Applications of Hybrid Neural Networks and Genetic Programming in Financial Forecasting

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Abstract

This thesis explores the utility of computational intelligent techniques and aims to contribute to the growing literature of hybrid neural networks and genetic programming applications in financial forecasting. The theoretical background and the description of the forecasting techniques are given in the first part of the thesis (chapters 1-3), while the contribution is provided through the last five self-contained chapters (chapters 4-8).

Chapter 4 investigates the utility of the Psi Sigma neural network when applied to the task of forecasting and trading the Euro/Dollar exchange rate, while Kalman Filter estimation is tested in combining neural network forecasts. A time-varying leverage trading strategy based on volatility forecasts is also introduced. In chapter 5 three neural networks are used to forecast an exchange rate, while Kalman Filter, Genetic Programming and Support Vector Regression are implemented to provide stochastic and genetic forecast combinations. In addition, a hybrid leverage trading strategy tests if volatility forecasts and market shocks can be combined to boost the trading performance of the models. Chapter 6 presents a hybrid Genetic Algorithm – Support Vector Regression model for optimal parameter selection and feature subset combination. The model is applied to the task of forecasting and trading three euro exchange rates. The results of these chapters suggest that the stochastic and genetic neural network forecast combinations present superior forecasts and high profitability. In that way, more light is shed in the demanding issue of achieving statistical and trading efficiency in the foreign exchange markets.

The focus of the next two chapters shifts from exchange rate forecasting to inflation and unemployment prediction through optimal macroeconomic variable selection. Chapter 7 focuses on forecasting the US inflation and unemployment, while chapter 8 presents the Rolling Genetic – Support Vector Regression model. The latter is applied to several forecasting exercises of inflation and unemployment of EMU members. Both chapters provide information on which set of macroeconomic indicators is found relevant to inflation and unemployment targeting on a monthly basis. The proposed models statistically outperform traditional ones. Hence, the voluminous literature, suggesting that non-linear time-varying approaches are more efficient and realistic in similar applications, is extended. From a technical point of view, these algorithms are superior to non-adaptive algorithms; avoid time consuming optimization approaches and efficiently cope with dimensionality and data-snooping issues.

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Declaration

I declare that, except where explicit reference is made to the contribution of others, that this dissertation is the result of my own work and has not been submitted for any other degree at the University of Glasgow or any other institution.

Signature:

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"Human behavior flows from three main sources: Desire, Emotion, and ***Knowledge.****''*

Plato

*"****Effort*** *only fully releases its reward after a person refuses to quit."*

Napoleon Hill

*"****Success*** *is not final, failure is not fatal: it is the courage to continue that counts."*

Winston Churchill

List of Abbreviations

A/D	Accumulation/Distribution Rule
AIC	Akaike Information Criterion
AO-RW	Atkeson and Ohanian Random Walk
ARMA	Autoregressive Moving Average
BB	Bollinger Bonds
BH	Buy and Hold
CHB	Channel Breakout Rule
CHO	Chaikin Oscillator
CPI	Consumer Price Index
CT	Contrarian Rule
DM	Diebold-Mariano test
DPO	Detrended Price Oscillator
DTB	Double Tops and Double Bottoms Rule
ECB	European Central Bank
EMA	Exponential Moving Average
FP	Flags and Pennants Rule
FR	Filter Rule
GA	Genetic Algorithm
GA-SVR	Genetic Algorithm - Support Vector Regression
GP	Genetic Programming
GRR	Granger-Ramanathan Regression
HONN	Higher Order Neural Network
HS	Head and Shoulder Rule
k-NN	Nearest Neighbours Algorithm
LASSO	Least Absolute Shrinkage and Selection Operator
MA	Moving Average

MACD	Moving Average Convergence/Divergence
MDM	Modified Diebold-Mariano test
MLP	Multi-Layer Perceptron
MT	Momentum Rule
NN	Neural Network
OT	Oscillator Rule
PO	Price Oscillator
PSN	Psi Sigma Network
RBF	Radial Basis Function
RG-SVR	Rolling Genetic – Support Vector Regression
RNN	Recurrent Neural Network
RSI	Relative Strength Index
RW	Random Walk
SIC	Schwarz Bayesian Information Criterion
SMA	Simple Moving Average
SO	Stochastic Oscillator
STAR	Smooth Transition Autoregressive Model
SVM	Support Vector Machine
SVR	Support Vector Regression
TR	Triangles and Rectangles Rule
TRB	Trading Range Break Rule
TRIX	Triple Exponential Moving Average
UNEMP	Unemployment Rate
VOLB	Volatility Breakout Rule
WMA	Weighted Moving Average

Chapter 1

Introduction

1.1 General Background and Motivation

The majority of human activity is motivated, influenced and driven by forecasts, namely predictions of the future. This can be verified by numerous examples in daily life. For instance, an employee going to work on time every morning has to go through a subconscious forecasting process in his mind. In that case the forecasted variable is the time needed to reach the workplace. The accuracy of this daily forecast depends on many factors and assumptions, such as distance between home and office, traffic, walking pace, weather etc. Although some factors can be fixed through time, most of them are constantly changing, resulting in punctual and late employees. Unwillingness to set assumptions for a forecast is equivalent to not being willing to forecast at all. Consequently, forecasting and uncertainty are concepts highly inter-connected.

In financial decisions, though, the impacts of wrong forecasts are substantially greater than being late for work one morning. Additionally, the financial world is so complex that forecasts might be affected by a myriad of factors compared to the simple example above. Investors attempt to forecast events that might affect a company, such as sales expectations, and then decide whether the price of its shares will increase or not. A business decision to lend or borrow money would depend on forecasts of future cash flows or expected returns. Economists in central banks are particularly interested in the extrapolation of future inflation or unemployment trends, since these lead to monetary policy changes. Therefore, the development of accurate financial forecasting techniques is of paramount importance, especially in times of global economic turmoil and market uncertainty. This is when financial time series are found to be most 'noisy' and non-linearities and structural breaks rule the common macroeconomic explanatory variables.

During these periods the abovementioned task becomes extremely challenging for academic researchers, investors and relevant market and policy practitioners. Under this context, all previous parties attempt to model economic and financial activity with computational techniques that would be successful, where traditional statistical approaches would fail.

Computational intelligence is a scientific field that develops and models techniques that could achieve human cognitive capabilities. These capabilities could be described in short by three words: Reasoning; Understanding; and Learning. According to Bezdek (1994) a computationally intelligent system has pattern recognition ability and exhibits computational adaptivity and fault tolerance. At the same time, though, its turn-around speed and error rates approximate the human brain's performance. Such computational approaches have been extensively utilized in forecasting applications. Specifically, Neural Networks (NNs), Genetic Algorithms (GAs) and Support Vector Machines (SVMs) are very common in the voluminous financial forecasting literature (see amongst others Adya and Collopy (1998), Tay and Chao (2001 and 2002), Chen *et al.* (2003), Kim (2006), Ahn and Kim (2009) and Huang *et al.* (2013)).

The difference of such models with statistical ones lies in their adaptive nature. They can take many different forms and have as inputs any potential explanatory variable. Non-linearity is not possible to be measured in statistical terms and therefore these models have the advantage in tasks where the exact nature of the series under study is unknown. Sceptics argue that the lack a formal statistical theoretical background behind such approaches makes them useless in Finance. However, financial series are dominated by factors (e.g. behavioural factors, politics…) that time-series analysis and statistics are unable to capture in a single model. Hence, a statistical model that will capture such pattern in a time-series is in the long-run infeasible. Although computational models present encouraging results, there is an open discussion regarding their ability to overcome computational and complexity issues, deriving from their underlying engineering structure and atheoritical exploitation of the available financial data.

Over-fitting is one of the issues that can arise during statistical inference using flexible computational models. The term applies when a supervised learning algorithm is trained to perform well in a training dataset, but fails in the important test period. One solution to this problem is the split of the dataset into an in-sample and out-of-sample period. Thus, the model's parameters are only tuned in-sample. Popular anti-over-fitting techniques are the 'early stopping procedure' (Lin *et al.* (2009) and Prechelt (2012)), cross validation (Zhang *et al.* (1999), Amjady and Keynia (2009) and Sermpinis *et al.* (2012b)) and pruning parameter approaches (Castellano *et al.* (1997) and Wang *et al.* (2010)). Another related drawback of computational intelligence methods is the dimensionality issues deriving from the large inputs fitted to the model. This is highly correlated with the optimal *feature selection process,* where from the sparse training space the model selects only appropriate data subsets to optimize its parameters. This issue can be handled with techniques such as principal component methods (Jollife, 1986), filtering techniques (Mundra and Rajapakse, 2007), and embedded techniques (Hsieh *et al.*, 2011). Finally, one serious disadvantage of some computational intelligence techniques is the low degree of theoretical *interpretability*. Many consider them 'black boxes' because of their computational complexity, which requires professional expertise. Over-simplifying them, though, leads to opposite results in terms of performance. The feature selection is one way to create a trade-off between the previous statements. Implementing or incorporating fuzzy rules in these algorithms could be another efficient solution (Hua *et al.* (2007) and Khemchandani *et al.* (2009)).

The promising empirical evidence from computational intelligence techniques, such as NNs, GAs and SVMs, allows them to remain in the central scope of much financial research. On the other hand, the inefficiencies deriving from the abovementioned computational issues point out that these models perform well in a task-specific modelling environment. Therefore, generalizing their performance to a more universal modelling framework presents limitations. For the sake of providing a point of reference, similar limitations apply to most modern statistical and econometric models. A recent trend to dealing with these limitations is to introduce hybrid models that combine the attributes of each technique, minimize over-fitting effects and optimally cope with the curse of high dimensionality (see amongst others Huang *et al.* (2012), Dunis *et al.* (2013) and Lin *et al.* (2013)). All the above conclude in a general application framework, which motivates this thesis.

1.2 Outline and Contribution

In light of the motivation outlined above, this thesis contributes in the field of computational financial economics by developing new hybrid/adaptive predictive models based on advanced computational intelligence techniques and examining various financial forecasting and trading applications. These applications are presented in five self-contained chapters (chapters 4-8). In order to avoid unnecessary repetitions, all the forecasting techniques and models used in these chapters are thoroughly described in chapter 3. Finally, chapter 2 is a survey of the trading techniques used in financial forecasting. This is presented prior of all the other chapters in order to motivate and explain the trading rationale of the applications in chapters 4-6.

In Chapter 4 a robust NN, namely the Psi Sigma Neural Network (PSN), is applied to the task of forecasting and trading the Euro/Dollar exchange rate. At the same time, the value of Kalman Filter estimation in combining NN forecasts is tested. Additionally, a time-varying leverage trading strategy based on volatility forecasts is introduced to further improve the performance of the models and their combinations. Based on several statistical criteria, the results show that the stochastic NN forecast combinations present superior forecasts. Furthermore, the trading strategy is successful in an economic sense, leading to high profitability from all models under study.

Through chapter 5 the literature of forecasting and trading the Euro/Dollar exchange rate is extended and the contribution is threefold. Firstly, three NNs are trained with a specialized fitness function to forecast this exchange rate. The function creates a trade-off between statistical accuracy and trading profitability. Secondly, techniques, such as the Kalman Filter, Genetic Programming (GP) and Support Vector Regression (SVR), are implemented to provide stochastic and genetic forecast combinations. Thirdly, a hybrid leverage trading strategy is introduced. The trading strategy tests if volatility forecasts and market shocks can be combined with forecasted daily returns in order to improve the trading performance of the models under study.

In chapter 6 a hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model for optimal parameter selection and feature subset combination is proposed. The GA-SVR model is applied to the task of forecasting and trading three euro exchange rates. Taking the previous chapters one step further, this application uses a feature space comprising from individual NNs' forecasts (as presented in chapter 4 and 5) and forecasts from traditional models. The GA-SVR forecast combinations present the best performance in terms of statistical accuracy and trading efficiency for all the exchange rates under study. That way, two key targets are achieved through this chapter. Firstly, the proposed model fills the gap of the literature regarding the exploitation of GAs in order to tune the SVR parameters, instead of the SVM ones. Secondly, the theory of combining forecasts to achieve higher accuracy is validated and expanded. The extension refers to the fact that the model combines the forecasts that are found more relevant for each task, instead of taking simple averages, whether using equal or not weights, of the individual models.

In general the three previous chapters attempt to shed more light in the demanding issue of achieving statistical and trading efficiency in the foreign exchange markets through computational intelligent models. Successful application of the proposed trading strategies, in conjunction with the training fitness functions suggested, leads to one conclusion: the necessity for a shift from purely statistically based models to models that are optimized in a hybrid trading and statistical approach.

The focus of the next two chapters shifts from exchange rate forecasting to inflation and unemployment prediction through optimal macroeconomic variable selection. Chapter 7 focuses on forecasting changes in monthly US inflation and unemployment. The proposed hybrid GA-SVR model features several novelties, as it captures asymmetries and nonlinearities evident in the given set of predictors; it selects the optimal feature subsets; and it provides a single robust SVR forecast. The rolling forward sample evaluation adds validity to the results of the forecasting exercise. Most importantly, it indicates which predictors are significant in the pro-crisis period, while it shows if these remain significant in crisis and after crisis periods. Chapter 8 introduces an extension of the GA-SVR, namely the Rolling Genetic – Support Vector Regression (RG-SVR) model in forecasting the monthly inflation and unemployment of eight EMU countries. Similarly to chapter 7, RG-SVR selects optimal indicators from a large space of potential inputs. Instead of using rolling samples, RG-SVR implements a rolling window exercise. This provides a mapping of the relevant inflation and unemployment predictors in a month per month and country per country analysis. The task is also achieved with the minimum complexity in terms of support vectors. Both models outperform traditional models with constant or limited sets of independent variables. Hence, they extend the voluminous literature which suggests that non-linear time-varying approaches are more efficient and realistic in similar studies. From a technical point of view, these algorithms are superior to non-adaptive algorithms, avoid time consuming optimization approaches and efficiently cope with dimensionality and data-snooping issues.

In general, each chapter includes the specific motivation, modelling techniques, empirical results, technical details and contribution. Thus, the reader is able to follow the rationale of each application in a practical and concise way. Most chapters are considered for publication, while they are already presented to academic peers through conferences. Chapter 2 is a forthcoming chapter of a book. Chapter 4 has been presented in Forecasting

Financial Markets 2011 conference in Marseille. Its extended version is published in the academic journal Decision Support Systems. Similarly, Chapter 5 has been included in the Asset Pricing Workshop 2012 organized by University of Glasgow. It has also been presented in Forecasting Financial Markets 2012 conference in Marseille. Currently it is under resubmission to the academic Journal of International Financial Markets, Institutions and Money. Finally, Chapters 6 and 7 have been presented in Forecasting Financial Markets 2013 in Hannover. At the moment they are being review by the academic Journal of American Statistical Association and Journal of Forecasting respectively.

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Chapter 2

Financial forecasting and trading strategies: a survey

2.1 Technical Analysis Overview

Forecasting the market behavior has always been in the center of scientific research by academics, financial and government institutions, investors, market speculators and practitioners. This task has proven to be extremely challenging and controversial due to the noisy and non-stationary nature of financial time series, especially in periods of economic turmoil. In order to quantify the results of financial forecasts in practical market terms, the above mentioned parties combine their forecasting methods with sets of rules regarding trade orders and capital management. These rules are called *trading strategies*. This chapter attempts to present a general survey of the trading rules originating from the technical market approach and link them with their modern automated equivalents and trading systems.

Technical analysis is a financial market technique that focuses on studying and forecasting the 'market action', namely the price, volume and open interest future trends, using charts as primary tools. Charles Dow set the roots of technical analysis in late 18th century. The main principle of his Dow Theory is the trending nature of prices, as a result of all available information in the market. These trends are confirmed by volume and do persist despite the 'market noise', as long as there are not definitive signals to imply otherwise.

Another interesting definition of technical analysis is given by Pring (2002, p.2). *'The technical approach to investment is essentially a reflection of the idea that prices move in trends that are determined by the changing attitudes of investors toward a variety of economic, monetary, political, and psychological forces.'* Furthermore he adds that *'the art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early* *stage and ride on that trend until the weight of the evidence shows or proves that the trend has reversed.'*.

In order to fully understand the concept of technical analysis, it is essential to clearly distinct it from the fundamental one. It is also important to discuss the Efficient Market Hypothesis and the Random Walk Theory.

2.1.1 Technical Analysis vs. Fundamental Analysis

In order to fully understand the concept of technical analysis, it is essential to clearly distinct it from the fundamental one. The premises of the technical approach are basically that market action discounts all available information, prices move in trends and history tends to repeat itself. On the other hand, fundamental analysis is based on information regarding supply and demand, the two major economic forces affecting the prices' direction change. Both approaches aim to solve the same problem, but *'the fundamentalist studies the cause of market movement, while the technician studies the effect'* (Murphy, (1996, p. 5)).

In reality the complete separation between the fundamentalist and the technician is not so easy to be made, although there is always basis of conflict. For example, institutions that need a long term assessment of their stock turn to fundamental analysis, while short-term traders use technical one. The company's financial health is evaluated with the technical approach, whereas its long-term potential is based on fundamental approximations. Such examples show that both techniques have advantages and disadvantages and one does not exclude the other. The greatest benefit derived from fundamental analysis is the ability to understand market dynamics and not panic in periods of extreme market volatility. On the other hand, technical analysis does not utilize any economic data or market event news, just simple tools that are easy to understand in comparison with fundamental indicators. The technicians are also able to adapt in any trading medium or time dimension and therefore they gain extra market flexibility compared to fundamentalists. In conclusion, technical analysis appears able to capture trends and extreme market events that the fundamental one discovers and explains, after they are already been well established.

2.1.2 Efficient Market Hypothesis and Random Walk Theory

Fama (1970) introduced the concept of capital market efficiency. This influential paper established the framework implied by the context of the term '*Efficient Market Hypothesis'*. According to Fama (1970), a market is efficient if the prices always reflect and rapidly adjust to the known and new information respectively. The basis of this hypothesis is the existence of rational investors in an uncertain environment. A rational investor is following the news and reacts immediately to all important news that affect directly or indirectly his investment, capital, security price etc. The Efficient Market Hypothesis is also connected with the *Random Walk Theory*, which suggests that the market price movements are random.

The assumptions of the Efficient Market Hypothesis can be summarized as:

- Prices reflect all relevant information available to investors.
- All investors are rational and informed.
- There are no transaction costs and no arbitrage opportunities (perfect operational and allocation efficiency).

Fama (1970) further classifies market efficiency into three forms, based on the information taken under consideration:

- *The weak form* applies when all past information is fully reflected in market prices. The weakly efficient markets are linked with the Random Walk Theory. If the current prices fully reflect all past information, then the next day's price changes would be the result of new information only. Since the new information arrives at random, the price changes must also be random.
- *The semi-strong form* requires all publicly available information to be reflected in market prices. This form is based on the competition among analysts, who attempt to take advantage of the new information constantly generating from market actions. If this competition is perfect and fair, then there would be no analyst who would be able to make abnormal profits.
- *The strong form* implication is that market prices should reflect all available information, including that available only to insiders. This form of market

efficiency is the most demanding, because it concludes that profits cannot be achieved by inside information.

There is a general agreement that developed financial markets would meet the conditions of semi-strong efficiency, despite of some anomalies. These anomalies are related to abnormal returns that can be evident simultaneously with the release time of the new information. On the other hand, the concept of strongly efficient markets is not easily accepted. This is because most of the countries already have anti-insider-trading laws, in order to prevent excessive returns from inside information.

Accepting or not the Efficient Market Hypothesis is one of the core financial debates of our times. The relevant literature is voluminous (see amongst others Jensen (1978), LeRoy and Porter (1981) Malkiel (2003), Timmerman and Granger (2004), Yen and Lee (2008), Lim and Brooks (2011) and Guidi and Gupta (2013)). The empirical results of this extensive literature are ambiguous and controversial. Especially during the 1980s and 1990s, the Efficient Market Hypothesis was under siege. Recent case studies present more results in favor of the market efficiency, but the debate is still ongoing. In fact, the main question remains: *'Does market efficiency exist?'* The practical market experience shows that trends are 'somewhat' existent and predictable, so strictly speaking the Efficient Market Hypothesis can be stated as false (Abu-Mostafa and Atiya, 1996). There is also the opinion that science tries to find the best hypothesis. Therefore, criticism is of limited value, unless the hypothesis is replaced by a better one (Sewell, 2011).

