaptive and universal function approximators (Nag & Mitra, 2002).

The forecasting ability of ANN models was put into question due to the emergence of newer non-parametric techniques, such as Support Vector Machines (SVMs), which were able to make predictions with a greater degree of accuracy (Cao & Tay, 2003; Hock & Cao, 2001; Ince & Trafalis, 2007; Kamruzzaman, Sarker, & Ahmad, 2003; Pai, Hong, Chang, & Chen, 2006;). One of the main advantages of SVMs over ANNs lies in the capacity of the former to improve the generalisation property of the latter (Cristianini & Shawe-Taylor, 2000). Comparisons were made among the predictive abilities of SVMs, ANNs, ARIMAs and hybrid models. Kamruzzaman and Sarker (2003) illustrate the dominance of SVM models over ANN and ARIMA models in Australian foreign exchange rate forecasting. By analysing different performance metrics such as the normalized mean square error (NMSE) and the mean absolute error (MAE), Cao and Tay (2001) show that SVMs can be trained faster and be better forecasters than back-propagation ANNs.

Hansen, McDonald and Nelson (2006) compare the predictive potential of SVMs with that of three ARIMA models in time series forecasting. Their results show that SVMs clearly outperform its ARIMA alternatives achieving the best results in almost all of the domains under study. Pai and Lin (2005) show that, using the same dataset, a hybrid ARIMA-SVM model is able to outperform the forecasts of its individual ARIMA and SVM components, and also that of a random walk model in stock price forecasting. Ince and Trafalis (2006) give supporting evidence as to the advantages of using support vector regression (SVR) methods over ANNs based models. By building a hybrid model comprised of linear and non-linear techniques, the SVRs prove to be better predictors than ANNs based on selected performance metrics such as the MAE and the mean squared error. As previous research has indicated and due to the advantages shown by SVMs over ANNs and linear models, this paper will make use of SVM models in order to address its objective in the most convincing way possible.

The rest of this paper is organized in the following way. Section 5.2 presents selected works on the use of sentiment indicators in the forecasting literature. Section 5.3 discusses the theoretical model by describing the ESI and SVMs. In Section 5.4, the empirical study and its results are presented. Finally, Section 5.5 presents the conclusions and outlines future research lines.

5.2 Sentiment indicators in the forecasting literature

Carroll et al. (1994) study whether an index of consumer sentiment (ICS) produced by the University of Michigan could be considered a useful predictor in household spending. Through the use of a linear regression model, the predictive capacity of lagged values of ICS is measured for future changes in consumption spending. The results clearly show that the lagged values of ICS have a considerable explanatory power for future changes in household spending, and that the ICS could be considered a powerful decisive force for the US economy.

Easaw and Heravi (2004) try to determine whether four indices of consumer sentiment were able to forecast UK household consumption growth, and consequently whether these indices could be considered accurate and useful predictors as well. Through the use of a linear regression model, the forecasting ability of these four indices is measured. The results show that the explanatory power of the sentiments-augmented model is greater than the baseline model which left out any sentiment factor. In terms of its ‘out-of-sample’ forecasting ability, the sentiments-augmented model makes better forecasts at times of higher consumption growth and higher consumer confidence.

Hansson et al. (2005) examine whether the information contained in business surveys could help predict GDP growth. Four vector autoregression (VAR) models are used to achieve this purpose. One of them incorporates a dynamic factor model (DFM) whose purpose is twofold: to serve as a kind of filtering procedure for getting rid of unimportant noise in the survey data and for dimension reduction. This DFM-VAR model is expected to outperform the other VAR alternatives because of its use of survey variables and of its filtering technique. The results show that in most cases the forecasting performance and accuracy of a VAR can be improved if it includes a DFM filter. Also, the DFM-based VAR clearly outperforms its rivals by having a lower RMSE than its competing VAR models in short and medium horizons.

Cotsomitis and Kwan (2006) study the impact consumer sentiment had on household spending within a multicountry framework. Through the use of a linear regression model and two indices of consumer sentiment, specifically the consumer confidence indicator (CCI) and the economic sentiment indicator (ESI), it is shown that the predictive capacity of the CCI is useful in 3 out of the 9 countries examined. The ESI shows predictive power in 5 out of the 9 countries surveyed. Based on these results, the authors express their doubts about the predictive power of the CCI and ESI for household spending. Claveria et al. (2007) analyze the usefulness of business and consumer surveys in macroeconomic forecasting. The aim is to do a forecasting comparison between the models that use survey variables from those that do not with the purpose of seeing if the predictions of the macroeconomic variables are improved by the inclusion or exclusion of the survey data. The results show that the RMSEs of the models with survey variables tend to be lower than the RMSEs of the models without survey information. However, these lower RMSEs are statistically significant in a limited number of cases.

Gormus and Gunes (2010) investigate the effect of a consumer confidence index (CCI) on real exchange rate data for Turkey. Through the use of GARCH-M and OLS models, the authors are able to show that CCI had an impact on exchange rates.

5.3 The Theoretical Model

5.3.1 Economic Sentiment Indicator

The ESI forms part of the business and consumer surveys produced by the European Commission Directorate General for Economic and Financial Affairs (hereafter referred to as European Commission DG-ECFIN, 2009). These surveys provide valuable information for short and long term macroeconomic forecasting at EU, Member state and euro-area level. The ESI is one of three aggregate monthly indices published by the European Commission DG-ECFIN whose purpose is to gauge expert's opinions and expectations about the current and expected trend of five sectors of the European economy: namely, industry, services, construction, retail trade and consumers. These opinions and expectations are added in the form of balances which are later used in the financial building of a composite confidence indicator. The latter one is computed as the arithmetic means of answers to a set of questions related to a particular surveyed sector.

The harmonized questionnaires, which are mostly of qualitative nature, cover a broad range of issues such as expectations about production, selling prices and employment, short-term developments in the construction sector, intentions on major purchases, and assessments of current business conditions, among others topics. The surveys, which are carried out by professional organizations comprised of researchers, academics, consultants and financial officials, make use of a common methodology and a common timetable for purposes of homogeneity. The size of the surveyed sample varies across countries depending on the heterogeneity of the economy of its EU and euro-area members. The sample size is directly proportional to the population size of each country. More than 124.000 companies and 39.000 consumers across the EU are surveyed on a monthly basis.