2.1.3 Profitability of Technical Analysis and Criticism

From all the above, it is clear that technical analysis is in contrast with the idea of market efficiency. The main reason for this conflict is that technical analysis opposes the accepted view of what is profitability in an efficient capital market. Technical analysis is based on the principal that investors can achieve greater returns than those obtained by holding a randomly chosen investment with comparable risk for a long time. Hence, the market can be indeed beaten.

However, claiming that there is a direct link between profitability and technical trading rules is justified. For example, Brock *et al.* (1992) in their pioneering paper present evidence of profitability of several trading rules using bootstrap methodology, when applied to the task of forecasting the Dow Jones Industrial Average index. Bessembinder and Chan (1995) extend the use of those rules to predict Asian stock index returns with similar results. These studies created a research trend in technical analysis' efficiency and utility. Menkhoff and Schmidt (2005), Hsu and Kuan (2005) and Park and Irwin (2007) summarize relevant empirical evidence in surveys that focus on the profitability of the technical approach. Especially the latter provide an interesting separation of the corresponding literature into two periods: The early (1960– 1987) and modern (1988–2004) studies periods. This classification is based on the available tools, factors, models, tests and drawbacks that the researcher of period had to face (i.e. Transaction costs, Risk Factor Analysis, Data Mining and Pattern Recognition issues, Parameter Optimization, Out-of-sample verification processes, Bootstrap and White Reality Checks, Neural Networks and Genetic Programming architectures). Park and Irwin (2007) also note that most of the studies conducted in 1960s were more or less published during and after the 1990s. The main reasons for that is, firstly, the fact that the computational resources 'flourished' during that period. Secondly, the benefits of technical analysis also emerged through several seminal papers, which till that period were not well known to the scientific public.

Taken all the above under consideration, it is very logical to wonder why technical analysis remains under constant criticism. Especially academics have an extreme and attacking attitude towards the technical approach, which can be 'colourfully' described as follows. *'Technical analysis is anathema to the academic world. We love to pick on it. Our bullying tactics are prompted by two considerations: (1) the method is patently false; and (2) it's easy to pick on. And while it may seem a bit unfair to pick on such a sorry target, just remember: it is your money we are trying to save.'* (Malkiel, (2007, pp. 127-128)).

The main reasoning for this critique can be summarized as:

- Technical analysis does not accept the Efficient Market Hypothesis.
- Widely cited academic studies conclude that technical rules are not useful (Fama and Blume (1966); Jensen and Benington (1970)).
- Traders use the well-known charts and see the same signals. Their actions go in a way that the market complies with the overriding wisdom. Thus, technical analysis is a 'self-fulfilling prophecy'.
- Chart patterns tell us where the market has been, but cannot tell us where it is going. In other word the past cannot predict the future.

- The technical approach is 'trapped' between the psychology of the trader and the 'insensitivity' of an automatic computational system, where no human intervention is allowed in real time.

2.2 Technical Trading Rules

There is a wide variety of technical trading rules applied everyday by market practitioners, trading experts and technical analysts. This section attempts to present an overview of the 'universe' of these rules and to classify them in some basic categories.

2.2.1 The benchmark 'Buy-and-Hold' Rule (BH)

The 'Buy-and-Hold' rule (BH) is a passive investment strategy, which is thought to be the benchmark of all trading rules in the market. BH aligns with the Efficient Market Hypothesis (see Section 1). Its principle is that investors buy stocks and hold them for a long period of time, without being concerned about short-term price movements, technical indicators and market volatility. Although 'Buying-and-Holding' is not a 'sophisticated' investment strategy, historical data show that it might be quite effective, especially with equities given a long timeline. Typical BH investors use passive elements, such as dollar-cost averaging and index funds, focusing on building a portfolio instead of security research.

There is ground for criticism, especially from technical analysts, who after the Great Recession declared the death of BH rules. Corrado and Lee (1992), Jegadeesh and Titman (1993), Gençay (1998), Levis *et al.* (1999), Fernández-Rodríguez *et al.* (2000), O'Neil (2001), Barber *et al.* (2006) and recently Szafarz (2012) perform competitions of trading strategies, with BH being the main benchmark. Although in most cases BH strategies are being outperformed, there are cases of returns of more than 10% per annum.

2.2.2 Mechanical Trading Rules

Charting is subjective to the technician's interpretation of the historical price patterns. Such subjectivity allows emotions to affect the technical decisions and trading strategies. This class of mechanical rules attempts to constrain these personal intuitions of the traders by introducing a certain decision discipline, which is based on identifying and following trends.

2.2.2.1 Filter Rules (FRs)

Filter Rules (FRs) generate long (short) signals when the market price rises (drops) multiplied by the per cent above (below) the previous trough (peak). This means that *'if the stock market has moved up 'x' per cent, it is likely to move up more than 'x' per cent further before it moves down by 'x' per cent'* (Alexander, (1961, p.26)). A trader using FRs, assumes that in each transaction he/she could always buy at a price exactly equal to the low plus '*x*' per cent and sell at the high minus '*x*' per cent, where '*x*' is the size of the filter (threshold). Such mechanical rules attempt to exploit the market's momentum. Setting up a filter rule requires two decisions. The first is the specification of the threshold. The second is the determination of the window length, meaning how far back the rule should go in finding a recent minimum. These decisions are obviously connected with the subjective view of the trader on the historical data at hand and the relevant past experience. Common thresholds values fluctuate between 0.5 percent and 3 percent, while a typical window length is about five trading days.

FRs have a prominent place among the common tools in technical analysis, although the studies of the 1960s tend to understate their performance in comparison to the 'buy-and-hold' rule. Several examples in the literature show that filtering techniques are capable of exhibiting profits. Dooley and Shafer (1983) conduct one of the earliest studies that focus on applying FRs to trading in the foreign exchange market. Their results show substantial profitability for most thresholds implemented over the period 1973–1981 for the DEM, JPY and GBP currencies. Sweeney (1986) suggests that a filter of 0.5% is outperforming a BH of 4% per annum strategy, using daily USD/DEM data during late

1970s. The bootstrap technique first used by Brock *et al.* (1992) and later by Levich and Thomas (1993) address the issue of the significance of such FRs' returns in the context of the stock market. Qi and Wu (2006) report evidence on the profitability and statistical significance of over 2000 trading rules, including FRs with various threshold sizes. Dunis *et al.* (2006 and 2008) forecast feature spreads with neural networks and apply filter trading rules. In their approach, they experiment beyond the boundaries of the traditional threshold approaches by implementing correlation and transitive filters (see Guégan and Huck (2004) and Dunis *et al.* (2005) respectively). These FRs, especially the transitive one combined with a recurrent neural network, present impressive results in terms of annualised returns. FRs can be used also as technical indicators that measure the strength of the trend. Dunis *et al.* (2011) also apply filter strategies to the task of forecasting the EUR/USD exchange rate. In their application, their confirmation filter does not allow trades that will result in returns lower than the transaction costs. Finally, Kozyra and Lento (2011) compare filter trading rules with the contrarian approach (see Section 2.4) and note that the filter technique is less profitable in periods of high market volatility in particular.

2.2.2.2 Moving Average Rules (MAs)

Moving Average rules (MAs) are also common mechanical indicators and their applications are known for many decades in trading decisions and systems. In simple words, a MA is the mean of a time series, which is recalculated every trading day. Their main characteristic is the length window, namely the number of trading days that are going to be used to calculate the rolling mean of the high frequency data. MAs are identifiers of short- or long-term trends, so the window length can be short (short MAs – 1 to 5 lags) or long (long MAs- 10 to 100 lags). The intuition behind them is that buy (sell) signals are triggered when closing prices cross above (below) the x day MA. Another variation is to buy (sell) when x day MA crosses above (below) the y day MA.

Assuming that the length window is n days, the current period's t closing price P_t, MAs can be further divided into three main categories:

- Simple MA (SMA): $SMA_{t+1} = (1/n)(P_t + P_{t-1} + ...P_{t-n+1})$ (2.1)
- Exponential MA (EMA): $EMA_{t+1} = EMA_t + \alpha(P_t - EMA_t)$ (2.2)

- Weighted MA (WMA):

$$WMA_{t+1} = \left[nP_t + (n-1)P_{t-1} ... + 2P_{t-n+2} + P_{t-n+1})\right] / \left[n(n+1)/2\right] \tag{2.3}$$

The SMA is an average of values recalculated every day. The EMA is adapting to the market price changes by smoothing constant parameter α. The smoothing parameter expresses how quickly the EMA reacts to price changes. If α is low, then there is little reaction to price differences and vice versa. The WMA give weights to the prices used a lags. These weights are higher in recent periods, giving higher importance in recent closing prices. All these MAs are using the closing price as the calculation parameter, but open, high and low prices could also be used.

MAs are also well documented in the literature. Brock *et al.* (1992) and Hudson *et al.* (1996) analyse the Dow Jones Industrial Average and Financial Times Industrial Ordinary Index respectively with MAs and conclude that they have predictive ability if sufficiently long series of data are considered. Especially from the first study, it is suggested the best rule is 50-day MA, which generates an annual mean return of 9.4%. Applications of artificial intelligence technologies, such as artificial neural networks and fuzzy logic controllers, have also uncovered technical trading signals in the data. For example, Gençay (1998 and 1999) investigates the non-linear predictability of foreign exchange and index returns by combining neural networks and MA rules. The forecast results indicate that the buy–sell signals of the MAs have market timing ability and provide statistically significant forecast improvements for the current returns over the random walk model of the foreign exchange returns. LeBaron (1999) finds that a 150-day MA generates Sharpe ratios of 0.60–0.98 after transaction costs in DEM and JPY markets during 1979–1992. LeBaron and Blake (2000) further examine their profitability and note that it would be interesting to determine more complex combinations of MAs that are able to project even higher returns. Gunasekarage and Power (2001) apply the variable length MA and fixed length MA in forecasting the Asian stock markets. The first rule examines whether the short-run MA is above (below) the long-run MA, implying that the general trend in prices is upward (downward). The second rule focuses on the crossover of the long-run MA by the short-run MA. Their results show that equity returns in these markets are predictable and that the variable length MA is very successful.

On the other hand, Fong and Wong (2005) attempt to evaluate the fluctuations of the internet stocks with a recursive MA strategy applied to over 800 MAs. Their empirical results show no significant trading profits and align the internet stocks with the Efficient Market Hypothesis. Chiarella *et al.* (2006) analyze the impact of long run MAs on the market dynamics. When examining the case of the impact between fundamentalists and chartists being unbalanced, they present evidence that the lag length of the MA rule can destabilize the market price. Zhu and Zhou (2009) analyze the efficiency of MAs from an asset selection perspective and based on the principle that existing studies do not provide guidance on optimal investment, even if trends can be signaled by MAs. For that reason, they combine MAs with fixed rules in order to identify market timing strategies that shift money between cash and risky assets. Their approach outperforms the simple rules and explains why both risk aversion and degree of predictability affect the optimal use of the MA. Milionis and Papanagiotou (2011) test the significance of the predictive power of the MAs on the New York Stock Exchange, Athens Stock Exchange and Vienna Stock Exchange. Their contribution is that the proposed MA performance is a function of the window length and that it outperforms BH strategies. This happens especially when the changes in the performance of the MA occur around a mean level, which is interpreted as a rejection of the weak-form efficiency. Finally, Bajgrowicz and Scaillet (2012) revisit the historical success of technical analysis on Dow Jones Industrial Average index from 1897 to 2011 and use the false discovery rate for data snooping. In their review they present the profitability of MAs during these years, but call into serious question the economic value of technical trading rules that have been reported in the period under study.

2.2.2.3 Oscillators (OTs) and Momentum Rules (MTs)

The third class of mechanical trading rules consists of the Oscillators (OTs) and Momentum Rules (MTs). OTs are techniques that do not follow the trend. Actually, they try to identify when the trend is apparent for too long or 'dying'. Therefore they are also called *'non-trending market indicators'*. The main drawback of MAs is the inability to identify the quick and violent swifts in price direction, which lead to capital loss by generating wrong trading signals. This performance gap is filled from OT indices. Their basic intuition is that a reversal trend is eminent, when the prices move away from the average. Simple OT rules are based on the difference between two MAs and generate buy (sell) signals when prices are too low (have risen extremely). Nonetheless, being a difference of MA rules, OTs can also present buy and sell position, when the index crosses zero. The boundaries between OTs and MTs can be a bit vague depending on the case, because MTs can be applied to MAs and OTs. The main difference is that OTs are nontrend indicators, whereas MTs are capitalizing on the endurance of a trend in the market. A simple MT rule would be the difference between today's closing price and the closing price of *x* days ago. The trading signal is generated based on this momentum. To put it simply, the buy (sell) signal is given when today's closing price is higher than the closing price *x* days ago. Setting properly the *x* day's price that is going to be used is also a matter of trader intuition, market knowledge and historical experience (5 and 20 days are common).

There are many types of OTs and MTs used in trading applications. Some typical examples are summarized, interpreted in short and followed by relevant research applications below:

- *Moving Average Convergence/Divergence* (MACD): MACD is calculated as the difference between short- and long-term EMAs and identifies where crossovers and diverging trends to generate buy and sell signals.
- *Accumulation/Distribution* (A/D): A/D is a momentum indicator which measures if investors are generally buying (accumulation) or selling (distribution) base on the volume of price movement.
- *Chaikin Oscillator* (CHO): CHO is calculated as the MACD of A/D.
- *Relative Strength Index* (RSI): The RSI is calculated based on the average 'up' moves and average 'down' moves and is used to identify overbought (when its value is over 70 – sell signal) or oversold (when its value is under 30-buy)
- *Price Oscillator* (PO): PO is identifying the momentum between two EMAs.
- *Detrended Price Oscillator* (DPO): DPO eliminates long-term trends in order to easier identify cycles and measures the difference between closing price and SMA.
- *Bollinger bands* (BB): BBs are based on the difference of closing prices and SMAs and determine if securities are overbought or oversold.
- *Stochastic Oscillator* (SO): SO is based on the assumptions that as prices rise, the closing price tends to reach the high prices in the previous period.
- *Triple EMA* (TRIX): TRIX is a momentum indicator between three EMAs and triggers buying and selling signals base on zero crossovers.

The exact specifications and formulas of the abovementioned indicators can be found in Gifford (1995), Chang *et al.* (1996) and Edwards and Magee (1997) or in any common textbook of technical analysis. Their utility though has been eminent years before that. The pioneering paper of Brock *et al.* (1992) presents evidence of profitability of MACD, as for MAs and FRs mentioned above. Kim and Han (2000) propose a hybrid genetic algorithm – neural network model that uses OTs, such as PO, SO, A/D and RSI, along with simple momentum rules to predict the stock market. Leung and Chong (2003) compare the profitability of MA envelopes and BBs. Their results suggest BBs do not outperform the MA envelopes, despite being able to capture sudden price fluctuations. Shen and Loh (2004) propose a trading system with rough sets to forecast S&P 500 index, which outperforms BH rules. In order to set up this hybrid trading system, they search for the most efficient rules based on the historical data from a pool of technical indicator, such as MACD, RSI and SO. Lento *et al.* (2007) also present empirical evidence that prove BBs' inability to achieve higher profits compared to a BH strategy, when tested on tested on the S&P/TSX 300 Index, the Dow Jones Industrial Average Index, NASDAQ Composite Index and the Canada/USD exchange rate. Chong and Ng (2008) examine the profitability of MACD and RSI using 60-year data of the London Stock Exchange and found that the RSI as well as the MACD rules can generate returns higher than the BH strategy in most cases.

Ye and Huang (2008) extends Frisch's (1993) damping OT with a non-classical OT. The non-classical OT introduces Quantum Mechanics in the market, which is treated as an apparatus that can measure the value and produces a price as a result. With the numerical simulations presented, the OT under study explains qualitatively the persistent fluctuations in stock markets. Aggarwal and Krishna (2011) explore Support Vector Machines and Decision Tree classifiers in the task of direction accuracy prediction. In their application, the company's stock value history is evaluated based on the daily high, open, close, low prices and volumes traded over the last 5-10 years. The performance of their techniques provides impressive forecasting accuracy of over 50% and is tested with several OTs and MTs (i.e. MACD, DPO, SO, A/D and RSI). Finally, Dunis *et al.* (2011) and more recently Sermpinis *et al.* (2012b) forecast exchange rates with several neural networks. In those applications, MACD are used as benchmarks, but they do not present significant profitability.

2.2.3 Other Trading Rules

The rules presented above are the main market indicators of technical analysis, but their 'universe' is in a way limitless. Technical analysts and practitioners tend to create new trading rules, which in reality are small specification alternatives of the existing ones. Such offsprings are commonly cited in the literature with different and more appealing names, despite their direct correlation with the basic mechanical rules presented in the previous section.

2.2.3.1 Contrarian Rules (CTs)

One such example is the contrarian approach in trading, or in other words the *Contrarian Rules* (CTs). Their logic and specification is very simplistic. For every simple trading rule that triggers a sell signal, there is the corresponding CT that triggers a buy signal and vice versa. Technical analysts, that use the contrarian approach, believe that the price changes can be temporary and the market tends to return to its steady state. Typical handbooks that refer to CTs are LeBaron and Vaitilingam (1999) and Siegel (2000). Forner and Marhuenda (2003) explore the profitability of the momentum and contrarian in the Spanish stock market. They find that a 12-month momentum strategy and the five-year contrarian strategy yield significant positive returns, even after risk adjustments have been made. Menkhoff and Schmidt (2005) compare BH, MT and CT traders and suggest that the later are overconfident and willing to hold on against the market. In other words, contrarians are long-run arbitrageurs, but tend to perform worse than Buyers-and-Holders or MT traders. More recently, Park and Sabourian (2011) also compare the 'herding' and 'contrarian' psychology of trade agents. The 'herding' trader follows the trend, whereas a 'contrarian' goes against it. Their main conclusion is that herding and contrarianism lead to price volatility and lower liquidity. It is also noted that herding trades are self-enforcing, while contrarian trades are self-defeating.

2.2.3.2 Trading Range Break Rules (TRBs)

Trading Range Break Rules (TRBs) is also an evident class of technical rules in the literature. TRBs can be thought as MT indicators, since their main premise is that a positive or negative momentum is built, when a stock breaks through or falls below its trading range after several days of trading. Trading range is the spread between the recent minimum and maximum of the current price. TRBs generate buy positions, when the current price exceeds the recent maximum by at least a band. Similarly, they emit sell signals, when the current price falls below the recent minimum by at least the band. For example, Brock *et al.* (1992) and Bessembinder and Chan (1995) apply TRBs over the period 50, 150 and 200 days and use bands of 0 and 1%. Coutts and Cheung (2000) investigates the applicability and validity of trading rules in the Hang Seng Index on the Hong Kong Stock Exchange for the period January 1985 to June 1997.

Although TRBs are by far the most common, in terms of implementation they fail to provide positive abnormal returns, net of transaction costs and opportunity costs of investing. Park and Irwin (2007) in their technical analysis survey also include TRBs in the pool of profitable trading rules. In a more recent application, Wang *et al.* (2012) present a weight reward strategy, which combines MAs and TRBs to create a pool of 140 component trading rules. The proposed hybrid trading system employs a Particle Swarm Optimization algorithm and the optimized combinations of MAs and TRBs are found to outperform the best individual MA and TRB.

2.2.3.3 Breakout Rules

Another interesting category of trading rules is the *Channel Breakout* (CHB) and *Volatility Breakout* (VOLB) rules. The CHBs are originating from Richard Donchian, a pioneer in futures' trading (Kestner, 2003). The idea behind them is that a 'channel' of price changes is incorporated in the trading strategy. This '*x* days' channel' is created by the plot of the high and lows of the price during *x* days and is also a measure of market volatility. Trading entries happen when prices remain into the channel. A buy (sell) position is taken when today's close is higher (lower) than the previous *x* day's closes.

The VOLBs entries are decided in a similar logic, but based on the three following parameters:

- The reference value gives a measurement value to the price move.
- The volatility measure is a computational calculation of the market volatility and it is used to identify significant movements from random prices.
- The volatility multiplier specifies how sensitive the price move is.

The combination of these parameters results in a high and low trigger point. This allows the trader to buy (sell) when the closing price is above the upper (below the lower) trigger. Levitt (1998) compared two trend following trading systems employing CHB and VOLB strategies using standard and Daily Market Time Data from 1987 to1996. Both rules are profitable but especially VOLB presents average annual returns of more than 10%. Qi and Wu (2006) in their extensive search of profitable trading rules suggest that the best rule for trading the JPY and CHF exchange rate is the CHB rule. Marshall *et al.* (2008) examine the profitability of intraday technical analysis in US equity market and compare FRs, MAs, TRBs and VOLBs. Their findings show that VOLBs are the most profitable family of trading indicators.

2.2.3.4 Pattern Rules

Head-and-Shoulders (HSs), *Double-Tops-and-Double-Bottoms* (DTBs), *Triangles-and-Rectangles* (TRs) and *Flags-and-Pennants* (FPs) are types of rules that attempt to identify and establish pattern on pricing charts. They can also be thought as classes of MAs, OTs or MTs, and their short descriptions are given below:

- HS is a trading rule based on the tops of 'up-trends' and bottoms of 'down-trends'. In each period, the higher price peak (head), the two higher picks before (left shoulder) and after the head (right shoulder) are identified. The two lowest prices (points) during this period create a line, called HS 'neckline'. In an 'up-trend', a HSs rule will act as a reversal point, only when the price succeeds to break down the HS 'neckline'. Alternatively, it will go up and may retest the HS 'neckline' in the future. HSs are commonly used by daily currency traders.
- DTBs are also frequently used as reversal pattern indicators by the FOREX market participants. A 'double top' is formed by two price peaks at approximately the

same level and the 'neckline' is similarly formed as in HSs. This pattern is completed, when a price closes below the lowest price that has been reached between the two peaks.

- TRs are formed by two converging trend lines (triangles) or pairs of horizontal trend lines (rectangles), one connecting highest peaks and one connecting lower peaks. A triangle is completed when the closing price goes outside one of its trend lines (similar to the CHBs). The vertical line (called base) connecting the initial point of the converging trend line is called 'base' and the point of convergence is called 'apex of the triangle'. The 'base' and the 'apex' are used to identify prices breakouts and moves respectively. Similarly, a rectangle is completed when the prices closes out of the horizontal trend lines. In the rectangles there is no 'base' or 'apex', but the distance between the horizontal lines is always recalculated, if a rectangle is completed.
- FPs are indicators of pattern continuation. The 'flag' is a rectangle that slopes against the eminent trend, while 'pennants' are formed a symmetrical triangles (see TRs). The FP patterns are completed, when the closing price breaks through one of their trend lines.

The applications of the above pattern rules are quite extensive in the literature too. Clyde and Osler (1998) examine how graphical technical modelling methods may be viewed as equivalent to nonlinear prediction methods. Evidence in support of this hypothesis is presented by applying HS algorithm to high-dimension nonlinear data and they suggest that HSs can be successful in pattern identification and prediction. Lo *et al.* (2000) develop a pattern detection algorithm based on kernel regressions. Their methodology is able to identify price patterns, including HSs in the US stock market over the period 1962–1996. Lucke (2003) also explores if HSs are profitable technical indicators in FOREX markets. In the study many HS combination are implemented, but the results present not significant or even negative returns. Hsu and Kuan (2005) reexamine the utility of technical analysis and in their survey pattern rules like, HSs, DTBs, TRs and FPs, have a prominent place in the 'universe' of the trading rules under study. Friesen *et al.* (2009) develop a theoretical framework that confirms the apparent success of both trend-following and pattern-based technical trading rules, as HSs and DBTs. Finally, extensive applications and specifications for the above pattern rules can also be found in Murphy (2012).

2.3 Automated Trading Strategies and Systems

Many issues and variables have to be taken under consideration by managers and market practitioners, in order to reach the final specification and implementation phase of a trading strategy. These can be summarized as follows:

- Identifying trading opportunities
- Trading schedule and timing
- Trading costs
- Price appreciation and market impact
- Risk evaluation of alternative strategies
- Ability of execution of each strategy

All the above can be evaluated through fundamental or technical approaches. Nonetheless, the modern market practice has a tendency to turn to market technical indicators, whose variety and computational demands are increasing exponentially. This is the main reason that technical analysis and computing appear to be linked now more than ever before. Charting software are applied every day to actual or virtual financial markets. Optimization algorithms are automatically integrated in trading platforms, such as Bloomberg, and make the life of the intraday trader much easier. Consequently, modern trading projects aim to develop automated decision support systems based on technical market technology and evolutionary computing. Fuzzy logic, artificial neural networks, genetic algorithms and programming are already established as the core of the automated trading approach (Deboeck, 1994).

Allen and Karjalainen (1999) present an automated decision tree that selects the optimal technical rules by genetic algorithms. Dempster and Jones (2001) also try to emulate successful trade agents by developing a rule system based on combinations of different indicators at different frequencies and lags, which are selected with genetic programming optimization process. Shapiro (2002) notes that merging technologies, such us neural networks, evolutionary algorithms and fuzzy logic can provided alternatives to a strictly knowledge-driven reasoning decision system or a purely data-driven one and lead to more accurate and robust solutions. Thawornwong *et al.* (2003) evaluate the use neural networks as a decision maker to uncover the underlying nonlinear pattern of these indicators. The overall results indicate that the proportion of correct predictions and the profitability of stock trading guided by these neural networks are higher than those guided by their benchmarks. Dempster and Leemans (2006) propose the use of adaptive reinforcement learning as the basis for a fully automated trading system application. The system is designed to trade foreign exchange (FX) markets relying on a layered structure consisting of a machine learning algorithm, a risk management overlay and a dynamic utility optimization layer. Their approach allows for a risk-return trade-off to be made by the user within the system, while the trading system is able to make consistent gains and avoid large draw-downs out-of-sample. Izumi *et al.* (2009) construct an artificial-market system based on support vector machines and genetic programming. Their system evaluates the risks and returns of the strategies in various market environments and tests the market impact of automated trading. Their results reveal that the market impact of the strategies may not only depend on their rule content but also on the way they are combined with other strategies.

The above cited applications prove that automated trading is and will be dominant in financial markets and forecasting tasks, although its academic philosophy appears to be ambiguous. The utility of trading systems is usually criticized in the traditional financial literature, because of their dependence on strict engineering and computational rules. The modern market reality, though, shows that returns are driven by trading systems' results, rather than the human trading behavior. On the other hand, automated trading applications and algorithms present practical drawbacks associated mainly with their parameter calibration. Therefore, financial researchers and computer engineers need to shed more light in this demanding and complex optimization problem.

Chapter 3

Forecasting Techniques

3.1 Literature Review

Neural Networks (NNs) are computational models that embody data-adaptive learning and clustering abilities, deriving from parallel processing procedures (Kröse and Smagt, 1996). They provide enough learning capacity and are more likely to capture the complex non-linear relationships which are dominant in the financial markets. Those advantages are well documented in the literature and a review of relevant studies is presented in De Gooijer's and Hyndman's (2006). However, skeptics on the NNs argue that they present practical inefficiencies related to the 'parameter' tuning process and the generalization of their performance. For that reason, researchers apply either novel NN algorithms that try to overcome some of these limitations (Ling *et al.* (2003) or forecast combination techniques that seem able to combine the virtues of different networks for superior forecasts (see amongst others Harrald and Kamstra (1997) and Teräsvirta *et al.* (2005)).

The most common NN architecture is the MLP and seems to perform well at time-series financial forecasting (Makridakis *et al.* (1982)). The empirical evidence, though, are contradictory in many cases. For example, Tsaih *et al.* (1998) attempt to forecast the S&P 500 stock index futures and in their application Reasoning Neural Networks perform better than MLPs. Lam (2004) examines the financial forecasting performance of feed-forward NNs and concludes that they fail to outperform the maximum benchmarks in all cases. Ince and Trafalis (2006a) forecast the EUR/USD, GBP/USD, JPY/USD and AUD/USD exchange rates with MLP and Support Vector Regression and their results show that MLP achieves less accurate forecasts. Finally, according to Alfaro *et al.* (2008) the AdaBoost algorithm is superior to MPLs, when applied to the task of forecasting bankruptcy of European firms. On the other hand, Tenti (1996) and Dunis and Huang (2003) achieved encouraging results also by using RNNs to forecast the exchange rates. But the PSN architecture presents remarkable empirical evidence compared to both MLP and RNN. PSNs were first introduced by Ghosh and Shin (1991) as architectures able to capture high-order correlations. Ghosh and Shin (1991 and 1992) also present results on their forecasting superiority in function approximation, when compared with a MLP network and a Higher Order Neural Network (HONN). Ghazali *et al.* (2006) compare PSN with HONN and MLP in terms of forecasting and trading the IBM common stock closing price and the US 10-year government bond series. PSN presented improved statistical accuracy and annualised return compared with both benchmarks. Satisfactory forecasting results of PSN were presented by Hussain *et al.* (2006) on the EUR/USD, the EUR/GBP and the EUR/JPY exchange rates using univariate series as inputs in their networks. On the other hand, Dunis *et al.* (2011) also study the EUR/USD series with PSN and fail to outperform MLP, RNN and HONN in a simple trading application.

Bates and Granger (1969) and Newbold and Granger (1974) suggested combining rules based on variances-covariances of the individual forecasts, while Granger and Ramanathan (1984) presented a regression combination forecast framework with encouraging results. According to Palm and Zellner (1992), it is sensible to use simple average for combination forecasting, while Deutsch *et al.* (1994) achieved substantially smaller squared forecasts errors combining forecasts with changing weights. The regression framework, presented in the 90s, performs poorly though in many cases, which leads the research to turn to more sophisticated methods. For example, Chan *et al.* (1999) suggested the use of Ridge Regression, while Swanson and Zeng (2001) use Bayesian Information Criteria. However, in real applications there are also contradictory results regarding both these models (see Stock and Watson (2004) and Rapach and Strauss (2008)).

Time-series analysis is often based on the assumption that the parameters are fixed. However, in reality financial data and the correlation structure between financial variables are time-varying. Harvey (1990) and Hamilton (1994) both suggest using state space modelling, such as *Kalman Filter,* for representing dynamic systems, where unobserved variables (so-called 'state' variables) can be integrated within an 'observable' model. Anandalingam and Chen (1989) compare Kalman Filter with Bayesian combination forecast model, while Sessions and Chatterjee (1989) conclude that recursive methods are found to be very effective. LeSage and Magura (1992) extend the Granger-Ramanathan combination method by allowing time-varying weights and their methodology outperforms traditional and other forecast combinations. Terui and Dijk (2002) also suggest that the combined forecasts perform well, especially with time varying coefficients. Stock and Watson (2004) try to forecast the output growth of seven countries and note that time-varying combination forecasts can lack in robustness, despite performing well in many cases. Kalman Filter is also considered an optimal time-varying financial forecast for financial markets (Dunis and Shannon, 2005). Finally, according to Goh and Mandic (2007) the recursive Kalman Filter is suitable for processing complex-valued nonlinear, non-stationary signals and bivariate signals with strong component correlations.

Support Vector Machines (SVMs) were originally developed for solving classification problems in pattern recognition frameworks. The introduction of Vapnik's (1995) insensitive loss function has extended their use in non-linear regression estimation problems (Support Vector Regressions (SVRs)). SVRs' main advantage is that they provide global and unique solutions and do not suffer from multiple local minima, while they present a remarkable ability of balancing model accuracy and model complexity (Kwon and Moon (2007) and Suykens (2005)).

Support vector hybrid applications (SVMs and SVRs) are already very popular in the literature (Lo, 2000). Lee *et al.* (2004) propose the multi-category SVM as an extension of the traditional binary SVM and apply it in two different case studies with promising results. They note that their proposed methodology can be a useful addition to the class of nonparametric multi-category classification methods. Liu and Shen (2006) advance the previous mentioned approach by presenting the multi-category ψ-learning methodology. The main advantage of their model is that the convex SVM loss function is replaced by a non-convex ψ-loss function, which leads to smaller number of support vectors and a more sparse solution. Wang and Shen (2007) propose multiclass SVM, which performs classification and variable selection simultaneously through an L1-norm penalized sparse representation. This methodology appears to be very competitive in terms of prediction accuracy when compared with other multiclass classification techniques like the OVA approach. Wu and Liu (2007) introduce the Robust Truncated Hinge Loss SVM and claim that their model can overcome drawbacks of traditional SVM models, such as the outliers' sensitivity in the training sample and the large number of support vectors. Hsu *et al.(*2009) integrate SVR in a two-stage architecture for stock price prediction and present empirical evidence that show that its forecasting performance can be significantly enhanced compared to a single SVR model. Lu *et al.* (2009) and Yeh *et al.* (2011) propose also hybrid SVR methodologies for forecasting the TAIEX index and conclude that that they perform better than simple SVR approaches and other autoregressive models. Finally, Huang *et al.* (2010) forecast the EUR/USD, GBP/USD, NZD/USD, AUD/USD, JPY/USD and RUB/USD exchange rates with a hybrid chaos-based SVR model. In their application, they confirm the forecasting superiority of their proposed model compared to chaos-based neural networks and several traditional non-linear models.

Genetic Algorithms (GAs) and their class, namely the *Genetic Programming* (GP), are popular evolutionary approaches for solving complex computational problems with high degree of optimization difficulty. The theory of GAs was first presented by Holland (1975) and since then GAs are in the center of the research undertaken by the machine learning community. Genetic applications in financial forecasting are numerous (see amongst others Mahfoud and Mani (1996), Allen and Karjalainen (1999), Kim and Han (2002). Their success, though, is ambiguous since they are unable to efficiently perform local searching. Therefore, researchers combine the virtues of GAs with the ones of SVMs in order to overcome these limitations. For example, Leigh *et al.* (2002) present novel experiments of combining pattern recognition, NNs and genetic algorithms, in order to forecast price changes for the NYSE Composite Index. From their approach stock market purchasing opportunities are identified and encouraging decision-making results are achieved. Min *et al.* (2006) and Wu *et al.* (2007) use hybrid GA-SVM models in order to forecast the bankruptcy risk. In both applications, the GAs optimizes the parameters of the SVM and selects the financial ratios that most affect bankruptcy. Dunis *et al.* (2013) developed a GA-SVM algorithm and applied to the task of trading the daily and weekly returns of the FTSE 100 and ASE 20 indices. Pai *et al.* (2006) also apply linear and non-linear SVM with genetically optimized parameters in forecasting exchange rates, while Chen and Wang (2007) forecast the tourist demand in China by applying GAs in the parameter optimization process of their SVR model. More recently, Yuang (2012) suggests that a GA-SVR model is more efficient than traditional SVR and neural network models, when applied to the task of forecasting sales volume.

3.2 Neural Networks Architectures

A standard neural network has at least three layers. The first layer is called the input layer (the number of its nodes corresponds to the number of explanatory variables). The last layer is called the output layer (the number of its nodes corresponds to the number of response variables). An intermediary layer of nodes, the hidden layer, separates the input from the output layer. Its number of nodes defines the amount of complexity the model is capable of fitting. In addition, the input and hidden layer contain an extra node called the bias node. This node has a fixed value of one and has the same function as the intercept in traditional regression models. Normally, each node of one layer has connections to all the other nodes of the next layer.

The network processes information as follows: the input nodes contain the value of the explanatory variables. Since each node connection represents a weight factor, the information reaches a single hidden layer node as the weighted sum of its inputs. Each node of the hidden layer passes the information through a nonlinear activation function and passes it on to the output layer if the calculated value is above a threshold.

The training of the network (which is the adjustment of its weights in the way that the network maps the input value of the training data to the corresponding output value) starts with randomly chosen weights and proceeds by applying a learning algorithm called back-propagation of errors[1] (Shapiro, 2000).The learning algorithm simply tries to find those weights which minimize an error function (normally the sum of all squared differences between target and actual values). Since networks with sufficient hidden nodes are able to learn the training data (as well as their outliers and their noise) by heart, it is crucial to stop the training procedure at the right time to prevent over-fitting (this is called 'early stopping'). This can be achieved by dividing the dataset into 3 subsets respectively called the training and test sets used for simulating the data currently available to fit and tune the model and the validation set used for simulating future values. The training of a network is stopped when the mean squared forecasted error is at minimum in the test-sub period. The network parameters are then estimated by fitting the training data using the above mentioned iterative procedure (back-propagation of errors). The iteration length is optimised by maximising the forecasting accuracy for the test dataset. Then the predictive value of the model is evaluated applying it to the validation dataset (out-of-sample dataset).

[1] Back-propagation networks are the most common multi-layer networks and are the most commonly used type in financial time series forecasting (Kaastra and Boyd, 1996)

3.2.1 Multi-Layer Perceptron (MLP)

One of the NN architectures used in this thesis' applications is the Multi-Layer Perceptron (MLP). MLPs are feed-forward layered NNs, trained with a back-propagation algorithm. According to Kaastra and Boyd (1996), they are the most commonly used types of artificial networks in financial time-series forecasting. The training of the MLP network is processed on a three-layered architecture, as described previously. A typical MLP model is shown in the following figure.

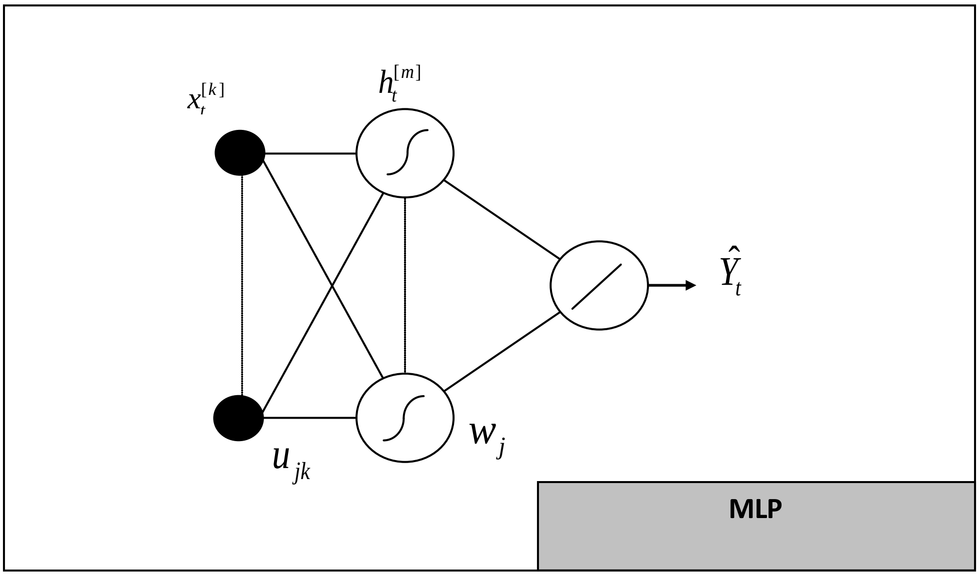


Figure 3-1: A single output, fully connected MLP model (bias nodes are not shown for simplicity)

Where:

- $x_t^{[n]} \left(n = 1, 2, \cdots, k+1\right)$ are the inputs (including the input bias node) at time t
- $h_t^{[m]} \left(m = 1, 2, ..., j+1\right)$ are the hidden nodes outputs (including the hidden bias node) at time t
- $\hat{Y}_t$ is the MLP output
- u_{jk}, w_j are the network weights
- is the transfer sigmoid function $S(x) = \dfrac{1}{1+e^{-x}}$ (3.1)
- is a linear function $F(x) = \sum_i x_i$ (3.2)

The Error Function to be minimized is:

$$E\left(u_{jk}, w_j\right) = \frac{1}{T}\sum_{t=1}^{T}\left(Y_t - \hat{Y}_t\left(u_{jk}, w_j\right)\right)^2 \tag{3.3}$$

In the last equation Y_t is the target value.

MLPs are used in chapters 4-8 with some slight modifications in their training process. These alterations are explained within each chapter.

3.2.2 Recurrent Neural Network (RNN)

The Recurrent Neural Network (RNN) is another popular NN model. The complete explanation of RNN models is beyond the scope of this thesis. Nonetheless, a brief explanation of the significant differences between RNN and MLP architectures is summarized. An exact specification of RNNs is given by Elman (1990).