5.3.2 Support Vector Machines

SVM is a supervised learning method initially used for classification but soon extended for regression and other learning problems. It has firmly grounded in the framework of Statistical Learning Theory, developed mainly by Vapnik and Chevornenkis over the last decades (Vapnik, 1998). Models established by SVM algorithms have the property of having excellent generalization capability. This is due to the use of structural risk minimization principle whereas other learning methods such as artificial neural networks use the empirical risk minimization. The basic ideas of the SVM theory for regression are presented below.

Suppose we are given training data $\{(x_1, y_1),(x_2, y_2),...,(x_N, y_N)\} \subset \chi \times$ R, where χ denotes the space of the input patterns. In ε-SV regression, the goal is to find a function f(x) that has at most ε deviation from the actually obtained targets y_i for all the training data, and at the same time is as flat as possible. In the linear case, if $\chi = R^d$, this function takes the form:

$$f(x) = \sum_{i=1}^{N} w_i \phi_i(x) + b \qquad (1)$$

with $w \in R^d$, $b \in$ R. , where $\phi_i(x)$ represents the feature which is nonlinearly mapped from the input space x. The constants w_i and b are obtained from the minimization of the regularized risk function:

$$R(C) = C\frac{1}{N}\sum_{i=1}^{N} L_\varepsilon(d_i, y_i) + \frac{1}{2}\|w\|^2 \qquad (2)$$

$$L_\varepsilon(d, y) = \begin{cases} |d-y|-\varepsilon & |d-y| \geq \varepsilon, \\ 0 & otherwise, \end{cases} \qquad (3)$$

where both C and ε are prescribed parameters. The regularized constant C estimates the tradeoff between the empirical error and model flatness. The first term $L_\varepsilon(d, y)$ describes the ε-insensitive loss function where errors below ε are not penalized, knowing ε beforehand. The term $\frac{1}{2}\|w\|^2$ measures function flatness. By using the slack variables ζ and ζ^* which represent the distance from the actual values to their respective boundary values of ε-tube, equation (2) becomes:

Minimize:

$$R(w, \zeta, \zeta^*) = \frac{1}{2}\|w\|^2 + C^*(\sum_{i=1}^{N} \zeta_i + \zeta_i^*) \qquad (4)$$

Subjected to:

$$w\phi(x_i) + b_i - d_i \leq \varepsilon + \zeta_i^*, \qquad (5)$$

$$d_i - w\phi(x_i) - b_i \leq \varepsilon + \zeta_i, \qquad (6)$$

$$\zeta_i, \zeta_i^* \geq 0 \qquad (7)$$

$i = 1, 2, ..., N$.

Afterwards, equation (1) becomes:

$$f(x, a_i, a_i^*) = \sum_{i=1}^{N} (a_i - a_i^*) K(x, x_i) + b \quad (8)$$

where a_i, a_i^* represent the Lagrange multipliers introduced. The equality $a_i * a_i^* = 0, a_i \geq 0, \ a_i^* \geq 0, i = 1, ..., N,$ is satisfied by the Lagrange multipliers and these are obtained by maximizing the dual form of equation (4) which takes the following form:

$$\phi(a_i, a_i^*) = \sum_{i=1}^{N} d_i (a_i - a_i^*) - \varepsilon \sum_{i=1}^{N} (a_i + a_i^*) - \frac{1}{2} \sum_{i=1}^{N} \sum_{j=1}^{N} (a_i - a_i^*)(a_j - a_j^*) K(x_i, x_j) \quad (9)$$

with the constraints:

$$\sum_{i=1}^{N} (a_i - a_i^*) = 0$$
$$0 \leq a_i \leq C, i = 1, 2, ..., N$$
$$0 \leq a_j \leq C, i = 1, 2, ..., N$$

In equation (8), *K(x ,x_i)* is called the kernel function. Its value is equal to the inner product of two vectors x_i and x_j in the feature space $\phi(x_i)$ and $\phi(x_j)$ such that Mercer's condition is satisfied, $K(x_i, x_j) = \phi(x_i) * \phi(x_j)$. The kernel function used in this study is the Gaussian kernel function:

$K(x_i, x_j) = \exp(-\|x_i - x_j\|^2 / (2\sigma^2))$.

For simplicity purposes and as it was stated above, the dual formulation of the optimization problem in the nonlinear case is:

maximize:

$$-\frac{1}{2} \sum_{i,j=1}^{N} (\alpha_i - \alpha_i^*)\left(\alpha_j - \alpha_j^*\right) K\left(x_i, x_j\right)$$

$$-\varepsilon \sum_{i=1}^{N} (\alpha_i + \alpha_i^*) + \sum_{i=1}^{N} y_i \left(\alpha_i - \alpha_i^*\right)$$

subject to: $\sum_{i=1}^{N} (\alpha_i - \alpha_i^*) = 0$ and $\alpha_i, \alpha_i^* \in [0, C]$

where α_i and α_i^* are related to the Lagrange multipliers. The parameters *w* and *b* can be obtained from these multipliers and the input patterns.

5.4 Empirical Study

5.4.1 Data set description

The period under consideration is from December 15, 1999 (Wednesday) to March 18, 2009 (Wednesday). The data set comes from the Pacific Exchange Rate Service database (2009). The data set of the world's major currencies is used, specifically European Euros (EUR), US Dollar (USD), British Pound (GBP), Chinese Yuan (CNY), Canadian Dollar (CAD), Japanese Yen (JPY) and Indian Rupee (INR). The European euro is selected as the base currency. Weekly analysis is performed in this research using every Wednesday's closing price as the target price.

The euro zone ESI and the simple moving-averages (SMA) are used as inputs to the SVM models. Since weekly analysis is performed, the input feature vector F = {F1, F2, F3, F4, F5, F6} = {SMA1, SMA10, SMA20, SMA30, SMA40, SMA50}, where SMA 1 is the previous Wednesday closing price, and SMA10, SMA20, SMA30, SMA40, SMA50 is the simple moving average for a 10, 20, 30, 40, and 50-weeks period, respectively. Firstly, the model is run with the moving averages variables and a prediction is attempted. Since the purpose of the experiment is to test the impact of ESI on exchange rates, ESI is added to the feature vectors used in the first model. So instead of having 5 input vectors, the new model has 6. Then, the resulting model with 6 input feature vectors is run again and a new prediction is attempted. At the end, a variation was introduced where the purpose was to forecast not the current Wednesday closing price but the difference between the current and its previous value, $x_t - x_{t-1}$. For this purpose, time series with and without the ESI were used as input feature vectors.