A simple recurrent network has an activation feedback which embodies short-term memory. The advantages of using recurrent networks over feed-forward networks for modeling non-linear time series have been well documented in the past. However, as mentioned by Tenti (1996), "the main disadvantage of RNNs is that they require substantially more connections and more memory in simulation than standard back-propagation networks" (p. 569), thus resulting in a substantial increase in computational time. However, having said this, RNNs can yield better results in comparison with simple MLPs due to the additional memory inputs.

A simple illustration of the architecture of an Elman RNN is presented below.

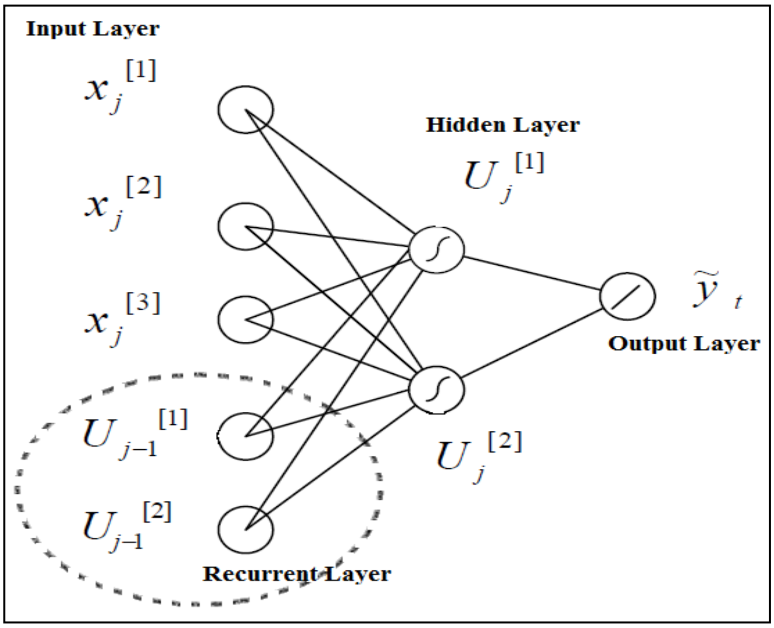


Figure 3-2: Elman RNN with two nodes in the hidden layer

Where:

- $x_t^{[n]}(n=1,2,...,k+1), u_t^{[1]}, u_t^{[2]}$ are the RNN inputs at time t (including bias node)
- $\tilde{y}_t$ is the output of the RNN
- $d_t^{[f]}(f=1,2)$ and $w_t^{[n]}(n=1,2,...,k+1)$ are the weights of the network
- $U_t^{[f]}, f=(1,2)$ is the output of the hidden nodes at time t
- (sigmoid symbol) is the transfer sigmoid function : $S(x)=\frac{1}{1+e^{-x}}$ (3.4)
- (linear symbol) is a linear function: $F(x)=\sum_i x_i$ (3.5)

The Error Function to be minimized is:

$$E(d_t, w_t)=\frac{1}{T}\sum_{t=1}^{T}(y_t-\tilde{y}_t(d_t, w_t))^2 \quad (3.6)$$

In short, the RNN architecture can provide more accurate outputs because the inputs are (potentially) taken from all previous values (see inputs $U_{j-1}^{[1]}$ and $U_{j-1}^{[2]}$ in the figure above). RNNs are used in chapters 4-8 and any changes in their training procedure are included within each chapter, similarly to MLPs.

3.2.3 Psi Sigma Network (PSN)

The final NN architecture utilized throughout the forecasting applications of this thesis is the Psi Sigma Network (PSN). The PSNs are a class of Higher Order Neural Networks with a fully connected feed-forward structure. Ghosh and Shin (1991) are the first to introduce the PSN, trying to reduce the numbers of weights and connections of a Higher Order Neural Network. Their goal was to combine the fast learning property of single-layer networks with the mapping ability of Higher Order Neural Networks and avoid increasing the required number of weights. The training process is again three-layered.

The PSN architecture of a one-output layer is shown in figure 3-3 below.

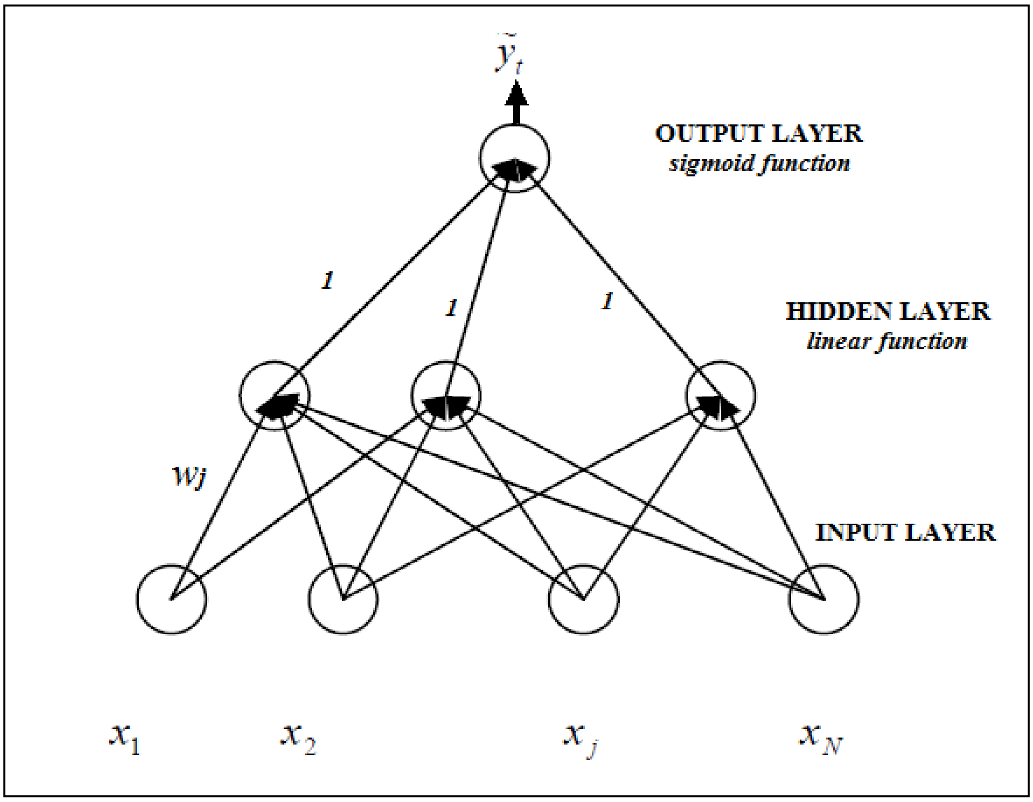


Figure 3-3: A PSN with one output layer

Where:

- x_t $(n=1,2,\ldots,k+1)$ are the model inputs (including the input bias node)
- $y_t, \tilde{y}_t$ are the PSN input and output respectively
- w_j $(j=1,2..,k)$ are the adjustable weights (k is the desired order of the network)

- The hidden layer activation function: $h(x) = \sum_i x_i$ (3.7)
- The output sigmoid activation function (c the adjustable term):

$$\sigma(x) = \frac{1}{1+e^{-xc}} \tag{3.8}$$

The Error Function minimized in this case:

$$E(c, w_j) = \frac{1}{T}\sum_{t=1}^{T}\left(y_t - \tilde{y}_t(w_k, c)\right)^2 \tag{3.9}$$

The training of the PSN is achieved also with the back-propagation and the 'early-stopping' procedure, as described previously. The structure of the PSN and the sigmoid output function require the normalisation of the inputs and the de-normalisation of the outputs. Based on Ghazali *et.al* (2006), the inputs are normalised between the values of 0.2 and 0.8 and at the end the outputs of the network are de-normalised back.

For example, a Psi Sigma network is considered and fed with a $N+1$ dimensional input vector $x = (1, x_1, ..., x_N)^T$. These inputs are weighted by K weight factors $w_j = (w_{0j}, w_{1j}, ..., w_{Nj})^T$, $j = 1,2,..K$ and summed by a layer of K summing units. As mentioned before, K is the desired order of the network. The output of the j-th summing unit, h_j in the hidden layer, is given by:

$$h_j = w_j^T x = \sum_{k=1}^{N} w_{kj} x_k + w_{oj} \;, j=1,2,\ldots, K \tag{3.10}$$

Hence, the output $\tilde{y}$ of the network is:

$$\tilde{y} = \sigma\left(\prod_{j=1}^{K} h_j\right) \tag{3.11}$$

Note that by using products in the output layer the capabilities of higher order networks are directly incorporated with a smaller number of weights and processing units. For example, a k-th degree higher order neural network with d inputs needs $\sum_{i=0}^{k} \frac{(d+i-1)!}{i!(d+1)!}$ weights if all products of up to k components are to be incorporated. A similar PSN needs only $(d+1)*k$ weights.

It should also be noted that the sigmoid function is neuron adaptive. As the network is trained not only the weights but also c is adjusted (see equation 3.8). This strategy seems to provide better fitting properties and increases the approximation capability of a neural network by introducing an extra variable in the estimation, compared to classical architectures with sigmoidal neurons (Vezzi *et al.*, 1998).

The price for the flexibility and speed of Psi Sigma networks is that they are not universal approximators. A suitable order of approximation (or else the number of hidden units) must be chosen by considering the estimated function complexity, amount of data and amount of noise present. The PSN architecture is utilized in chapters 4-6. Some expansions to their training are also presented in each chapter.

3.3 Kalman Filter Modelling

Kalman Filter is an efficient recursive filter that estimates the state of a dynamic system from a series of incomplete and noisy measurements. In the applications of this thesis it is used in order to perform time-varying forecast combinations. These individual forecasts are derived by the previously mentioned NN architectures. Nonetheless, the Kalman Filter process description is needed to fully grasp the motivation behind these implementations. The description is given in detail in Appendix A.

The time-varying coefficient combination forecast suggested in chapters 4 and 5 is shown below:

- Measurement Equation: $$f^t_{c_{NNs}} = \sum_{i=1}^{3} a_i^t f_i^t + \varepsilon_t, \quad \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \qquad (3.12)$$
- State Equation: $$a_i^t = a_i^{t-1} + n_t, \quad n_t \sim NID(0, \sigma_n^2) \qquad (3.13)$$

Where:

- $f^t_{c_{NNs}}$ is the dependent variable (combination forecast) at time t
- f_i^t $(i = 1, 2, 3)$ are the independent variables (individual forecasts) at time t
- a_i^t $(i = 1, 2, 3)$ are the time-varying coefficients at time t for each NN
- ε_t, n_t are the uncorrelated error terms (noise)

When Kalman Filter is applied, all a_i^t are estimated in time, along with the log-likelihood of the model based on the observations up to time *t*. Then the likelihood function is maximized with a numerical optimization algorithm, based on σ_n^2. The updated alphas for the state equation are estimated at time *t* based on the new observations at time *t* and then the state estimates are propagated in time *t+1*. Thus, the Kalman Filter update can be considered as the best unbiased linear estimate of the individual forecasts f_i^t, given $f_{c_{NNs}}^t$ and the prior information.

After Kalman Filter and the numerical optimization algorithm, a Kalman smoothing algorithm should be applied, because the accuracy is increased to the end of the sample. This algorithm 'smoothes' the estimates by running backwards in time and using information acquired after time *t* and allows this model to compute forecasts, which use all available measurement data over the forecast sample. Following Welch and Bishop (2001) and Dunis *et al.* (2010) in this study the alphas are calculated by a simple random walk, while it is set $\varepsilon_1 = 0$.

3.4 Support Vector Regression (SVR)

Support Vector Machine (SVM) is a well-known approach in the machine learning community. It was originally developed for solving classification problems in supervised learning frameworks. The introduction of the ε-sensitive loss function by Vapnik (1995) though established Support Vector Regression (SVR) as a robust technique for constructing data-driven and non-linear empirical regression models. Recently SVR and its hybrid applications have become popular for time-series prediction and financial forecasting applications. They provide global and unique solutions and do not suffer from multiple local minima (Suykens, 2002), while SVRs seem also able to cope well with high-dimensional, noisy and complex feature problems. Moreover, they present a remarkable ability of balancing model accuracy and model complexity, depending on the available data (Montana and Parrella (2008), Lu *et al. (*2009)).

SVR is one of the core forecasting techniques in the following chapters. In chapter 5 SVR is used as an individual forecast combination technique. Similarly, a genetic algorithm is intergraded to the SVR of chapter 6, aiming to improve traditional SVR forecast combination techniques. In chapters 7 and 8, the hybrid SVR approaches do not take into account individual forecasts from other forecasting techniques, but they select appropriate macroeconomic indicators in order to provide a single superior forecast. In all cases, though, a theoretical background is needed for the deeper understanding of the challenges arising from adopting such a technique in the forecasting tasks at hand. This background is provided below.

3.4.1 *ε*-SVR

Considering the training data $\{(x_1,y_1), (x_2,y_2), (x_n,y_n)\}$, where $x_i \in X \subseteq R, y_i \in Y \subseteq R, i = 1...n$ and n the total number of training samples, the SVR function can be specified as:

$$f(x) = w^T \varphi(x) + b \tag{3.14}$$

Here w and b are the regression parameter vectors of the function and $\varphi(x)$ is the non-linear function that maps the input data vector x into a feature space where the training data exhibit linearity (see figure 3-4 (c)). The ε-sensitive loss L_ε function finds the predicted points that lie within the tube created by two slack variables ξ_i, ξ_i^*:

$$L_\varepsilon(x_i) = \begin{cases} 0 \; if \; |y_i - f(x_i)| \leq \varepsilon \\ |y_i - f(x_i)| - \varepsilon \; if \; other \end{cases}, \varepsilon \geq 0 \tag{3.15}$$

In other words ε is the degree of model noise insensitivity and L_ε finds the predicted values that have at most ε deviations from the actual obtained values y_i (see figure 3-4 (a) and 3-4 (b)).

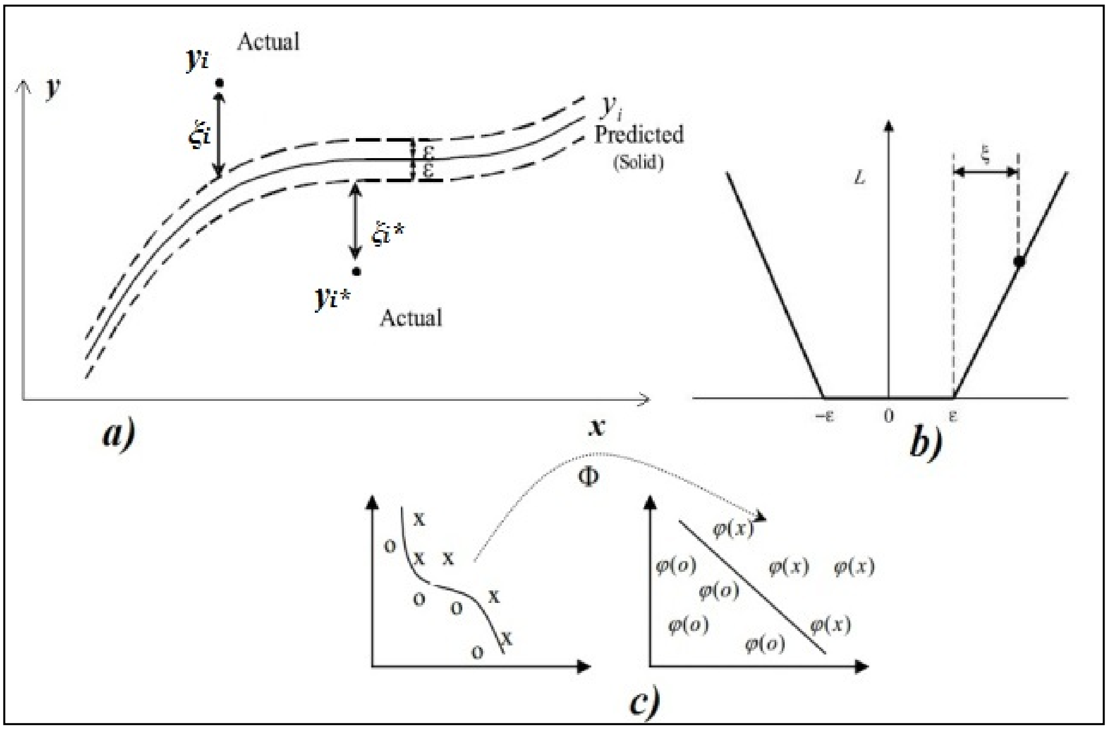


Figure 3-4: a) The f(x) curve of SVR and the ε-tube, b) plot of the ε-sensitive loss function and c) mapping procedure by φ(x)

The goal is to solve the following argument:

$$\text{Minimize} \quad C\sum_{i=1}^{n}(\xi_i+\xi_i^*)+\frac{1}{2}\|w\|^2 \text{ subject to } \begin{Bmatrix} \xi_i \geq 0 \\ \xi_i^* \geq 0 \\ C>0 \end{Bmatrix} \text{ and } \begin{Bmatrix} y_i - w^T\varphi(x_i)-b \leq +\varepsilon+\xi_i \\ w^T\varphi(x_i)+b-y_i \leq +\varepsilon+\xi_i^* \end{Bmatrix} \tag{3.16}$$

The above quadratic optimization problem is transformed in a dual problem and its solution is based on the introduction of two Lagrange multipliers a_i, a_i^* and mapping with a kernel function $K(x_i, x)$:

$$f(x)=\sum_{i=1}^{n}(a_i-a_i^*)K(x_i,x)+b \text{ where } 0\leq a_i, a_i^* \leq C \tag{3.17}$$

Factor b is computed following the Karush-Kuhn-Tucker conditions. A detailed mathematical analysis of the above solution is given by Vapnik (1995). Support Vectors (SVs) are called all the x_i that contribute to the previous equation, thus they lie outside the ε-tube, whereas non-SVs lie within the ε-tube.[2] Increasing ε leads to less SVs' selection, whereas decreasing it results to more 'flat' estimates. The norm term $\|w\|^2$ characterizes the complexity (flatness) of the model and the term $\left\{\sum_{i=1}^{n}(\xi_i+\xi_i^*)\right\}$ is the training error, as specified by the slack variables. Consequently the introduction of the parameter C satisfies the need to trade model complexity for training error and vice versa (Cherkassky and Ma, 2004).

3.4.2 *v*-SVR

The v-SVR algorithm encompasses the ε parameter in the optimization process and controls it with a new parameter $v\in(0,1)$ (Basak *et al.*, 2007). In v-SVR the optimization problem transforms to:

Minimize $C\left(v\varepsilon+\frac{1}{n}\sum_{i=1}^{n}(\xi_i+\xi_i^*)\right)+\frac{1}{2}\|w\|^2$ subject to $\begin{Bmatrix}\xi_i\geq 0\\ \xi_i^*\geq 0\\ C>0\end{Bmatrix}$ and $\begin{Bmatrix}y_i-w^T\varphi(x_i)-b\leq+\varepsilon+\xi_i\\ w^T\varphi(x_i)+b-y_i\leq+\varepsilon+\xi_i^*\end{Bmatrix}$ (3.18)

The methodology remains the same as in ε-SVR and the solution takes a similar form:

$$f(x)=\sum_{i=1}^{n}(a_i-a_i^*)K(x_i,x)+b \text{ where } 0\leq a_i,a_i^*\leq\frac{C}{n}$$

(3.19)

Based on the 'v-trick', as presented by Scholkopf *et al.* (1999), increasing ε leads to the proportional increase of the first term of $\left\{v\varepsilon+\frac{1}{n}\sum_{i=1}^{n}(\xi_i+\xi_i^*)\right\}$, while its second term decreases proportionally to the fraction of points outside the ε-tube. So v can be considered as the upper bound on the fraction of errors. On the other hand, decreasing ε leads again to a proportional change of the first term, but also the second term's change is proportional to

[2] A SV is either a boundary vector ($(a_i-a_i^*)\in[-C/n,C/n],\xi_i=\xi_i^*=0$) or an error vector ($a_i,a_i^*=C/n \text{ and } \xi_i,\xi_i^*>0$).

the fraction of SVs. That means that ε will shrink as long as the fraction of SVs is smaller than v, therefore v is also the lower band in the fraction of SVs.

3.4.3 SVR parameter selection

Although SVR has emerged as a highly effective technique for solving non-linear regression problems, designing such a model can be impeded by the complexity and sensitivity of selecting its parameters. This procedure can be summarized in the following steps:

1. Selection of the kernel function
2. Selection of the regularization parameter C
3. Selection of parameters of the kernel function
4. Selection of the tube size of the ε-sensitive loss function

This selection can be even more complicated and computationally demanding, since individual optimization of the parameters of the above steps is not sufficient. Thus, SVR's performance depends on all parameters being set optimally. Numerous approaches for this optimization have been presented in literature. For example in the ε-SVR, parameter ε can be set simply as a non-negative constant for convenience ($\varepsilon=0$ or equal to a very small value) (see Trafalis and Ince (2000)). This parameter can also be calculated by maximizing the statistical efficiency of a location parameter estimator (Smola *et al.* (1998)). Many researchers turn to the v-SVR approach because it is easier to control parameter ε with parameter v (see Scholkopf *et al.* (1999) and Basak *et al.* (2007)). Cherkassky and Ma (2004) apply RBF kernels in v-SVR and propose a data-driven choice of parameter C, based on the range of the output values of the training data. But the most popular approach is to use the cross-validation technique (see amongst others Cao *et al.* (2003) and Duan *et al.* (2003)) or grid-search algorithms over the dataset (Scholkopf and Smola (2002) and Smola and Scholkopf (2004)).

3.5 Genetic Algorithms Modelling

All the genetic approaches adopted in the forecasting tasks of the thesis are presented in this subsection of the chapter. Genetic Algorithms (GAs), formerly introduced by Holland (1975), are search algorithms inspired by the principle of natural selection. They are useful and efficient if the search space is big and complicated or there is not any available mathematical analysis of the problem. They form populations of candidate solutions, called *chromosomes*. Those are optimized via a number of evolutionary cycles and genetic operations, such as *crossovers* or *mutations*. Chromosomes consist of genes, which are the optimizing parameters. At each iteration (generation), a fitness function is used to evaluate each chromosome. In that way the quality of all the solutions is measured. Then, the fittest chromosomes are selected to survive. This evolutionary process is continued until some termination criteria are met. In general, GAs have the ability to cope with large search spaces and at the same time resist to get trapped in local optimal solutions, like other search algorithms. GAs are integrated in all the hybrid models of chapters 6-8. In every each one of these applications, the GA implemented has a dual goal: The optimization of the SVR parameters and the optimal feature subset selection.

Genetic Programming (GP) algorithms, as presented by Koza (1992), are a class of GAs. The intuition behind this technique is the Darwinian principle of reproduction and survival of the fittest. The Darwinian Theory is applied through GPs to a population of computer programs of varying sizes and shapes, which run in various environments in order to produce forecasts at a high level of accuracy (Chen, 2002). The GP technique is used in chapters 5 and 7. The aim of the GP in chapter 5 is to genetically combine individual forecasts. On the other hand, in chapter 7 it provides a single forecast by identifying connections between the available macroeconomic indicators through evolutionary steps.

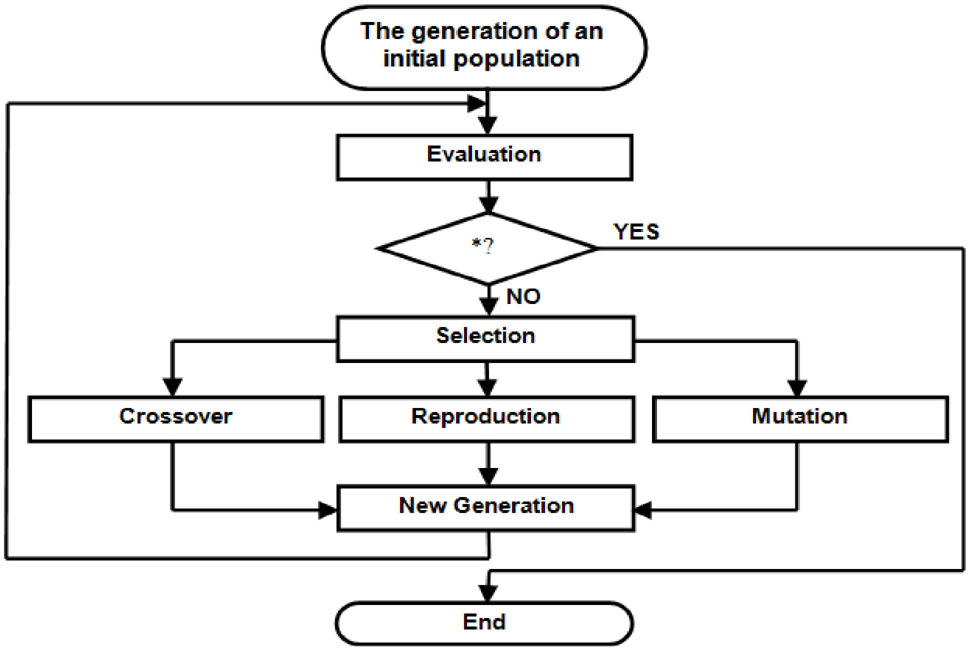
3.5.1 Genetic Programming (GP)

Dissimilar to previously analyzed NN architectures, GP creates an initial population of models and evolves it using genetic operators. The result is to perform mathematical expressions that best fit to the given input (data). The GP application proposed and implemented in chapters 5 and 7 forms tree-based structures. These structures comprise of sub-trees (models) with input and output. It uses algebraic expressions that enable the analysis and optimization of results in a genetic tree. This tree consists of nodes, which are essentially functions that perform actions within its structure. The maximum tree depth is the maximum length of each model (of each tree structure) and it depends on the functions and terminals of each individual model. The NNs' individual forecasts and the pool of macroeconomic indicators are used as inputs in chapter 5 and 7 respectively. The output signals are then generated through the nodes' functions.

In the design phase of this GP algorithm the main focus is on optimizing execution time and limiting the *'bloat effect'*, a similar issue to over-fitting in NNs mentioned in the beginning of this chapter. The GP reproduces newer models replacing the weaker ones in the population according to their fitness. In this case, the fitness value is defined as the Mean Squared Error (MSE) of the forecast. Obviously the lowest MSE is considered as a criterion of better fitness. Then, the best models (tournament winners) are exposed to two genetic operators, known as *mutation* and *crossover*. Mutation is the creation of a new model that is mutated randomly from an existing one. This is calibrated in the model by setting a mutation probability. On the other hand, crossover is the creation of two new models from existing ones by genetically recombining randomly chosen parts of them. In this way, future trials will contain parts from superior models. With the crossover trial parameter the practitioner is able to specify the number of generations allowed to this GP algorithm.

This genetic procedure creates superior offsprings, replacing the worst models (tournament losers), and rearranges the initial population for the next iteration. This is constrained by the size of the models, namely the tournament size, and their goodness of fit. The iterations stop and the final forecast results are obtained when the model reaches the critical value of the termination criterion. The termination criterion is in general arbitrarily chosen and task-specific. For example, in chapter 5 the termination criterion is set based on optimizing the trading performance with the least possible 'bloat effect' in the in-sample period. Since in chapter 7 there is no trading undertaken, the critical value is calculated through the same process, but now taking into account the statistical performance of each in-sample period. The functionality aspects of GP and the genetic operators are described in detail by Koza and Andre (1996) and Koza and Poli (2005).

A final step to the optimal setup of this model is to run the GP algorithm in a steady-state mode. This allows only a single member of the population to be replaced at a time. This decision is justified. The GP should hold a greater selection strength and genetic drift over other algorithms, such as a typical GA. Additionally, steady state algorithms also offer exceptional multi-processing capabilities (Lozano *et al.*, 2008). The following flowchart describes the general structure of a typical GP algorithm.



* The symbol '?' refers to the termination criterion

Figure 3-5: GP Architecture

3.5.2 Hybrid Genetic Algorithm – Support Vector Regression Modelling

Chapters 6-8 introduce and apply hybrid models that integrate GAs into the SVR procedure, as this is described previously. The aim of such an implementation is the optimal tuning of the SVR parameters and the optimal feature selection. Optimization of the parameters leads to higher degrees of adaptivity to the given inputs. Feature selection is an optimization problem that refers to the search over a space of possible feature subsets in order to find those that are optimal with respect to specific criteria. Such a problem requires a search strategy that picks the feature subsets and an evaluation method that tests their goodness of fit. Many searching strategies have been proposed in literature, but those who seem to attract more attention are the randomized searches, where probabilistic steps are applied (Sun *et al.*, 2004). Therefore, the use of GAs for such a task is appropriate and justified (Siedlecki and Sklansky (1989)).

3.5.2.1 Hybrid Genetic Algorithm – Support Vector Regression (GA-SVR)

This subsection presents the hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model for optimal SVR parameter and feature subset combination (chapter 6) or selection (chapter 7). The proposed model genetically searches over a large pool of potential inputs and provides an out-of-sample optimized SVR forecast for each series under study. In order to achieve this, a simple GA is used. Its chromosome comprises *feature genes* that encode the best feature subset and *parameter genes* that encode the best choice of parameters. One such chromosome is depicted in chapter 6 (see figure 6-1).

The lack of information on the noise of the training datasets makes the *a priori* ε-margin setting of ε-SVR a difficult task. In order to overcome this and decrease the computational demands of the methodology, a RBF v-SVR approach is taken during the design of this hybrid model. The virtues of using RBF kernels are stated by many researchers, when SVR is applied in financial forecasting (i.e. Min and Lee (2005), Ding *et al.* (2009) and Kao *et al.* (2013)). Their advantage is that they efficiently overcome over-fitting and seem to excel in directional accuracy. A RBF kernel is in general specified as:

$$K(x_i, x) = \exp(-\gamma \|x_i - x\|^2), \gamma > 0 \tag{3.20}$$

where γ represents the variance of the kernel function. Consequently, the parameters optimized by the GA are C, v and γ.[3]

The GA uses the *one-point crossover* and the *mutation operators*. The one-point crossover provides two offsprings from every two parents. Then the algorithm randomly selects the parents and a crossover point c_x. The two offsprings are made by both concatenating the genes that precede c_x in the first parent with those that follow (and include) c_x in the second parent. The probability for selecting an individual as a parent for

[3] As shown in subsection 3.4 x_i are the support vectors and x the data vectors.

the crossover operator is called *crossover probability* and in all the applications is generally set high to ensure that some population is kept for the next generation. In that way the GA creates better new chromosomes from good parts of the old chromosomes. The offspring produced by the crossover operator replaces their parents in the population. On the other hand, the mutation operator places random values in randomly selected genes with a certain probability named as *mutation probability*. This operator is very important for avoiding local optima and exploring a larger surface of the search space. This probability is always set low in order to prevent the algorithm from performing a random search.

For the selection step of the GA, *the roulette wheel selection process* is used (Holland (1995)). In roulette wheel selection chromosomes are selected according to their fitness. The better the chromosomes are, the more chances to be selected they have. *Elitism* is used to raise the evolutionary pressure in better solutions and to accelerate the evolution. The best solution is copied without changes to the new population. Thus, the best solution found can survive at the end of every generation. Similarly to the NNs, the GA-SVR model requires training and test subsets to validate the goodness of fit of each chromosome. The population of chromosomes is initialized in the training sub-period. The optimal selection of chromosomes is achieved through a fitness function. Then, the optimized parameters and selected predictors of the best solution are used to train the SVR and produce the final optimized forecast, which is evaluated over the out-of-sample period. In genetic algorithm modelling, though, fitness functions need to be increasing functions. The fitness function is chosen based on the forecasting task at hand. The details of the fitness functions used in each application are given at each specific chapter.

Finally, the size of the initial population and the maximum number of generations needs to be chosen beforehand. This is done through a sensitivity analysis from the user of the algorithm based on the given inputs to the algorithm. These details are also provided in each chapter. Another issue that needs to be taken into account is the population convergence which is associated with the termination criterion of the GA. In all chapters, the population is deemed as converged when the average fitness across the current population is less than 5% away from the best fitness of the current population. In that way, the GA avoids keeping populations that their diversity is very low. If the algorithm evolved such populations, it would be unlikely to produce different and better individuals than the existing ones or those qualified to be kept in previous generations. The flowchart of the designed GA-SVR is shown in figure 3-6.

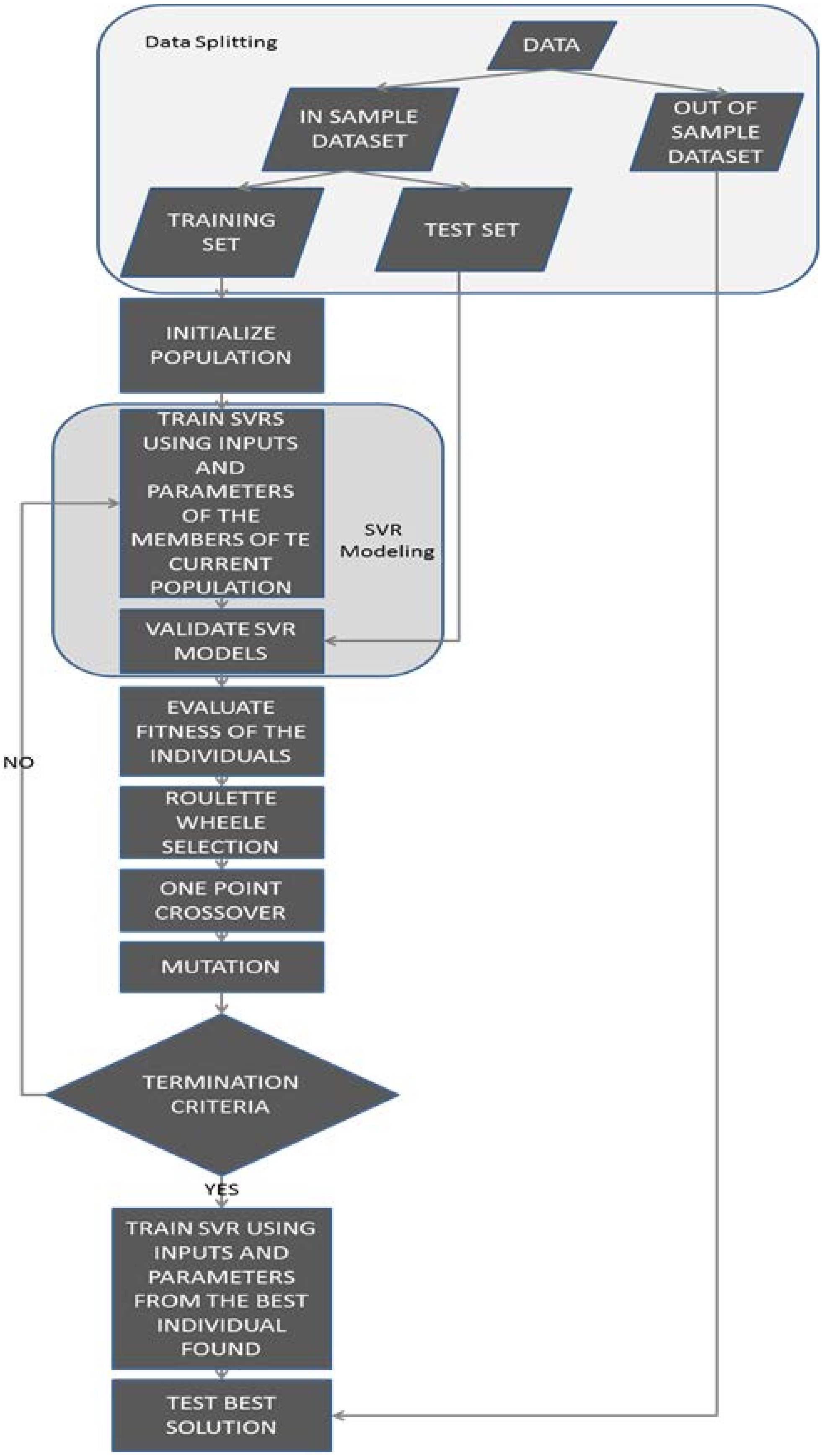


Figure 3-6: Hybrid GA-SVR and RG-SVR flowchart

3.5.2.2 Hybrid Rolling Genetic – Support Vector Regression (RG-SVR)

The GA-SVR previously explained is providing a single out-of-sample optimized SVR forecast for each series under study. Nonetheless, it is selecting parameters and feature subsets based on a fixed in-sample period. It is well established in the financial and economic literature, that the more recent the data are, the more significant is the information that they incorporate. Thus, the relevance of the predictors should have a changing composition. In order to expand the mapping ability of the algorithm to the given inputs and derive more realistic forecasts, the GA-SVR is extended to a Rolling Genetic – Support Vector Regression (RG-SVR) in chapter 8.

The logic and the design of the RG-SVR model is the same as in GA-SVR. The novelty lies in the fact that each chromosome is now selected through a rolling in-sample period (rolling window). The algorithm requires the window size to be further divided in a training and test subset in order to validate the goodness of fit of each chromosome, as in GA-SVR. The population of chromosomes is initialized in each training sub-period. The optimal selection of chromosomes is achieved, when their forecasts maximize the fitness function in the test-sub period. These optimized parameters and selected predictors of the best solution are used to train the SVR and produce the final optimized forecast for the next observation. After this is completed, the window rolls forward by one observation and the procedure is repeated. In that way, the RG-SVR model presents single rolling forecasts. For each of these forecasts, the algorithm retains the optimized C, γ and v parameters and set of optimal predictors, creating an image of how the relevance of these inputs fluctuates as time goes by.

The flowchart of this technique is also given by the previous figure. The reader should bear in mind, though, that the in-sample dataset in this case is changing in every iteration. In addition, the out-of-sample dataset represents just the next observation, since the model derives only one forecast at each loop. This brings forward again the curse of dimensionality in such techniques, as referred in the general motivation of this thesis. The integrated rolling forward estimation raises the computational demands of the algorithm. Its accuracy depends on the trade-off between a high-complexity model (over-fitting) and a large-margin (incorrect setting of the SVR 'tube'). For that reason, another new attribute of RG-SVR is that the SVR procedure is performed with the minimum support vectors.

Chapter 4

Forecasting and Trading the EUR/USD Exchange Rate with Stochastic Neural Network Combination and Time-Varying Leverage

4.1 Introduction

The term of Neural Network (NN) originates from the biological neuron connections of human brain. The artificial NNs are computation models that embody data-adaptive learning and clustering abilities, deriving from parallel processing procedures (Krose and Smagt, 1996). The NNs are considered a relatively new technology in Finance, but with high potential and an increasing number of applications. However, their practical limitations and contradictory empirical evidence lead to skepticism on whether they can outperform existing traditional models.

The motivation of this chapter is to investigate the statistical and trading performance of a novel Neural Network (NN) architecture, the Psi Sigma Neural Network (PSN), and explore the utility of Kalman Filters in combining NN forecasts. Firstly, the EUR/USD European Central Bank (ECB) fixing series is applied to a Naive Strategy, an Autoregressive Moving Average (ARMA) model and three NNs, namely a Multi-Layer Perceptron (MLP), a Recurrent Network (RNN) and a PSN. Secondly, the Kalman Filter is compared with four forecast combination methods. That is the traditional Simple Average, the Bayesian Average, Granger- Ramanathan's Regression Approach (GRR) and the Least Absolute Shrinkage and Selection Operator (LASSO). The models' performance is estimated using the EUR/USD ECB fixing series of the period of 2002-2010, using the last two years for out-of-sample testing. Finally, a time-varying leverage strategy based on RiskMetrics volatility forecasts is introduced.

The results show that PSN outperforms its NN and statistical benchmarks in terms of annualised returns and information ratios. The NN forecast combinations, excluding the Bayesian Average model, present improved annualised returns and information ratios and in almost all cases outperform every individual NN performance. More specifically, the Kalman Filter outperforms all individual models and combination forecasts. The Kalman Filter forecasts are also found statistically different from their benchmarks under the Diebold-Marino test (1995). Finally, all models except ARMA show substantial increase in their trading performance, after applying the time-varying leverage strategy,

In section 4.2 follows the detailed description of the EUR/USD ECB fixing series, used as dataset in this study. Section 4.3 gives an overview of the forecasting, while section 4.4 describes the forecast combination methods implemented. The statistical and trading performance of the models is presented in Sections 4.5 and 4.6. Finally, some concluding remarks are summarized in section 4.7.