Knowing that weekly data is needed in order to run the experiment, the monthly values for the ESI indicator are assumed to be constant during their respective four week period (each week was assigned its respective monthly value). Since the target forecast is the current Wednesday's exchange rate and due to limitations of availability of information, the ESI value of the previous month is used to forecast the exchange rate of the current month.

5.4.2 Experimental process and results

With the data collected, two different experiments are run using the statistical software package known as R Project for Statistical Computing (2006). The first experiment doesn't make use of ESI while the second one does use it. Each experiment produces an SVM model with a Gaussian kernel component. Different values are assigned to the regularized parameter C and the kernel constant sigma σ . The values for the parameter C are: 1, 10, 100, and 1000. The values assigned to the variable σ are: 0.05, 0.1, 0.2, and 0.3. Greater values for σ were considered, but the results were worse. There are 4 possible values for σ and 4 for C, thus having 16 possible combinations in every single experiment. The best combination of C and σ is selected by using a standard 10-fold cross validation method.

5.4.3 Performance metrics

The performance metrics used to evaluate our results are the RMSE and the mean absolute percentage error (MAPE). The RMSE and the MAPE are well known for their usefulness in evaluating the accuracy of a forecasting model. They are defined as:

$$RMSE(\hat{Y}) = \sqrt{\sum_{i=1}^{n} \frac{(Y_i - \hat{Y}_i)^2}{n}} \tag{3}$$

$$MAPE(\hat{Y}) = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{Y_i - \hat{Y}_i}{Y_i} \right| \tag{4}$$

Where Y_i and $\hat{Y}_i$ represent the actual and predicted values respectively, and n is the size of the series set. Since the exchange rate ratios to be forecasted are expressed in different scales, the resulting RMSEs cannot be used for comparison purposes. For this reason, the MAPE allows us to compare any kind of prediction. It averages the absolute values of the errors and produces a measure of relatively overall fit. For this reason, even though the results are expressed using two performance metrics, the MAPE has been selected as the main criterion for evaluating our findings.

5.4.4 Results

Because of the high volatility found in exchange rates, the vast majority of forecasts are done with uncertainty. Nowadays, to give a precise estimate of an exchange rate ratio could be considered an illusive task. It makes sense to consider the forecasts as estimates rather than fixed numbers. For this reason and due to the degree of difficulty in forecasting exchange rates, confidence intervals for the mean of the errors have been calculated. For each currency pair, the applied cross-validation process came up with a

95% confidence interval (CI) for the mean of the errors. The output for all experiments is the weekly exchange rate of the EUR against the USD, GBP, CNY, CAD, JPY and INR. The forecasting horizon is the current Wednesday exchange rate.

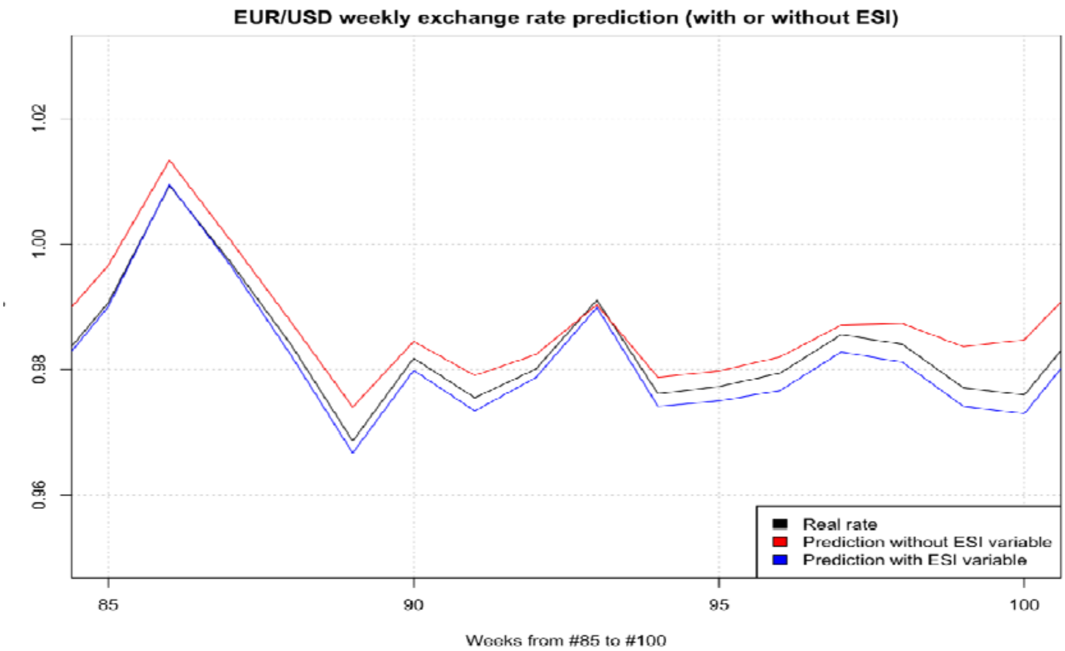
In Table 5.1, the RMSEs and MAPEs for each currency pair are shown. These errors represent the minimum and maximum values for a 95% confidence interval. When comparing two estimated values, if their confidence intervals do not overlap, then those estimations are said to be statistically significantly different. For instance, given the EUR/USD currency pair and for any performance metric, if the confidence intervals are non-overlapping, it can be concluded that ESI makes a significant impact on the performance prediction at a 95% confidence level.

Metric	ESI	USD	GBP	CAD
RMSE	No Yes	[0.01380, 0.01390] [0.01380, 0.01390]	[0.01170, 0.01180] [0.01170, 0.01180]	[**0.01750, 0.01760**] [**0.01710, 0.01720**]
MAPE	No Yes	[**0.00817, 0.00818**] [**0.00829, 0.00834**]	[**0.00573, 0.00581**] [**0.00550, 0.00560**]	[0.00671, 0.00746] [0.00686, 0.00720]
Metric	**ESI**	**CNY**	**INR**	**JPY**
RMSE	No Yes	[0.10190, 0.10290] [0.10220, 0.10260]	[**0.59320, 0.59620**] [**0.58040, 0.58420**]	[1.7700, 1.7900] [1.7580, 1.7760]
MAPE	No Yes	[**0.00718, 0.00729**] [**0.00797, 0.00811**]	[**0.00807, 0.00816**] [**0.00753, 0.00760**]	[0.00838, 0.00860] [0.00842, 0.00872]

Table 5.1: 95% CI for the 6 currency pairs
Bold indicates significant differences

According to the RMSEs in Table 5.1, ESI makes no additional contribution to the existing models of the EUR/USD, GBP/EUR, EUR/CNY, EUR/JPY currency pairs since overlapping occurs. The situation is different in the EUR/CAD and EUR/INR currency pairs. The margins of the confidence intervals obtained by using ESI are lower than the margins of the model without it, i.e. non-overlapping occurs. Hence, in these cases, the introduction of ESI makes a significative difference there. However, the MAPEs of the EUR/CAD currency pair make that difference insignificant. The MAPEs of the EUR/USD, GBP/EUR, EUR/CNY, EUR/INR currency pairs make it statistically significantly different.