4.2 The EUR/USD Exchange Rate and Related Financial Data

The European Central Bank (ECB) publishes a daily fixing for selected EUR exchange rates: these reference mid-rates are based on a daily concentration procedure between central banks within and outside the European System of Central Banks, which normally takes place at 2.15 p.m. ECB time. The reference exchange rates are published both by electronic market information providers and on the ECB's website shortly after the concentration procedure has been completed. Although only a reference rate, many financial institutions are ready to trade at the EUR fixing and it is therefore possible to leave orders with a bank for business to be transacted at this level.

In this chapter, the EUR/USD is examined over period 2002 -2010, using the last two years for out-of-sample. In order to train the NNs, the in-sample dataset is further divided in two sub-periods (see chapter 3).

PERIODS	TRADING DAYS	START DATE	END DATE
Total Dataset	2295	3/01/2002	31/12/2010
Training Dataset ***(In-sample)***	1270	3/01/2002	29/12/2006
Test Dataset ***(In-sample)***	511	02/01/2007	31/12/2008
Validation Dataset ***(Out-of-sample)***	514	02/01/2009	31/12/2010

Table 4-1: The EUR/USD Dataset - Neural Networks' Training Datasets

The graph below shows the total dataset for the EUR/USD and its volatile trend since early 2008.

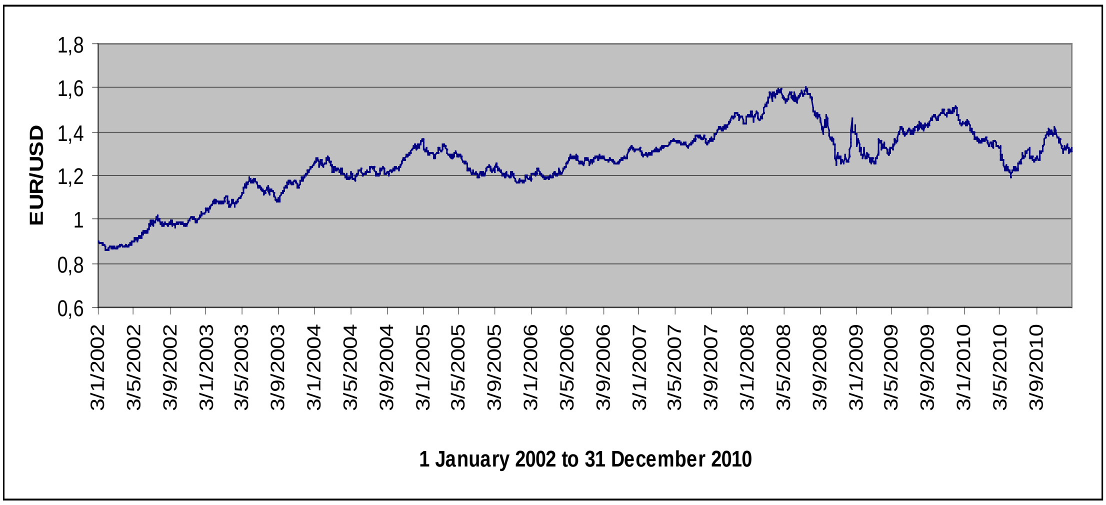


Figure 4-1: EUR/USD Frankfurt daily fixing prices

The EUR/USD time series, shown above, is non-normal and non-stationary. Jarque-Bera statistics confirm its non-normality at the 99% confidence interval with slight skewness and low kurtosis. To overcome the non-stationary issue, the EUR/USD series is transformed into a daily series of rate returns. So given the price level P_1, P_2, …, P_t, the return at time t is calculated as:

$$R_t = \left(\frac{P_t}{P_{t-1}}\right) - 1 \tag{4.1}$$

The stationary property of the EUR/USD return series is confirmed at the 1% significance level (ADF and PP test statistics) and its summary statistics are shown in Figure 4-2. From those it is obvious that the slight skewness and low kurtosis remain. The Jarque-Bera statistic confirms again that the EUR/USD series is non-normal at the 99% confidence interval. For more details on Jarque-Bera statistics see Jarque and Bera (1980).

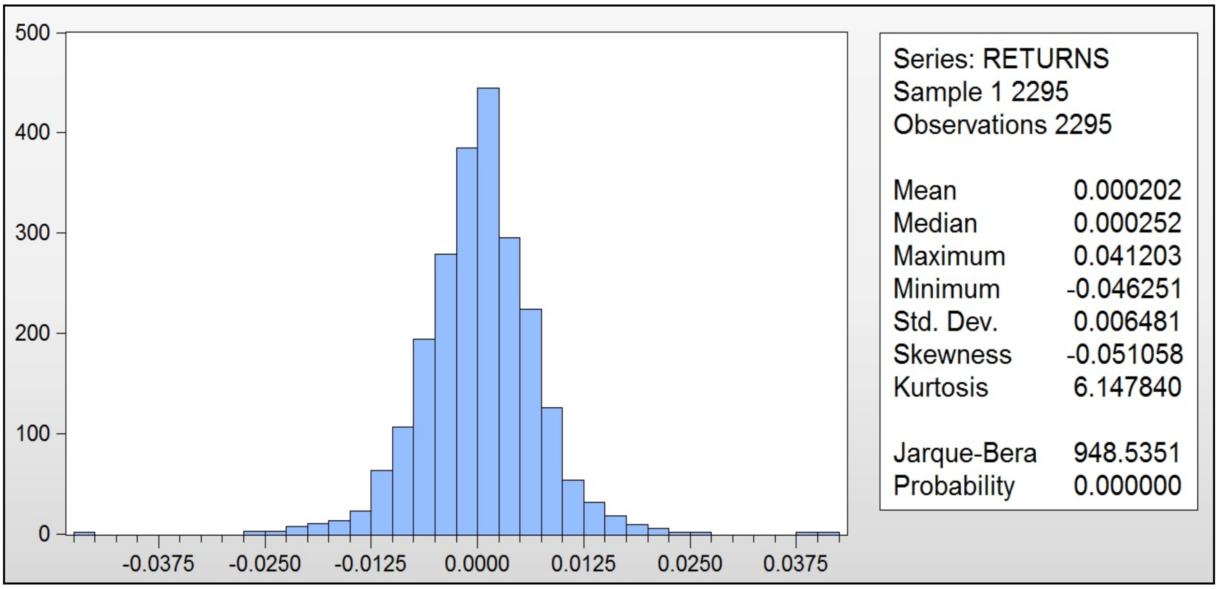


Figure 4-2: EUR/USD Returns Summary Statistics

There is no formal theory behind the selection of the inputs of a neural network. Therefore, neural networks experiments and a sensitivity analysis on a pool of potential inputs in the training dataset are conducted to help with this decision. The aim is to select the set of inputs for each network which is the more likely to lead to the best trading performance in the out-of-sample dataset. In this application, the set of variables that provide the higher trading performance for each network in the test sub-period are selected. Surprisingly, this set of inputs is identical for all neural network models. All sets of inputs are presented in table 2 below[4].

[4] They are also explored as inputs autoregressive terms of other exchange rates (e.g. the USD/JPY and GBP/JPY exchange rates), commodities prices (e.g. Gold Bullion and Brent Oil) and stock market prices (e.g. FTSE100 and DJIA). However, the set of inputs presented in table 4-2 gave to the NNs the highest trading performance in the training period and were thus retained.

Number	Explanatory Variables	Lag*
1	EUR/USD Exchange Rate Return	1
2	EUR/USD Exchange Rate Return	2
3	EUR/USD Exchange Rate Return	4
4	EUR/USD Exchange Rate Return	5
5	EUR/USD Exchange Rate Return	8
6	EUR/USD Exchange Rate Return	10
7	EUR/GBP Exchange Rate Return	1
8	EUR/GBP Exchange Rate Return	2
9	EUR/JPY Exchange Rate Return	1

* In this application the term 'Lag 1' means that today's closing price is used to forecast the tomorrow's one.

Table 4-2: Explanatory Variables

4.3 Forecasting Models

4.3.1 Benchmark Forecasting Models

In this chapter two traditional forecasting strategies, the Naive Strategy and the Auto-Regressive Moving Average (ARMA) model are used, in order to benchmark the efficiency of the NNs' performance.

4.3.1.1 Naive Strategy

The Naive Strategy is considered to be the simplest strategy to predict the future. That is to accept as a forecast for time *t+1*, the value of time *t*, assuming that the best prediction is the most recent period change. Thus, the model takes the form:

$$\hat{Y}_{t+1} = Y_t \quad (4.2)$$

Y_t is the actual rate of return at time *t* and $\hat{Y}_{t+1}$ is the forecast rate of return at time *t+1*. In order to evaluate the Naive trading performance, a simulated strategy is used.

4.3.1.2 Auto-Regressive Moving Average Model (ARMA)

The ARMA model is based on the assumption that the current value of a time-series is a linear combination of its previous values plus a combination of current and previous values of the residuals (Brooks, 2008). Thus, the ARMA model embodies autoregressive and moving average components and can be specified as below:

$$Y_t = \varphi_0 + \varphi_1 Y_{t-1} + \varphi_2 Y_{t-2} + ... + \varphi_p Y_{t-p} + \varepsilon_t - w_1 \varepsilon_{t-1} - w_2 \varepsilon_{t-2} - ... - w_q \varepsilon_{t-q} \quad (4.3)$$

Where:

- Y_t is the dependent variable at time t
- $Y_{t-1}, Y_{t-2}, \ldots Y_{t-p}$ are the lagged dependent variables
- $\varphi_0, \varphi_1, \ldots, \varphi_p$ are the regression coefficients
- ε_t is the residual term
- $\varepsilon_{t-1}, \varepsilon_{t-2}, \ldots, \varepsilon_{t-q}$ are the previous values of the residual terms
- $w_1, w_2, \ldots, w_q$ are the residual weights

Based on the in-sample correlogram (training and test subsets), a restricted ARMA (13, 13) model is chosen as the best for an out-of-sample estimation (Appendix B.1). The ARMA model, used for this application, can be specified as follows:

$$Y_t = 0.0288 - 0.2689 Y_{t-3} + 0.6028 Y_{t-4} - 0.3921 Y_{t-6} - 0.6884 Y_{t-9} + 0.3641 Y_{t-13} + 0.2638 \varepsilon_{t-3} - 0.59 \varepsilon_{t-4}$$
$$+ 0.3916 \varepsilon_{t-6} + 0.6227 \varepsilon_{t-9} - 0.3165 \varepsilon_{t-13} \quad (4.4)$$

The evaluation of the ARMA model selected comes in terms of trading performance.

4.3.2 Neural Networks (NNs)

In this chapter three NN architectures, namely the MLP, RNN and the novel PSN, are used to forecast the series under study. All these models are thoroughly explained in chapter 6 (training process and specification). In this part it should be noted that the starting point for each network is a set of random weights. Therefore, forecasts can differ between networks. In order to eliminate any variance between the derived NN forecasts and add robustness to the results, a simple average of a committee of 10 NNs is used. Those 10 NNs are those 10 MLPs, RNNs and PSNs that present the highest profit in the training sub-period. This is a necessary process in order to eliminate any outlier network that could jeopardise the final conclusions. The technical characteristics of the NNs used in this task are presented in Appendix B.2.

4.4 Forecasting Combination Techniques

The five techniques that are used to combine the NNs forecasts are presented in this section. It is important to outline that a forecast combination targets either to follow the trend of the best individual forecast (*'combining for adaptation'*) or to significantly outperform each one of them (*'combining for improvement'*) (Yang, 2004). Consequently, the naive strategy and the ARMA are rejected from the combination techniques. Both strategies present a considerably worse trading performance than their NNs' counterparts both in-sample and out-of-sample. Therefore, their inclusion in the combination techniques would deteriorate their performance rather than improve it.

4.4.1 Simple Average

The first forecasting combination technique used in this chapter is Simple Average, which can be considered a benchmark forecast combination model. Given the three NNs' forecasts $f_{MLP}^{t}, f_{RNN}^{t}, f_{PSN}^{t}$ at time t, the combination forecast at time t is calculated as:

$$f_{c_{NNs}}^{t} = (f_{MLP}^{t} + f_{RNN}^{t} + f_{PSN}^{t}) / 3 \quad (4.5)$$

4.4.2 Bayesian Averaging

A Bayesian Average model specifies optimal weights for the combination forecast based on the Akaike Information Criterion (AIC) and Schwarz Bayesian Information Criterion (SIC). According to Buckland *et. al.* (1997) the Bayesian weights using AIC, can be estimated as:

$$w_{AIC,i} = \frac{e^{-0.5\Delta \mathrm{AIC}_i}}{\sum_{j=1}^{3} e^{-0.5\Delta \mathrm{AIC}_j}} \tag{4.6}$$

Where:

- $i=1,2,3$ for $f_{MLP}, f_{RNN}, f_{PSN}$ respectively
- $\Delta\mathrm{AIC}_i = \mathrm{AIC}_i - \mathrm{AIC}_{i,min}$ (4.7)

Based on the above, the combination forecast at time t is $f^t_{c_{NNs}} = (\sum_{i=1}^{3} w_{AIC,i} f_i^t)/3$ and in this case the AIC Bayesian models take the following form:

$$f^t_{c_{AIC}} = (0.33421 f^t_{MLP} + 0.33081 f^t_{RNN} + 0.33492 f^t_{PSN})/3 \tag{4.8}$$

The Bayesian Average weights for SIC are defined similarly and in this case the SIC Bayesian model is specified as follows:

$$f^t_{c_{SIC}} = (0.33421 f^t_{MLP} + 0.330833 f^t_{RNN} + 0.33491 f^t_{PSN})/3 \tag{4.9}$$

Equations 4.8 and 4.9 are similar as the AIC and SIC criteria for the NNs in the in-sample period are very close. For that reason, in the results only the Bayesian Average based on the AIC criterion is presented. This is the case where the results are marginally better in terms of trading performance in-sample. Nonetheless, the weights are in favor (maximized) of PSN, namely the model with the minimum AIC and SIC respectively. For details on the exact calculation of the AIC and SIC and their Bayesian Average weights see appendix B.3.

4.4.3 Granger and Ramanathan Regression Approach (GRR)

According to Bates and Granger (1969) a combining set of forecasts outperforms the individual forecasts that the set consists of. Taking this basic idea one step further, Granger and Ramanathan (1994) suggested three regression models as follows:

$$f_{c1} = a_0 + \sum_{i=1}^{n} a_i f_i + \varepsilon_1 \tag{4.10}$$

$$f_{c2} = \sum_{i=1}^{n} a_i f_i + \varepsilon_2 \tag{4.11}$$

$$f_{c3} = \sum_{i=1}^{n} a_i f_i + \varepsilon_3, \quad where \ \sum_{i=1}^{n} a_i = 1 \tag{4.12}$$

Where

- f_i, $i=1,...,n$ are the individual one-step-ahead forecasts,
- f_{c1}, f_{c2}, f_{c3} are the combination forecast of each model,
- α_0 is the constant term of the regression
- α_i are the regression coefficients of each model
- $\varepsilon_1, \varepsilon_2, \varepsilon_3$ are the error terms of each regression model

The model specified in equation 4.10, which is selected for this case, is usually preferred in order to avoid forecasts errors correlated with the individual forecasts f_i (Swanson and Zeng, 2001). Thus, the GRR model at time t used in this chapter is specified as shown below:

$$f_{c_{NNs}}^{t} = 0.0422 + 35.023 f_{MLP}^{t} + 13.461 f_{RNN}^{t} + 56.132 f_{PSN}^{t} + \varepsilon_t \tag{4.13}$$

However, the variety of data and the biased and correlated forecasts raise questions on GRR model selection or modification, which are further discussed in the literature (Diebold and Pauly (1987) and Coulson and Robins (1993)).

4.4.4 Least Absolute Shrinkage and Selection Operator (LASSO)

The LASSO Regression is a class of Shrinkage or Regularization Regressions, which applies when multicollinearity exists among the regressors (Sundberg, 2002). The main difference between this technique and the Ordinary Least Squares (OLS) Regression is that LASSO method also minimizes the residual squared error, by adding a coefficient constraint (similarly to Ridge Regression (Chan *et al.*, 1999)).

Compared to Ridge Regression, LASSO best applies in samples of few variables with medium/large effect such in this case (Hastie *et al.*, 2009). For more details on the mathematical specifications of LASSO see Wang *et al.* (2007). Given the vectors of independent and dependent variables:

$$\begin{pmatrix} X_1^T \\ \vdots \\ X_N^T \end{pmatrix} = \begin{pmatrix} x_{11} & \cdots & x_{1N} \\ \vdots & \ddots & \vdots \\ x_{N1} & \cdots & x_{NN} \end{pmatrix}, \quad Y = (y_1, ..., y_N)^T \tag{4.14}$$

and the training data $\{(\boldsymbol{X_1}, y_1), \ldots, (\boldsymbol{X_N}, y_N)\}$, the LASSO coefficients are estimated based on the following argument:

$$\hat{\beta}_{lasso} = \arg\min_{\beta} \left\{ \sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{d} \beta_i x_{ij} \right)^2 \right\} \quad \textit{subject to} \quad \sum_{j=1}^{d} \left| \beta_j \right| \le k, k > 0 \tag{4.15}$$

This argument is based on Breiman's non-negative garrote minimization process (Yuan and Lin, 2007). Here k stands for the *'tuning parameter'*, because it controls the amount of shrinkage applied to the coefficients (Tibshirani, 2011). In this case, I experimented with various values of k in the in-sample period and concluded that the best results in terms of trading performance are acquired when the constraint takes the following form:

$$\left|\beta_{MLP}\right| + \left|\beta_{RNN}\right| + \left|\beta_{PSN}\right| \le 10.6 \tag{4.16}$$

Subject to this constraint the model takes the form:

$$f_{c_{NNs}}^{t} = 3.284 f_{MLP}^{t} + 1.591 f_{RNN}^{t} + 5.623 f_{PSN}^{t} + \varepsilon_t \tag{4.17}$$

This LASSO constraint makes the model adaptive, since it creates a penalization balance on each estimate, by leading some coefficients to zero or close to zero (see the unconstrained regression of GGR (equation 4.13) compared to the LASSO one (equation 4.17). This process favors the PSN architecture.

4.4.5 Kalman Filter

Kalman Filter is an efficient recursive filter that is described in chapter 3 and appendix A. The time-varying coefficient combination forecast suggested in this chapter is shown below:

$$f^t_{c_{NNs}} = 5.80 f^t_{MLP} + 1.16 f^t_{RNN} + 75.89 f^t_{PSN} + \varepsilon_t \quad (4.18)$$

From the above equation, which represents the final state, the Kalman filtering process favors the PSN model. This is what one would expect, since it is the model that performs best individually. In order to achieve optimal Kalman Filter estimation, it is important though to introduce a noise ratio[5]:

$$n_r = \sigma^2_\varepsilon / \sigma^2_n \quad (4.19)$$

The results are becoming more adaptive when the noise ratio rises (Dunis *et al.*, 2010).When $\sigma^2_n = 0$, the model transforms to the typical OLS model.

4.5 Statistical Performance

As it is standard in literature, in order to evaluate statistically the derived forecasts, the RMSE, MAE, MAPE and Theil-U statistics are computed (see amongst others Dunis and Williams (2002) and Dunis and Chen (2005)). The statistical analysis will provide some information regarding the accuracy of the forecasts and strengthen the final conclusions. The RMSE and MAE statistics are scale-dependent measures but give a basis to compare volatility forecasts with the realized volatility while the MAPE and the Theil-U statistics are independent of the scale of the variables. In particular, the Theil-U statistic is

[5] As stated in chapter 3, the $\sigma^2_\varepsilon, \sigma^2_n$ represent the variances of the error terms of the measurement and state equations

constructed in such a way that it necessarily lies between zero and one, with zero indicating a perfect fit. A more detailed description of these measures can be found on Theil (1966) and Pindyck and Rubinfeld (1998), while their mathematical formulas are presented in appendix B.4. For all four of the error statistics retained (RMSE, MAE, MAPE and Theil-U) the lower the output, the better the forecasting accuracy of the model concerned.