Figures 5.1 and 5.2 shows a detail of the predictions of the EUR/USD and EUR/INR series with and without ESI. It can be observed that the visual differences are smaller in the EUR/USD series than in the EUR/INR one.



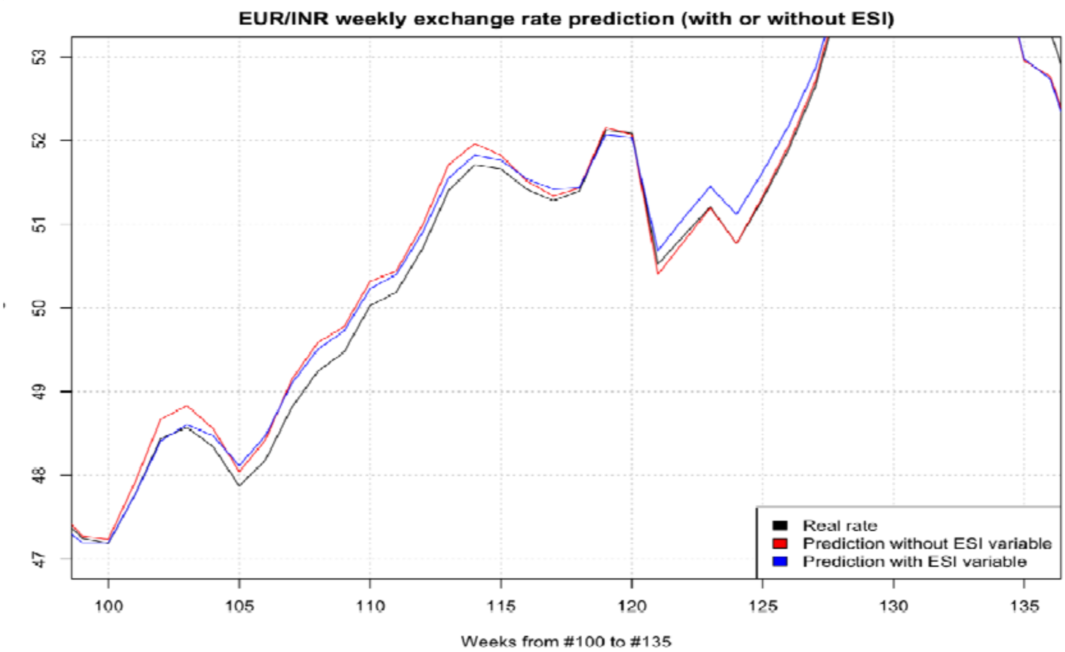
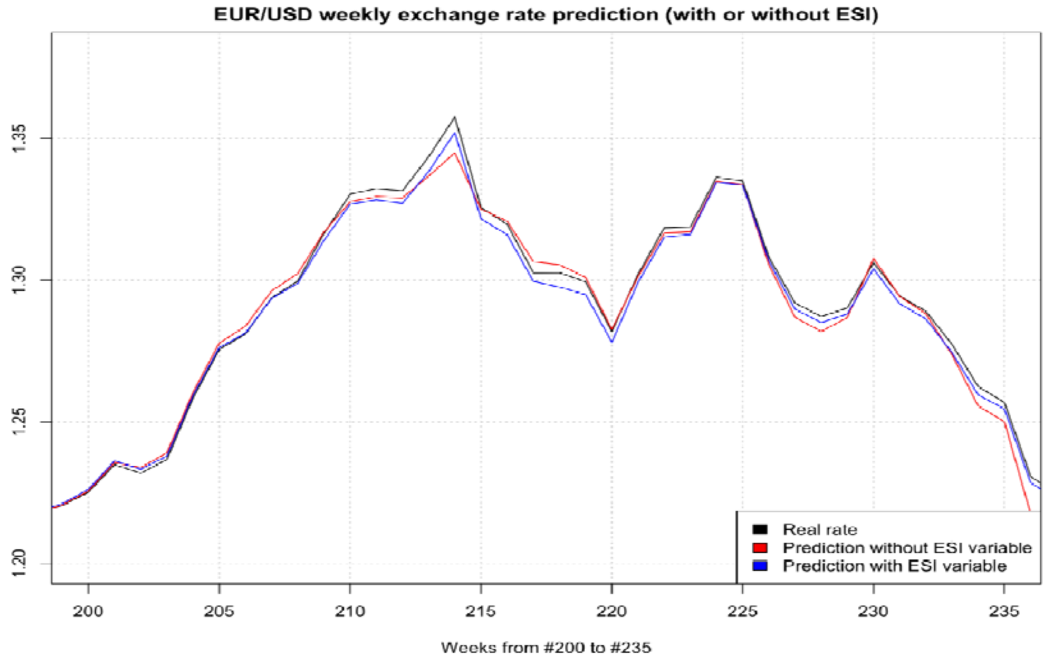


Figure 5.1: Comparison of predictions of EUR/USD (top) and of EUR/INR (bottom) series



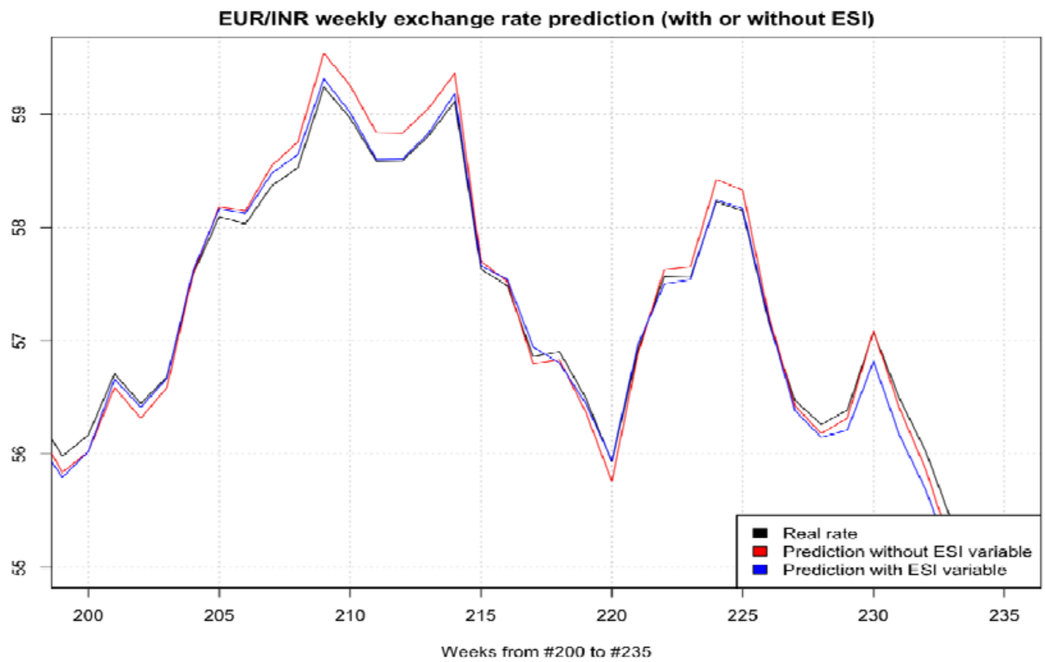


Figure 5.2: Comparison of predictions of EUR/USD (top) and of EUR/INR (bottom) series

In order to minimize the long-run trend effect so as to focus on the short-run effects, the differentiated series was considered. The behavior of the models that use these differentiated series is also similar (Table 5.2). Note that MAPE cannot be computed because the series to be forecasted have values near zero, and those values are used in the denominator of equation (4).

Metric	ESI	USD	GBP	CAD
RMSE	No	[0.01462, 0.01474]	[0.01257, 0.01266]	[0.01762,0.01773]
	Yes	[0.01471, 0.01484]	[0.01262, 0.01271]	[0.01772, 0.01778]

Metric	ESI	CNY	INR	JPY
RMSE	No	[0.10837, 0.10894]	[**0.61500, 0.61700**]	[1.8445, 1.8515]
	Yes	[0.10893, 0.10931]	[**0.61790, 0.62070**]	[1.8407, 1.8493]

Table 5.2: 95% CI for the differentiated series. Bold indicates significant differences

Only in the EUR/INR currency pair, the differences between the two models are accepted as significant at a 95% confidence level.

Table 5.3 shows a summary of the results showing the best choice according to each performance metric. The differentiated series is not considered.

Perf. Metric	No ESI	ESI	Indifferent
RMSE		CAD INR	USD GBP CNY JPY
MAPE	USD CNY	GBP INR	CAD JPY

Table 5.3: Best choice according to each performance metric, using ESI or not

By looking at the RMSEs in Table 5.3, ESI helps predict the EUR/CAD and EUR/INR exchange rates, but in a limited way only. As for the rest, it will make no difference to make a prediction with or without ESI. The MAPEs suggest that ESI is useful for forecasting the GBP/EUR and the EUR/INR exchange rates, but not to a great extent. It is interesting to see that according to both performance metrics, ESI has an impact on the performance prediction of the EUR/INR exchange rate ratio. The RMSEs for the differentiated series confirm this finding.

Further evidence that ESI provides limited or no additional information about the path of the exchange rate has been given in the form of a final experiment in which a random variable was added to the input data set for the EUR/USD series. Table 5.4 shows that when any random variable is added to the models, the errors increase considerably, contrary to what happened when the ESI was introduced.

Perf. Metric	Random var.	USD Min.	Max.
RMSE	No	0.01380	0.01390
	Yes	0.01510	0.01530
MAPE	No	0.00817	0.00818
	Yes	0.00892	0.00905

Table 5.4: 95% CI when a random variable is introduced for the €/$

5.5 Conclusions and future research

This paper investigated the impact, if any, of ESI on six exchange rate ratios: EUR/USD, GBP, CAD, CNY, JPY, and INR. Our results indicate that this sentiment indicator provides limited information about the path of the exchange rate. Only in one currency pair it appears to make a significant contribution, EUR/INR. One possible explanation might be that the economy of India has been growing at a gigantic pace and is experiencing a considerable increase in the level of economic activity along with countries like China, Brazil and Russia. Unlike China, India is not well known for any intervention in its exchange rate market. In the case of China, this sentiment indicator provides no additional information and its MAPE value suggests the EUR/CNY was better off without the ESI.

Why? Compared to India, China has a strong pulse in its markets and it is well known for its intentional interventions in its exchange rate mechanism. China could be much more cautious than India to allow freely floating exchange rates. One logical reason for this might be the issue of liability dollarisation. It looks like this could play a significant role as to the effect ESI has on the EUR/CNY exchange rate. It would be interesting to see the impact ESI will have on the exchange rate ratios of countries like Brazil and Russia. If significant contributions are obtained, a case for emerging economies could be sustained. The price levels of emergent economies are very susceptible to variations in exchange rates. Extreme variations in exchange rates could increase the aggregate inflation level at a higher speed than in most developed economies (Devereux, Lane & Xu, 2006).

Otherwise, business and consumer surveys should be considered orientative in nature and should not be taken as leading indicators in making decisions. They serve more as guides than as decisive tools in business scenarios. Further improvements needs to be made on the proper selection of input variables, suitable kernel functions, more variables, more performance metrics and more comparisons of linear and non linear forecasting models. Future research could explore the possibility of coming up with a hybrid model having an SVM and any other non-linear component such as ANNs or genetic algorithms. Recent research done on this field has shown the potential advantages and applications that could be obtained for exchange rate forecasting by combining these predictive tools. Another research possibility could be to examine the impact of external variables, such as political events, on the exchange rate mechanism. Recent political situations have shown that the governmental instability experienced by one country could have irreversible consequences on the economical development of neighboring countries, and thus affect or inhibit any advantageous agreement fostered by neutral parties.