The in-sample and out-of-sample period performances are presented in tables 4-3 and 4-4 respectively. The results indicate that from the individual forecasts, the PSN outperformed all other models in both the in-sample and out-of-sample periods. Similarly, for the forecast combinations methodologies the Kalman Filter beat its benchmarks for the four statistical criteria retained in both estimation periods. Adding to the above statistical performance of the Kalman Filter, the Diebold-Mariano (1995) statistic for predictive accuracy is also computed for both MSE and MAE loss functions. The details on the Diebold-Mariano statistic are given in appendix B.5. The results of the Diebold-Mariano statistic, comparing Kalman filter with each other method, are summarized in Table 4-5.

From the table 4-5, the null hypothesis of equal predictive accuracy is rejected for all comparisons and for both loss functions at 5% confidence interval, since the test results $|s_{MSE}|>1.96$ and $|s_{MAE}|>1.96$. Moreover, the statistical superiority of the Kalman Filter forecasts is confirmed as for both loss functions the realizations of the statistic are negative[6]. Finally, the second best model in statistical terms, the LASSO regression, has the closest forecasts with Kalman Filter.

[6] In this study the Diebold-Mariano test is applied to couples of forecasts (Kalman Filter vs. another forecasting model). A negative realization of the Diebold-Mariano test statistic indicates that the first forecast (Kalman Filter) is more accurate than the second forecast. The lower the negative value, the more accurate are the Kalman Filter forecasts.

	TRADITIONAL TECHNIQUES		NEURALNETWORKS			FORECAST COMBINATIONS				
	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**	**Kalman Filter**
MAE	0.0065	0.0045	0.0044	0.0042	0.0039	0.0037	0.0037	0.0035	0.0038	0.0033
MAPE	399.44%	122.20%	97.13%	93.35%	89.43%	84.98%	85.13%	82.78%	87.63%	71.51%
RMSE	0.0086	0.0060	0.0053	0.0050	0.0041	0.0036	0.0036	0.0032	0.0037	0.0023
Theil-U	0.7021	0.6948	0.6686	0.5087	0.4292	0.4522	0.4625	0.4245	0.4613	0.2713

Table 4-3: Summary of In-Sample Statistical Performance

	TRADITIONAL TECHNIQUES		NEURAL NETWORKS			FORECAST COMBINATIONS				
	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**	**Kalman Filter**
MAE	0.0084	0.0059	0.0058	0.0056	0.0048	0.0048	0.0048	0.0047	0.0046	0.0044
MAPE	405.62%	131.20%	112.37%	105.97%	97.88%	94.07%	93.76%	92.83%	92.05%	88.37%
RMSE	0.0107	0.0077	0.0061	0.0060	0.0054	0.0053	0.0051	0.0049	0.0053	0.0043
Theil-U	0.7958	0.8749	0.7301	0.6001	0.4770	0.5672	0.5598	0.5297	0.6142	0.5212

Table 4-4: Summary of Out-of-Sample Statistical Performance

	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**
S_{MSE}	-9.307	-9.321	-6.244	-5.698	-5.184	-4.869	-4.896	-4.351	-4.112
S_{MAE}	-9.845	-9.832	-9.189	-8.881	-8.159	-7.851	-7.873	-7.679	-7.352

Table 4-5: Summary results of Diebold-Mariano statistic for MSE and MAS loss functions

4.6 Trading Performance

4.6.1 Trading Strategy and Transaction Costs

The trading strategy applied in this chapter is to go or stay ‘long’ when the forecast return is above zero and go or stay ‘short’ when the forecast return is below zero. The ‘long’ and ‘short’ EUR/USD position is defined as buying and selling Euros at the current price respectively. The transaction costs for a tradable amount, say USD 5-10 million, are about 1 pip (0.0001 EUR/USD) per trade (one way) between market makers. But the EUR/USD time series is considered as a series of middle rates, the transaction costs is one spread per round trip. With an average exchange rate of EUR/USD of 1.369 for the out-of-sample period, a cost of 1 pip is equivalent to an average cost of 0.007% per position.

4.6.2 Trading Performance before Leverage

The trading performance measures and their calculation description are presented in appendix B.4. Table 4-6 presents the in-sample trading performance of the models and forecast combinations before and after transaction cost. All models present a positive trading performance after transaction costs. From the single forecasts the PSN outperforms each NN and statistical benchmark in terms of annualised return and information ratio. The other two artificial intelligence models, the RNN and the MLP, present the second and third best trading performance respectively. Concerning the forecast combinations, the Kalman Filter is found to have the best trading performance with an annualised return of 41.78% and an information ratio of 4.47 after transaction costs. It is also worth noting that all forecast combinations outperform the best single forecast, the PSN, in terms of trading performance.

The out-of-sample performance of the models before and after transaction costs is shown in table 4-7.The last two rows of this table suggest that the PSN continues to outperform all other single forecasts in terms of trading performance. From the forecast combinations point of view, only the Kalman Filter and the LASSO methods seem to beat the best single forecast. The Simple Average, Bayesian Average and GRR methods, which demonstrated a better performance in the in-sample period, seem unable to maintain this superiority in the out-of-sample period. Moreover, the trading performance of the Bayesian Average and Simple Average strategies is very close. This is expected as the AIC and the BIC information criteria for the three NNs are very close in the in-sample period. On the other hand, the GRR strategy still outperforms the MLP and the RNN models in terms of annualised return and information ratio. That could be thought as a trend to adapt to the best individual performance (*'combining for adaptation'*, (Yang, 2004)). Finally, the Kalman Filter achieves a 10% higher annualised return than the second best methodology, the LASSO regression. It seems that the ability of Kalman Filter to provide efficient computational recursive means to estimate the state of the process gives it a considerable advantage compared to the tested fixed parameters combination models.

	TRADITIONAL TECHNIQUES		NEURAL NETWORKS			FORECAST COMBINATIONS				
	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**	**Kalman Filter**
Annualised Return (excluding costs)	1.49%	13.87%	23.19%	26.14%	28.10%	32.74%	32.39%	33.99%	30.57%	42.63%
Annualised Volatility	9.68%	9.70%	9.38%	9.59%	9.23%	9.51%	9.52%	9.49%	9.54%	9.35%
Information Ratio (excluding costs)	0.15	1.43	2.47	2.73	3.05	3.44	3.4	3.58	3.21	4.56
Maximum Drawdown	-8.59%	-6.52%	-5.91%	-6.55%	-6.55%	-6.55%	-6.55%	-6.55%	-6.55%	-6.66%
Annualised Transactions	130	100	121	136	74	107	106	104	106	121
Transaction Costs	0.91%	0.70%	0.85%	0.95%	0.52%	0.75%	0.74%	0.73%	0.74%	0.85%
Annualised Return (including costs)	0.58%	13.17%	22.34%	25.19%	27.58%	31.99%	31.65%	33.26%	29.83%	41.78%
Information Ratio (including costs)	0.06	1.36	2.38	2.63	2.99	3.36	3.32	3.50	3.13	4.47

Table 4-6: Summary of In-Sample Trading Performance

	TRADITIONAL TECHNIQUES		NEURAL NETWORKS			FORECAST COMBINATIONS				
	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**	**Kalman Filter**
Annualised Return (excluding costs)	-4.80%	10.60%	14.80%	16.07%	18.37%	16.37%	16.59%	16.99%	20.23%	28.79%
Annualised Volatility	12.03%	11.07%	11.83%	11.02%	10.89%	10.85%	10.85%	11.02%	10.99%	10.92%
Information Ratio (excluding costs)	-0.4	0.96	1.25	1.46	1.69	1.51	1.53	1.54	1.84	2.64
Maximum Drawdown	-6.41%	-6.23%	-6.23%	-6.23%	-6.31%	-6.31%	-6.31%	-6.31%	-6.31%	-6.31%
Annualised Transactions	77	54	71	71	76	70	71	63	69	73
Transaction Costs	0.54%	0.38%	0.50%	0.50%	0.53%	0.49%	0.50%	0.44%	0.48%	0.51%
Annualised Return (including costs)	-5.34%	10.22%	14.30%	15.57%	17.84%	15.88%	16.09%	16.55%	19.75%	28.28%
Information Ratio (including costs)	-0.44	0.92	1.21	1.41	1.64	1.46	1.48	1.50	1.80	2.59

Table 4-7: Summary of Out-of-Sample Trading Performance

4.6.3 Leverage to exploit high Information Ratios

In order to further improve the trading performance of the previous models, a leverage is introduced based on RiskMetrics one day ahead volatility forecasts[7]. The details of the RiskMetrics model are in appendix B.6. The intuition of the strategy is to avoid trading when volatility is very high while at the same time exploiting days when the volatility is relatively low. As mentioned by Bertolini (2010) there are few papers on market-timing techniques for foreign exchange, with the notable exception of Dunis and Miao (2005, 2006). The opposition between market-timing techniques and time-varying leverage is apparent, as time-varying leverage can be easily achieved by scaling position sizes inversely to recent risk behaviour measures.

The process starts with forecasting with RiskMetrics the one day ahead realised volatility of the EUR/USD exchange rate in the test and validation sub-periods. Then, following Dunis and Miao (2005, 2006), these two periods are split into six sub-periods, ranging from periods with extremely low volatility to periods experiencing extremely high volatility. Periods with different volatility levels are classified in the following way:

Initially the average (μ) difference between the actual volatility in day t and the forecasted for day $t+1$ and its 'volatility' (measured in terms of standard deviation σ) are calculated. The periods where the difference is between μ plus one σ are classified as 'Lower High Vol. Periods'. Similarly, 'Medium High Vol.' (between $\mu + \sigma$ and $\mu + 2\sigma$) and 'Extremely High Vol.' (above $\mu + 2\sigma$) periods can be defined. Periods with low volatility are also defined following the same 1σ and 2σ approach, but with a minus sign. After the six periods are formed, the next step is to assign the appropriate leverage factors. In each sub-period, leverage is assigned starting with *0* for periods of extremely high volatility to a leverage of *2.5* for periods of extremely low volatility. The following table presents the sub-periods and their relevant leverages.

[7] A GJR (1, 1) is also explored to model in forecasting volatility. Its statistical accuracy in the test sub-period in terms of the MAE, MAPE, RMSE and the Theil-U statistics is only slightly better compared with RiskMetrics. However, when the utility of GJR in terms of trading efficiency is measured for our models within the context of the strategy in the test sub-period, the results in terms of annualised returns are slightly better with RiskMetrics for most of the models. Moreover, RiskMetrics is simpler to implement than the more complicated GJR. Therefore, in this chapter the results obtained with RiskMetrics are presented. It is also worth noting that the ranking of the models in terms on information ratio and annualised return is the same, whether GJR or RiskMetrics are used.

	Extremely Low Vol.	Medium Low Vol.	Lower Low Vol.	Upper High Vol.	Medium High Vol.	Extremely High Vol.
Leverage	2.5	2	1.5	1	0.5	0

Table 4-8: Classification of Leverage in Sub-Periods

The parameters of the strategy (μ and σ) are updated every three months by rolling forward the estimation period. So for example, for the first three months of the validation period, μ and σ are computed based on the eighteen months of the test sub-period. For the following three months, the two parameters are computed based on the last fifteen months of test sub-period and the first three of the validation sub-period. Figure 4-3 summarizes the leverages assigned in the trading days of the out-of-sample period, based on the above strategy. The cost of leverage (interest payments for the additional capital) is calculated at 1.75% p.a. (that is 0.0069% per trading day[8]). The final results are presented in table 4-9.

The most striking performance achieved by the time-varying leverage strategy is the significant reduction in the maximum drawdown, the essence of risk for an investor in financial markets. Not only do all models, except ARMA, experience a higher performance in terms of return or risk-adjusted return, but maximum drawdowns are reduced by as much as 50%, from 6.31% to 3.38% in the case of the Kalman Filter combination. Even the naive strategy seems to try to invert its previous discouraging performance (see table 4-7). The PSN still outperforms every NN and increases its annualised profit over 3%. Similarly the Bayesian Average and Simple Average combination methods present a 3% increase of annualised return, but they still cannot outperform the PSN and RNN individual performance. The other two forecast combination techniques, the GGR and the LASSO, also present an increased annualised return and information ratio. Finally, the Kalman Filter continues to present a remarkable trading performance with the highest information ratio and a 5.67% increase in terms of annualised return. When transaction and leverage costs are included, the profit decreases, but the trend of the results is not affected. That allows me to conclude, that in all cases the Kalman Filter can be considered by far the optimal forecast combination for the dataset and models under study.

[8] The interest costs are calculated by considering a 1.75% interest rate p.a. (the Euribor rate at the time of calculation) divided by 252 trading days. In reality, leverage costs also apply during non-trading days so that I should calculate the interest costs using 360 days per year. But for the sake of simplicity, I use the approximation of 252 trading days to spread the leverage costs of non-trading days equally over the trading days. This approximation allows me not to keep track of how many non-trading days a position is hold.

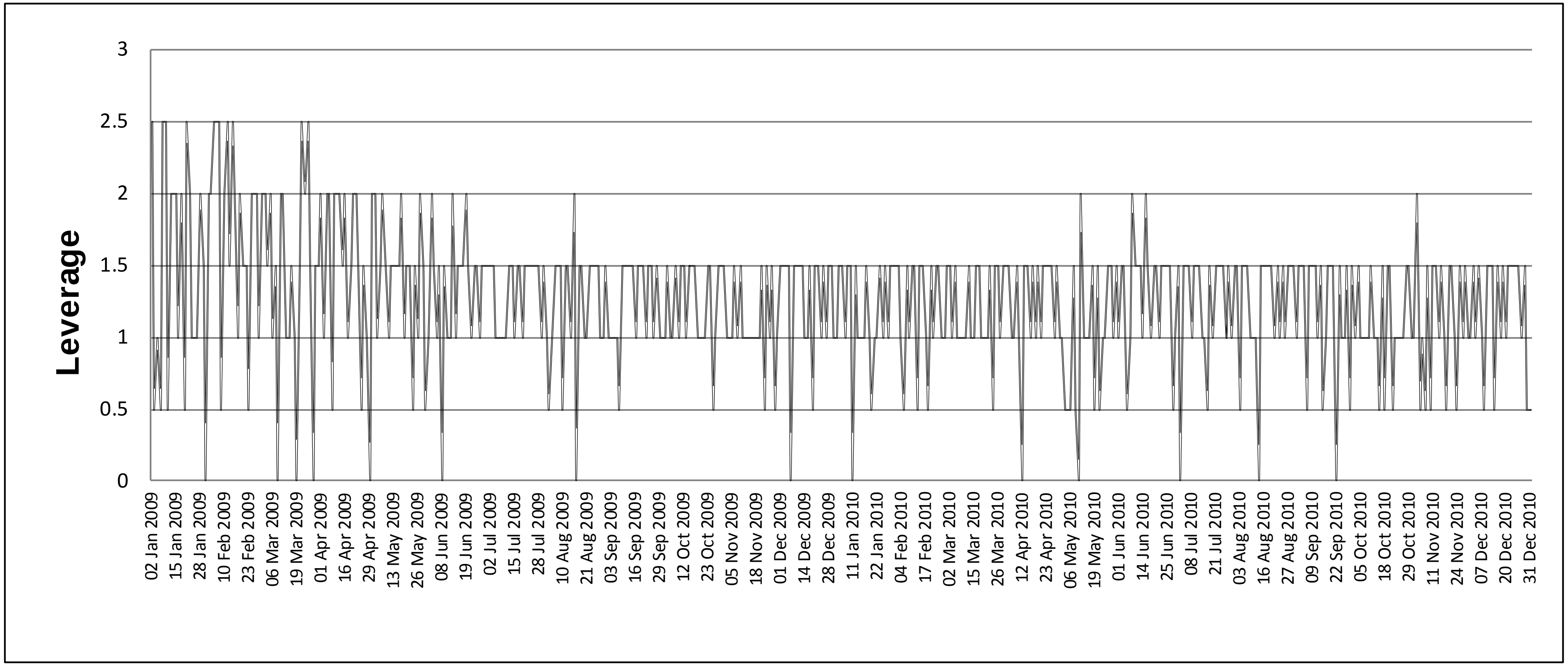


Figure 4-3: Leverages assigned in the out-of-sample period

	TRADITIONAL TECHNIQUES		NEURAL NETWORKS			FORECAST COMBINATIONS				
	NAIVE	**ARMA**	**MLP**	**RNN**	**PSN**	**Simple Average**	**Bayesian Average**	**GRR**	**LASSO**	**Kalman Filter**
Annualised Return (excluding costs)	-2.34%	7.28%	18.13%	19.44%	22.28%	19.12%	19.36%	22.37%	25.08%	34.46%
Annualised Volatility	10.14%	10.44%	9.90%	9.04%	9.85%	9.09%	9.13%	9.38%	9.20%	9.32%
Information Ratio (excluding costs)	-0.23	0.7	1.83	2.15	2.26	2.1	2.12	2.38	2.73	3.7
Maximum Drawdown	-3.50%	-3.20%	-3.66%	-3.14%	-3.66%	-2.98%	-3.21%	-2.83%	-2.94%	-3.38%
Annualised Transactions	122	90	115	117	122	111	113	97	110	114
Average Leverage Factor (ex post)	n.a.	n.a.	1.13	1.19	1.12	1.09	1.09	1.26	1.18	1.15
Transaction and Leverage Costs	1.79%	1.57%	1.74%	1.75%	1.79%	1.72%	1.73%	1.62%	1.71%	1.73%
Annualised Return (including costs)	-4.13%	5.71%	16.39%	17.69%	20.49%	17.40%	17.63%	20.75%	23.37%	32.73%
Information Ratio (including costs)	-0.41	0.55	1.66	1.96	2.08	1.91	1.93	2.21	2.54	3.51

Note: The average leverage factor ex post is computed as the ratio of the annualised returns after costs of tables 4-7 and 4-9 for those models which achieved an in-sample information ratio of at least 2 and, as such, would have been candidates for leveraging out-of-sample. In the final results of this table, I do not take into account the interest that could be earned during times, where the capital is not traded (non-trading days) or not fully invested.

Table 4-9: Summary of Out-of-Sample Trading Performance - final results

4.7 Conclusions

In this chapter the trading and statistical performance of a Neural Network (NN) architecture, the Psi Sigma Neural Network (PSN), is investigated. Then the utility of Kalman filters in combining NN forecasts is explored. Firstly, the EUR/USD European Central Bank (ECB) fixing series is applied to a Naive Strategy, an Autoregressive Moving Average (ARMA) model and three NNs, namely a Multi-Layer Perceptron (MLP), a Recurrent Network (RNN) and a PSN. Secondly, a Kalman filter-based combination is compared with four other forecast combination methods. That is the traditional Simple Average, the Bayesian Average, Granger- Ramanathan's Regression Approach (GRR) and the Least Absolute Shrinkage and Selection Operator (LASSO). The models' performance is estimated through the EUR/USD ECB fixing series of the period of 2002-2010, using the last two years for out-of-sample testing. Finally, a time-varying leverage strategy is introduced based on RiskMetrics volatility forecasts.

As it turns out, the PSN outperforms its benchmarks models in terms of statistical accuracy and trading performance. It is also shown that all the forecast combinations, outperform out-of-sample all the single models except the PSN for the statistical and trading terms retained. It is interesting that the 'combining for improvement' pattern that all combination forecasts showed in the in-sample period, changes regarding the out-of-sample combination forecasts. Simple Average, Bayesian Average and GRR do not continue to outperform PSNs' best individual performance but are better than MLP and RNN, while LASSO and Kalman Filter present the best results. It seems that the ability of Kalman Filter to provide efficient computational recursive means to estimate the state of the process gives it a considerable advantage compared to the fixed parameters combination models. Finally, all models except ARMA show a substantial increase in their trading performance and a striking reduction in maximum drawdowns after applying time-varying leverage. In all these cases, Kalman Filter remains the best approach. Its remarkable trading performance of Kalman Filter suggests that it can be considered as an optimal forecast combination for the models and time-series under study. These results should go some way towards convincing a growing number of quantitative fund managers to experiment beyond the bounds of the more traditional models and trading strategies. The results in table 4-9, with an information ratio in excess of 3, should also provide motivation for the use of Kalman Filter in combining model based forecasts.