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Chapter 6: Conclusions, limitations, and future research

6.1 Conclusions

This chapter will briefly present the conclusions of each of the chapters enclosed in this dissertation along with their respective limitations and insights for future research. First of all, I would like to state that chapters 2, 3, 4 served as cornerstones for the research done in chapter 5. A theoretical cornerstone is a fundamental assumption from which something is developed. For instance, a masonry cornerstone is the most important building block in the foundation of any building, concrete blocking or stonework. If the cornerstone is not set perfectly, the rest of the blocks or bricks will be off scale by further and further degrees as the building continues. At some point, the whole structure will have to be torn down, and the cornerstone reset. So it is when people say they have reached a cornerstone, it is a tearing down and a rebuilding of values or morals or ideas in order to rebuild a more solid foundation. Chapters 2, 3 and 4 served as indispensable and fundamental basis for the last piece of research in this dissertation. After a lot of sampling experiments and researching, chapter 5 emerged as the culmination of this research experience.

Before making a chapter by chapter conclusion, I would like to give an overall judgment about the methodologies and variables chosen and employed in this dissertation. I will go from a broad general overview followed by specific chapter by chapter conclusions.

6.2 General concluding remarks

I began this research with the following goal in mind: the improvement of exchange rate predictions. Needless to say, this objective has been achieved and it has been shown that a combination of technical and economic variables do have an effect on exchange rate predictions. As it has been stated in previous chapters, I went through a lot of brainstorming and several ideas popped up during the process. Firstly, I wanted to focus on specific improvements to a forecasting machine and the relation of several economic variables to fluctuations in exchange rates. I thought that if I could get the models to improve to their highest degree of accuracy, exchange rate predictions were going to improve respectively. After some analysis I realized this task was enormous due to the different existing forecasting techniques, besides the fact that there is no perfect forecasting model in foreign exchange markets.

In the foreign exchange market, financial traders use a variety of models some of which are non-linear, such as ANNs, or linear, such as some moving averages, in nature. A number of economic and technical variables are related to fluctuations in exchange rates that some of them will be modeled by linear techniques and others by non-linear ones. Forecasters tend to make improvements to their predicting models, but this doesn't necessarily mean that the chosen technique is unreliable. Improvements are simply upgrades a forecasting technique needs to adapt itself to a specific situation. The SVMs used in this research were constantly updated with different values so as to have the best model possible. With the results achieved, SVM proved to have excellent capabilities in forecasting exchange rate data. As the results presented in all the papers have demonstrated, it's impossible to give a precise forecast; the best we can get are approximations.

I also wanted to give a qualitative touch to the forecasting dilemma. Besides making use of all the historical economic variables known to be determinants of exchange rates, I wanted to contribute theoretically to the existing literature by adding a new predictor to exchange rates. Almost qualitative in nature, ESI was chosen for its relevance in these times of crisis. The scenario couldn't have been better: making use of a variable which measures expectations and hopes of financial traders and economists in the business community to gauge the speculative decisions made by investment professionals in foreign exchange markets. This is why ESI was selected as a predictor in this analysis. As first conclusion of this research, it was demonstrated that ESI is a contributing factor to the exchange rate predicament of an emerging economy.

Since economic variables have always been known to have a marked influence on exchange rate predictions, I wanted to see if technical analysis had the same or a bigger influence than fundamental economic variables. Lento and Gradojevic (2007) states the following:

> Depending on the trading horizon, between 12.8 and 40.8 per cent of foreign currency exchange traders in Hong Kong, Tokyo and Singapore use technical indicators as the basis of their trades. Also, technical analysis is used as the primary or secondary source of information for approximately 90 per cent of traders in London, while 60 per cent of these traders also hold technical analysis as at least as important as fundamental analysis. Technical analysis has been embraced by practicing investment analysts; however, the academic community has not been as accepting. Regardless of the academic point of view, technical

> analysis has enjoyed a renaissance on both Wall Street and Bay Street as most major brokerage firms now publish technical commentary on the market. (p. 13)

As second conclusion of this research, it was shown the relevance of using moving averages in foreign exchange forecasting. It was demonstrated that moving averages were able to capture trends or patterns found in past exchange rate data, thus increasing the reliability of the predictions.

Overall, chapter 2 showed that fundamental economic variables are valuable predictors in foreign exchange markets. These variables coupled with technical indicators proved to be the right approach in dealing with exchange rate uncertainty. Chapters 3, 4 and 5 gave supporting evidence as to the relevance and importance of technical indicators in exchange rate predictions. It was further demonstrated that ESI does help in forecasting exchange rates, thus giving additional proof as to the role played by business and consumer surveys in financial time series forecasting. This thesis also illustrated the point that the best forecasting model 'survives'. The best fitted model was chosen as the main forecasting technique. This demonstrated the idea that once all of a model's parameters have been statistically improved and verified, a model's contributions, in terms of forecasting performance, will be of great importance for foreign exchange markets.

6.3 Chapter by chapter conclusions

6.3.1 Paper 1 (Chapter 2)

Since exchange rates are considered very important in a country's level of trade, they are often one of the most analysed and manipulated economic measures of any government. As it has been seen, currency crisis are not only due to a government's effort to manipulate its national currency, but also to a wide variety of economic factors. Holden's (2007) study states the following:

> Economic theory and empirical evidence have identified a number of factors known to affect movements in exchange rates. In isolation, these have a predictable effect on currency values. However, since many economic variables are closely interconnected, they rarely, if ever, act in isolation from one another. This makes anticipating or explaining movements in exchange rates notoriously difficult, a difficult exacerbated by the fact that many factors known to affect

> currency values are evident only in hindsight. Furthermore, these factors are often themselves affected by movements in exchange rates. In other words, while the Canadian dollar moves in response to prevailing economic conditions, it influences those conditions as well. (p. 3)

Arguably, a variety of models could be developed with the sole purpose of incorporating one economic variable at a time so as to see its real effect on exchange rates. This can be done with the interest rate differential variable, the GDP, the productivity variable, and so on. But this hardly will tell the true story encompassing foreign exchange markets. Most fundamental economic variables are interrelated to one another that to isolate any one of them in a forecasting model can be seen as a naïve attempt at the problem. It is better to use them as groups of variables and see the overall effect on the market. This is why in chapter 2 this research incorporated several fundamental economic variables as a group of predictors in an exchange rate model. Chapter 2's findings confirm the idea of using interconnected economic variables as determinants of exchange rates.

Remarkable is the fact that the model which produced the most accurate predictions had quotients for both zones and the exchange rate of the previous period as input variables. A quotient relationship allows for cross-country comparisons to be made more easily. In the financial world, investability quotients (IQ) exist. An IQ is a term used by Standard and Poor's to describe how good a company's medium to long-term return potential is. Companies are scored on a scale from a minimum of 1 to a maximum of 250 (Piskora, 2008). In the article, Piskora states the following:

> The IQ is a proprietary Standard & Poor's measure of investment desirability. The IQ serves as an indicator of potential medium- to long-term return and as a caution against downside risk. Think of it as a metric of metrics. S&P's IQ combines models using proprietary analytical tools, technical measures, liquidity and volatility indicators, and quantitative analysis to come up with a total score. Under the IQ system, companies are scored on a scale of 1 to 250—similar to the standard measure of human intelligence—with higher numbers signaling stronger potential. The IQ model combines four submodels: 1) An S&P proprietary model based on STARS ranking, quality of earnings and dividend growth, and an outfit's credit rating; 2) A proprietary, multifactor statistical model that includes valuation, profitability, risk, and momentum factors; 3) A

> liquidity and volatility model that measures liquidity and downside risk; and 4) A technical model that looks at six-month relative strength. (p. 1)

It can be argued that depending on the quotient for both zones and the degree of investment desirability between one region and the other, a forecasting model can be developed for the region most desirable to invest in. This model will produce more accurate forecasts by incorporating the exchange rate of the previous period. In the end, the results showed that the best model was a blend of fundamental economic variables and technical analysis since the exchange rate used was that of the previous period. It would have been interesting to see what would have happened with more technical indicators as input variables.

In terms of model selection, Chapter 2 restates one of the objectives of this thesis which is Darwin's idea of 'survival of the fittest'. The best model in each experiment was selected for out-of-sample forecasting which is the standard procedure followed by financial researchers, academicians and traders in foreign exchange markets. While attempts were made to improve exchange rate predictions, it is unrealistic to think accurate forecasts can be made. Holden's research concludes by stating the following:

> In fact, the dollar's performance in recent years has highlighted the fact that it is nearly impossible to make accurate predictions about short-term exchange rate movements. Exchange rates are affected by too many variables-global commodity prices, economic policy and conditions in the United States, the ability of the Canadian economy to adapt to the higher dollar, to name but a few-for any such prediction to be reliable. (p. 14)

Realistically speaking, the best that can be gotten are approximations instead of exact forecasts. This is not a recognition of the random walk theory, but an implicit acknowledgment of the presence of uncontrollable and unpredictable economic forces in foreign exchange markets.

6.3.2 Paper 2 (Chapter 3) and Paper 3 (Chapter 4)

The conclusions of papers 2 and 3 are going to be presented together since both papers had the same objectives: the analysis of ESI, the use of moving averages and the choice of free-parameters selection. The difference between the two lies in the number of countries analysed. The paper in Chapter 3 analysed 2 zones (USA and Europe) whereas the paper in Chapter 4 analysed 7 countries or zones. In chapters 3 and 4, it can be seen that the use of a moving average, specifically the SMA, in conjunction with ESI brought a significant improvement in the overall forecasting performance of the model. The moving averages used in these two papers showed their ability in tracking down patterns or trends present in the data. This finding is supported by Lento and Gradojevic (2007). In their article, they state the following:

> Brock, Lakonishok, and LeBaron's landmark research is one of the most influential and referenced studies ever conducted on technical analysis. The study used bootstrapping techniques and two simple, yet popular, trading rules to reveal strong evidence in support of technical analysis's predictive nature. The data set was for the Dow Jones Index from 1897-1986. The authors argued that the patterns uncovered by technical rules cannot be explained by first order correlations or by the potential for changing expected returns caused by changes in volatility. The profits generated from the technical trading rules were not consistent with a random walk, AR (1), GARCH-M, or an exponential GARCH model. In a related study, Levich and Thomas provide further evidence of the profitability of technical trading rules. Moving average and filter rules produced profitable trading signals. The profits from the moving average rules were higher than those of the filter rules. (p. 13-14)

In chapters 3 and 4, the error reduction rate of models using SMA and EMA variables along with ESI was considerable. The advantages of incorporating ESI into a forecasting model are more than evident. ESI was able to lower errors rates as far as 10 % in some cases. This demonstrates that ESI does have an impact on the forecasting accuracy of the proposed models. This gives strong evidence as to the role played by ESI in foreign exchange markets. As additional proof of ESI's relevancy, sentiment indicators have been incorporated into a variety of economic reports produced by major investment and financial institutions. According to the Economic and Market Monitor report produced by BNP Paribas for the months of July-August 2011, sentiment indicators does have a pronounced influence on the general business climate of any region in both sides of the Atlantic. In the report, Cerisier (2011) states the following about the economy of France:

> More generally, and in line with the slump in the sentiment indicators seen in most countries in the region, the most recent survey data suggests that, while remaining at a level very favorable to growth in activity, the business climate

> may have peaked in early spring. Based on INSEE surveys, the deterioration started in April in industry and wholesale trade and spread to service activities in May. There was a pause in the trend in June, when manufacturers' sentiment even posted a sharp rebound. All in all, the synthetic index for all sectors had lost only one percentage point in June relative to its April high. Purchasing manager surveys, which are more volatile, but often fairly reliable regarding short-term fluctuations in activity, suggest a far sharper slowdown. The composite activity index (PMI) stood at 55.4 in June, a level that is still positive, but well below the peak observed in April (62.4). (p. 22)

This illustrates the point that economic sentiment indicators are becoming more relevant in today's financial world in which speculative investments are made almost on a daily basis.

6.3.3 Paper 4 (Chapter 5)

There are researchers who suggest that sentiment indicators are helpful markers in the task of forecasting some major macroeconomic variables as exchange rates are (Lim & Lim, 2009; Menkhoff & Rebitzky, 2008; Singh, Mehta & Varsha, 2011). Hartnett (2008) claims that sentiment indicators are leading signals for emerging market equities. Currency News (2011), an online world currency market publication, stresses the relationship between market sentiment and the GBP/USD exchange rates. The following is stated:

> Global equities markets had a mixed day yesterday, but the leading sentiment indicator, the S&P 500, closed down by over a percentage point at 1308, almost 3% lower than it was as recently as 21st February. This confirms a dip in global appetite for risk which would normally see the dollar benefit as the world's reserve currency of choice. The fact that the Dollar has suffered broad weakness since 21st February, whilst the Yen and Swiss Franc have appreciated, will provide concern for investors holding Dollars. (p. 1)

The results of paper 4 suggest that ESI provided a significant contribution to the EUR/INR exchange rate ratio only. This could be due to a variety of reasons, but mainly it can be attributed to the enormous economic expansion that the economy of India has been experiencing. This economic expansion and the fact that there has been almost no government intervention in its exchange rate mechanism has made the Indian foreign exchange market more attractive to traders willing to invest their money in powerful emerging economies (Shah & Patnaik, 2011).

Since in the previous papers there was almost no significant difference between SMA and EMA in terms of NMSE and error reduction rate, it was decided to use only SMA as inputs in this paper. At some points in chapters 3 and 4, SMA gave us the impression of performing better than EMA. However, this perception was not strongly sustained so as to affirm undoubtedly that SMA over performed EMA. This is why it was decided to stick with SMA for this last research effort. The SMA used in chapter 5 served as the basis on which the possible contributions made by ESI were going to be represented. Regarding the model's free-parameters selection, as it was shown and proven in the previous research papers, the most fitted SVM model was chosen as the main forecasting technique for out-of-sampling purposes.

6.4 Limitations

The overall limitation of this thesis is the non-comparability of the chosen forecasting technique against other linear and non-linear forecasting alternatives. This is a limitation which embraces all four papers of this dissertation, and inhibits the comparability of the results obtained in all four papers. Since no comparative study was done among different forecasting techniques, the positive or negative results obtained in a single experiment cannot be attributed to a model's misspecification or ability to fit the given data. If other predicting techniques had been employed and if the results had been similar, strong conclusive evidence could have been given to the financial community since the results would have been verified by all the forecasting methods employed. However, the conclusions presented in this dissertation have enough merits of their own to stand constructive criticism in the business environment.

6.5 Chapter by chapter limitations

6.5.1 Paper 1 (Chapter 2)

One of the major limitations found was related to the non-availability of monthly data for some of the economic variables used in the models. Information about the variables GDP, productivity and CAB was gathered on a quarterly basis instead of on a monthly basis as it was gathered for the inflation and interest rate variables. For the CAB indicator, the values for the first three months of 1999 were missing. In order to compensate for this shortcoming, the first three months for each one of the five indicators were not counted when performing the experiment.

Another limitation is that the selected economic variables are not the only economic variables having an influence on and/or causing fluctuations in exchange rates. Some of the variables used in this paper were chosen because they were known to be historical determinants of exchange rates. But variables such as unemployment rate, price indices, political risks and the level of the stock market were not taken into account as predictors in the models.

Also, in the last experiment the exchange rate of the previous period was used as an input in the SVM model. This proved to be a success since this last experiment produced the most accurate forecast. It would have been good to see what would have happened if more technical indicators had been used as inputs in the models. The sole use of economic fundamental variables in a model is considered by some traders a risky measure to take (Cheung & Chinn, 1999). The combination of economic variables and technical indicators is the preferred alternative to some economic models in foreign exchange markets.

6.5.2 Paper 2 (Chapter 3) and Paper 3 (Chapter 4)

One of the major limitations in these two papers was the business and consumer variable ESI. Knowing that weekly data was needed in order to run the experiments, the monthly values for the ESI indicator were assumed to be constant during their respective four week period (each week was assigned its respective monthly value). Since the target forecast was the next Wednesday's exchange rate and due to limitations of availability of information, the ESI value of the previous month was used to forecast the exchange rate of the current month.

Another limitation of this experiment lies in the technical indicators used. Besides SMA and EMA, there are other technical indicators that can be used for research purposes. For instance, the cumulative moving average and the weighted moving average are two techniques which traders find relevant for trend determination especially in a fast-moving market. Also, moving averages for an X-days period were calculated and used as inputs in the models. Moving averages with a shorter time period could have been calculated. Instead of doing a moving average of a 12 or 26-days period, moving averages of 1, 2, 3-hours or 10-20 minutes could have been obtained for better reliability. Due to problems of availability of the data, this idea was disregarded.

As it was mentioned in the limitations of chapter 2, the sole use of input variables having the same statistical or economical characteristics is a risky bet to place. It would have been better to see any of the SVM models making use of a combination of moving averages and interest rates variables, for example, or any other combination of moving averages and economic variables. (I mentioned interest rates but it could have well been any other economic variable).

6.5.3 Paper 4 (Chapter 5)

The same limitations as in the previous two chapters apply since the objectives and the methodology employed were the same. However, I would like to add that the principal finding of the paper was ESI's influence on the exchange rate ratio of Europe and India. India, which is a rapidly growing economy, is one emerging market that has attracted the attention of traders and investors worldwide. In the paper, an additional emerging market country was analysed: China. Although the findings were different, it would have been good to see what would have happened, regarding ESI's influence, on the exchange rates of other emerging market economies such as Russia, Brazil, and Mexico, among others. This wasn't done in the paper and it is the main limitation of this paper as I see it. If the results of other emerging market exchange rates are similar to the ones obtained for India, then a general principal (regarding ESI) for emerging economies could well be established.

6.6 Future research and final considerations

In future research, more economic and technical variables need to be considered as inputs of any forecasting model. Also additional performance metrics will add more light to the analysis of the results; if using SVM, more suitable kernel functions should be evaluated and the use of linear and non linear forecasting models will be highly recommended. Among the non-linear techniques, a hybrid model of SVM and some other non-linear component would share new light about this issue. Recent research done on this field has shown the potential advantages and applications that could be obtained for exchange rate forecasting by employing these powerful predictive tools.

External variables, such as political events, terrorist attacks and/or natural disasters, have had an influence on foreign exchange rates for a long time. The earthquake that hit Japan recently, the political havoc in the United States and/or the terrorist attack in Norway are all circumstances which have an influence on the perceptions and expectations of traders in foreign exchange markets.

As a final thought, four research articles constitute the basis of this dissertation. The overall research process of this thesis illustrates the way by which the use of artificial intelligence techniques, economic variables, technical indicators and business and consumer surveys improve exchange rate predictions. The contributions of each individual paper are like precious drops of water that raises the level of the ocean for everyone. These small contributions can make meaningful differences in specific areas of finance and artificial intelligence. It is my hope that someone will have the opportunity to tap into this area and to contribute that drop to the ocean of exchange rate forecasting so everyone can be uplifted by it.

Figure 6.1: Exchange rates of the world
Source: Microsoft Research

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