Chapter 5

Stochastic and Genetic Neural Network Combinations in Trading and Hybrid Time-Varying Leverage Effects

5.1 Introduction

Neural Networks (NNs) are similar to any advanced statistical model. They are optimized in an in-sample period and applied for prediction in an out-of-sample period. The difference between NNs and statistical models is that the first have an adaptive nature. NNs can take many different forms and have as inputs any potential explanatory variable. Therefore they are capable of exploring different forms of non-linearity and theoretically provide a superior performance than statistical-econometrical models. Non-linearity is not possible to be measured in statistical terms and therefore models such as NNs have the advantage in problems where the exact nature of the series under study is unknown.

Sceptics argue that the lack a formal statistical theoretical background in NNs makes them useless in Finance. However, financial series and especially exchange rates are dominated by factors (e.g. behavioural factors, politics…) that time-series analysis and statistics are unable to capture in a single model. Based on this, it can be argued that a time-series statistical model that will capture the pattern of exchange rates is in the long-run impossible. Statistical theory and mathematics will never be able to explain such a complex relationship. Researchers and traders should seek for the models that are closest to the actual pattern of the financial series under study. The flexibility and the non-linear nature of NNs make them perfect candidates for such a problem. This study aims to provide empirical evidence that will convince scientists and decision investment managers to experiment beyond the traditional bounds of mathematics and statistics.

This chapter attempts to evaluate the performance of a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN) and a Psi-Sigma Network (PSN) architecture in forecasting and trading the Euro/Dollar (EUR/USD) exchange rate. Then, the utility of Kalman Filter, Genetic Programming (GP) and Support Vector Regression (SVR) algorithms is explored as forecasting combination techniques. The used benchmarks for the NNs are a Random Walk model (RW), an Autoregressive Moving Average model (ARMA) and a Smooth Transition Autoregressive Model (STAR). The forecast combination techniques are then benchmarked by a Simple Average and a Least Absolute Shrinkage and Selection Operator (LASSO). The forecasts are evaluated in terms of statistical accuracy and trading efficiency. The EUR/USD exchange rate is highly liquid and well known for its high volatility in our days. It seems as the perfect series for a forecasting exercise with non-linear models.

The rationale of the chapter is multiple. It is explored if non-linear models such as NNs are able to outperform traditional models such as RW, ARMA and STAR. The STAR model acts as statistical non-linear benchmark, while the comparison of the results with a RW model adds to the on-going debate if financial forecasting models can outperform a RW. In this forecasting competition structural macroeconomic models are not included. Such models are presented by Flannery and Protopapadakis (2002), Andersen *et al.* (2003), Pierce and Solakoglu (2007), Evans and Speight (2010) and recently Bacchetta and Wincoop (2013). The main reason for that choice is the unavailability of daily data of relevant macroeconomic indicators. Comparing the models with benchmarks generated by lower frequency data would make the forecasting competition unfair and unequal.

This study also checks if statistical models like the LASSO and the Kalman Filter can combine the derived forecasts successfully in order to provide a superior trading performance. Their results will be benchmarked against those generated by two advanced non-linear techniques, a SVR and a GP model. SVR and GP algorithms have provided promising results in many field of Science, but they are rarely used as forecast combination techniques. The success of the best forecast combination model is also validated through the Modified Diebold-Mariano (1997) test.

The proposed trading strategy based on volatility forecasts tests if volatility forecasts and market shocks can be combined with the daily return forecasts to improve the trading performance of the models. Lastly the implemented loss function for NN models adds to the literature on the utility of NNs in Finance. Until now researchers are applying statistical loss functions to generate trading signals through NNs. However, statistical accuracy is not always synonymous with financial profitability. The proposed loss function attempts to bring a balance between these two terms.

Many researchers have attempted to forecast exchange rates, but their empirical results are often contradictory. Meese and Rogoff (1983a, 1983b) examine the Frenkel-Bilson, Dornbusch-Frankel, and Hooper-Morton structural exchange rate models and find that the random walk performs better. The authors conclude that the out-of-sample failure of these models is due to the volatile nature of exchange rates, the poor inflation measurements and their money demand misspecifications. On the other hand, Tenti (1996) presents promising results in predicting the exchange rate of the Deutsche Mark with three different RNN architectures. Hussain *et al.* (2006) provide statistical accurate results with PSN, when applied in forecasting the EUR/USD, EUR/GBP and EUR/JPY exchange rates and using two simple MLP and HONN architectures as benchmarks. Bissoondeeal *et al.* (2008) use linear and nonlinear methods in forecasting AUD/USD and GBP/USD exchange rates and conclude that NNs outperform the traditional ARMA and GARCH models. Moreover, Kiani and Kastens (2008) forecast the GBP/USD, USD/CAD and USD/JPY exchange rates with feed-forward and recurrent NNs. Although the USD/CAD forecasts fail to outperform the ARMA model benchmark, the results are satisfying when forecasting GBP/USD and USD/JPY exchange rates. Grossman and McMillan (2010) propose a time-varying ESTR equilibrium exchange rate model for forecasting the bilateral rates between the US Dollar and the Canadian Dollar, the Japanese Yen and the British Pound. Their non-linear model provides superior forecasts in terms of directional change accuracy when compared to their linear alternatives. Finally, Dunis *et al.* (2011) and Sermpinis *et al.* (2012a), who conduct a forecast and trading competitions with several different NNs architectures present ambiguous results over the superiority of their models.

The idea of combining forecasts to improve prediction accuracy originates from Bates and Granger (1969), who suggested combining rules based on variances-covariances of the individual forecasts. Since then, many forecasting combination methods have been proposed and applied in financial research. Donaldson and Kamstra (1999) use combination techniques, such as weighted OLS, to benchmark the performance of artificial NN forecasts of S&P 500 stock index and conclude that the NNs are more statistically accurate. Hu and Tsoukalas (1999) combine the individual volatility forecasts of four models with simple averaging, ordinary least squares model and a NN. Their result suggest that the NN combination model performed better during the August 1993 crisis, especially in terms of root mean absolute forecast error. De Menezes and Nikolaev (2006) present promising forecasting results with their polynomial neural network forecasting system, which combines genetic programming with NN models. Altavilla and De Grauwe (2008) compare the performance of linear and nonlinear models in forecasting exchange rates. Although linear models are better at short forecasting horizons and nonlinear models dominate at longer forecasting horizons, they suggest that combining different forecasting techniques generally produces more accurate forecasts. Guidolin and Timmermann (2009) combine forecasts of future spot rates with forecasts of macroeconomic variables and conclude that this improves the out-of-sample forecasting performance of US short-term rates. Andrawis *et al.* (2011) attempt to predict the daily cash withdrawal amounts from ATM machines. In their application, they forecast over one hundred time series with eight classes of linear and non-linear models. Their results show that a simple average of NN, Gaussian process regression and linear models' forecasts is the optimal. Ebrahimpour *et al.* (2011) apply and compare three NN combining methods and an Adaptive Network-Based Fuzzy Inference System to trend forecasting in the Tehran stock exchange. The mixture of MLP experts is the model that presents the best hybrid model in this competition, but all NN combining models present promising forecasting performance.

The rest of the chapter is organized as follows. Section 5.2 gives a detailed description of the EUR/USD ECB fixing series, used as a dataset. Section 5.3 is an overview of the benchmark and NNs models, while section 5.4 describes the forecast combination methods implemented. The statistical and trading performance of these models is presented in Sections 5.6 and 5.7. Finally, conclusions are given in Section 5.8.

5.2 The EUR/USD Exchange Rate and Related Financial Data

Similarly to the rational of the chapter 4, the ECB fixings of EUR/USD are selected for this forecasting and trading application. The ECB daily fixings of the EUR exchange rate are tradable levels and using them is a more realistic alternative to, say, London closing prices. In this chapter, the EUR/USD is examined over the period of 1999-2012 in three rolling forecasting exercises (F1, F2 and F3) on a daily basis. Each exercise studies a decade of the EUR/USD using the last two years for out-of-sample evaluation. F1 focus on the decade of 1999-2008 while F2 and F3 examine the periods 2001-2010 and 2003-2012 respectively. Table 5-1 presents these three sub-periods.

	F1		F2		F3	
PERIODS	**DAYS**	**PERIOD**	**DAYS**	**PERIOD**	**DAYS**	**PERIOD**
Total Dataset	2540	01/02/1999 - 31/12/2008	2560	02/01/2001 - 31/12/2010	2564	02/01/2003 - 31/12/2012
Training Dataset ***(In-sample)***	1517	01/02/1999 - 31/12/2004	1535	02/01/2001 - 29/12/2006	1537	02/01/2003 - 31/12/2008
Test Dataset ***(In-sample)***	512	03/01/2005 -29/12/2006	511	02/01/2007 -31/12/2008	514	02/01/2009 -31/12/2010
Validation Dataset ***(Out-of-sample)***	511	02/01/2007 -31/12/2008	514	02/01/2009 -31/12/2010	513	03/1/2011 -31/12/2012

Table 5-1: The EUR/USD Dataset and Neural Networks' Training Sub-periods for the three forecasting exercises

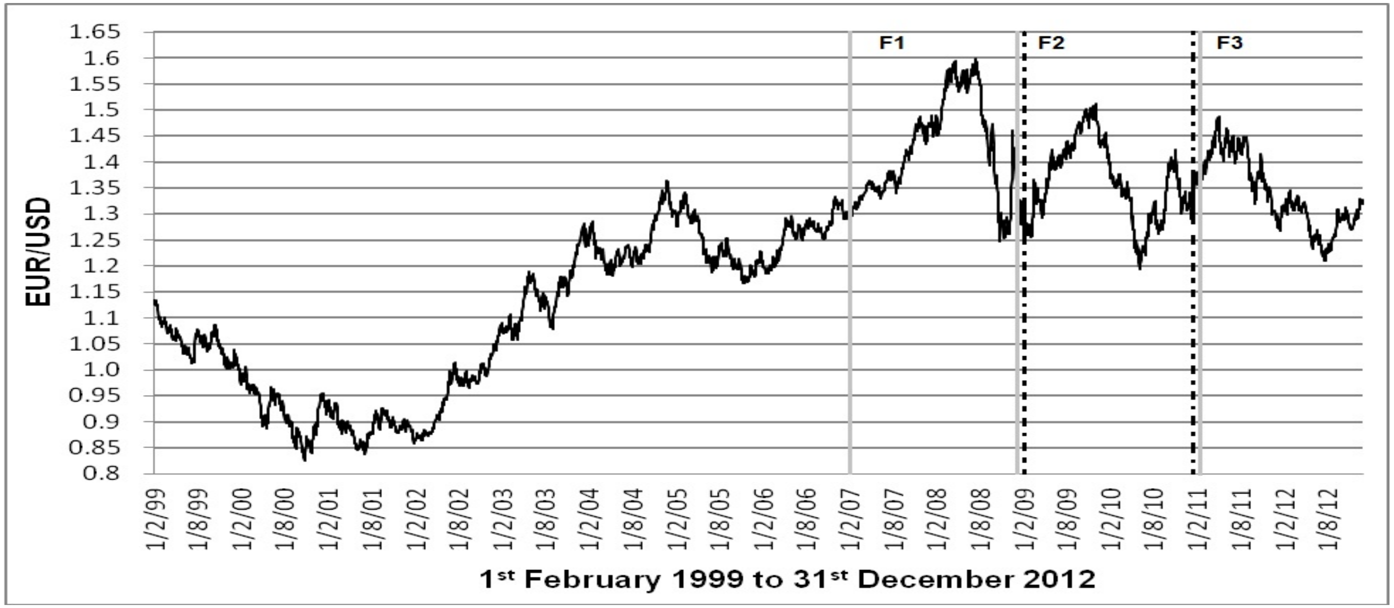


Figure 5-1: EUR/USD Frankfurt daily fixing prices and the three out-of-sample periods under study

The in-sample datasets for each exercise are further divided in two sub-periods, the training and test sub-period. This is done for training purposes of the NNs. The three rolling forward sub-periods add validity to the forecasting exercise and increase the robustness of the results. The out-of-sample periods are dominated by the effects of the debt and the mortgage crises. Using a rolling forward the estimation is an attempt to capture the effect of these crises to the extent that is possible. The rolling forward estimation and the fact that the parameterization of the models is conducted entirely in-sample acts as a shield against data-snooping bias' effects.

The previous figure shows the total dataset of the EUR/USD and its volatile trend. The out-of-sample periods of each exercise are also highlighted. The EUR/USD time series, shown above, is non-normal and non-stationary. Jarque-Bera statistics confirm its non-normality at the 99% confidence interval with slight skewness and high kurtosis. To overcome the non-stationary issue, the EUR/USD series is transformed into a daily series of rate returns. So given the price level $P_1, P_2, \ldots, Pt$ the return at time t is calculated as:

$$R_t = \left(\frac{P_t}{P_{t-1}} \right) - 1 \quad (5.1)$$

The Jarque-Bera statistic confirms again that the EUR/USD return series is non-normal at the 99% confidence interval. For more details on Jarque-Bera statistics see Jarque and Bera (1980).

5.3 Forecasting Models

5.3.1 Benchmark Forecasting Models

As mentioned previously, three traditional forecasting strategies, namely a RW, an ARMA and a STAR are used in order to benchmark the efficiency of the NN models. The aim of these models is to forecast the one day ahead return of the series under study for each forecasting exercise.

5.3.1.1 Random Walk (RW)

The RW is a process where the current value of a variable is calculated from the past value plus an error term. The error term follows the standard normal distribution. The specification of the model is:

$$\hat{Y}_t = Y_{t-1} + e_t, \; e_t \sim N(0,1) \tag{5.2}$$

In this equation $\hat{Y}_t$ is the forecasted value for period *t* and Y_{t-1} is the actual value of period *t-1*. The RW is a non-stationary process with a constant mean, but not a constant variance.

5.3.1.2 Auto-Regressive Moving Average Model (ARMA)

The ARMA model specification is described in chapter 4. Using as a guide the information criteria in the in-sample subset the optimal ARMA structures are selected. In all cases, the null hypotheses that all coefficients (except the constant) are not significantly different from zero and that the error terms are normally distributed are rejected at the 95% confidence interval. The specifications of the ARMA models selected for out-of-sample estimation in each exercise are presented below:

$$\left\{\begin{array}{l} \hat{Y}_t^{[F_1]} = 0.00012 + 0.4258Y_{t-1} - 0.0787Y_{t-2} + 0.1588Y_{t-5} - 0.6869Y_{t-9} - 0.4235\varepsilon_{t-1} + 0.0734\varepsilon_{t-2} \\ -0.1575\varepsilon_{t-5} + 0.6934\varepsilon_{t-9} \\ \hat{Y}_t^{\{F_2\}} = 0.00023 - 0.0758Y_{t-1} - 0.2157Y_{t-3} + 0.1331Y_{t-5} + 0.7891Y_{t-7} + 0.0905\varepsilon_{t-1} + 0.2095\varepsilon_{t-3} \\ -0.1104\varepsilon_{t-5} - 0.7879\varepsilon_{t-7} \\ \hat{Y}_t^{[F_3]} = 0.00013 + 0.9542Y_{t-1} - 0.1819Y_{t-3} + 0.8341Y_{t-6} - 0.9196Y_{t-7} - 0.9525\varepsilon_{t-1} + 0.1717\varepsilon_{t-3} \\ -0.8336\varepsilon_{t-6} + 0.9319\varepsilon_{t-7} \end{array}\right\} \tag{5.3}$$

5.3.1.3 Smooth Transition Autoregressive Model (STAR)

STARs initially proposed by Chan and Tong (1986) are extensions of the traditional autoregressive models (ARs). The STAR combines two AR models with a function that defines the degree of non-linearity (smooth transition function). The general two-regime STAR specification is the following:

$$\hat{Y}_t = \Phi_1' X_t (1 - F(z_t, \zeta, \lambda)) + \Phi_2' X_t F(z_t, \zeta, \lambda) + u_t \tag{5.4}$$

Where:

- $\hat{Y}_t$ the forecasted value at time t
- $\Phi_i = (\tilde{\varphi}_{i,0}, \tilde{\varphi}_{i,1}, ...\tilde{\varphi}_{i,p}), i = 1,2$ and $\tilde{\varphi}_{i,0}, \tilde{\varphi}_{i,1}, ...\tilde{\varphi}_{i,p}$ the regression coefficients of the two AR models
- $X_t = (1, \tilde{\chi}_t')'$ with $\tilde{\chi}_t' = (Y_{t-1}, ..., Y_{t-p})$
- $0 \leq F(z_t, \zeta, \lambda) \leq 1$ the smooth transition function
- $z_t = Y_{t-d}, d > 0$ the lagged endogenous transition variable
- ζ the parameter that defines the smoothness of the transition between the two regimes
- λ the threshold parameter
- u_t the error term

The main characteristic of a STAR is that $\hat{Y}_t$ is calculated at any given t as a weighted average of two AR models. The weights of the two AR models are defined based on the value of $F(z_t, \zeta, \lambda)$. The regime-switching ability of STARs derives from the fact that at each t a regime is selected based on the values of z_t and $F(z_t, \zeta, \lambda)$. In this chapter the series is best modelled as an Exponentional STAR process, following Lin and Terasvitra (1994).

. **5.3.2 Neural Networks (NNs)**

This chapter attempts to evaluate the performance of a MLP, RNN and PSN architecture in forecasting and trading the Euro/Dollar (EUR/USD) exchange rate. The specifications of these models are given in chapter 3 in detail. For training purposes of the NNs, the in-sample dataset is further divided in two sub-periods, the training and test sub-period. Similarly to the route taken in chapter 4, the sensitivity analysis on a pool of potential inputs in each one of the in-sample datasets is needed. In this application, the training sub-period is used to select as inputs the set of variables that provides the higher trading performance in the test sub-period. This optimization procedure is the most popular in NNs and superior to cross validation for datasets of that size (Zhu and Rohwer, 1996). The set of inputs for the F1, F2 and F3 can be found in appendix C.1.

The training process of the previous chapter is extended in these three exercises. The NNs are specially designed for financial purposes. Therefore, a novel fitness function is applied. This specialised fitness function focuses on achieving two goals at the same time. First of all, the annualised return in the test period should be maximized and secondly the Root Mean Square Error (RMSE) of the networks output should be minimized. Based on the above the fitness function for all the NNs takes the following form and equation 5.4 is maximized:

$$Fitness = Annualised\_Return - 10*RMSE \qquad (5.4)$$

After the optimization of the networks, the predictive value of each model is evaluated by applying it to the validation dataset (out-of-sample dataset). Since the starting point for each network is a set of random weights, forecasts can slightly differ between same networks. In order to eliminate any variance between the NN forecasts and add robustness to the results, a simple average of a committee of 20 NNs is used. This committee comprises of these NNs that provided the highest profit in each in-sample sub-period of F1, F2 and F3. This is necessary, because otherwise outlier networks can be included to the committee, used for the final forecasts. The characteristics of these NNs for each forecasting exercise are also presented in Appendix C.1.

Several NNs trading applications suffer for the data snooping effect. Data-snooping occurs when a given set of data is used more than once. This can leads to the possibility that the results achieved may be due to chance rather than an inherent merit in the method.

In order to avoid this effect, the guidelines of James *et al.* (2012) are followed. The data are clearly subdivided in in-sample (training and test subsets) and out-of-sample (validation subset). The out-of-sample subset is not used in any part of the NN parameter selection procedure. A final 'safe-lock' against data-snooping is provided by the implementation of the Hansen (2005) test. As benchmark for this comparison, a simple martingale model is used. The results indicate that the NNs committees (the forecasting performance of which is presented in the following sections) are free from the data snooping bias at the 5% level in all out-of-sample subsets.

5.4 Forecasting Combination Techniques

The techniques that are used to combine the NNs forecasts are presented in this section. Similarly to the approach of the previous chapter, RW, ARMA and STAR are discarded from the forecast combinations. The reason is that they all present considerably worse trading performances than their NNs' counterparts both in-sample and out-of-sample, throughout all exercises (as it will be shown in the next sections).

5.4.1 Simple Average

The first forecasting combination technique used in this chapter is a Simple Average, which can be considered a benchmark forecast combination model. Given the three NNs' forecasts $f_{MLP}^{t}, f_{RNN}^{t}, f_{PSN}^{t}$ at time *t*, the combination forecast at time *t* and exercise F_i is calculated as:

$$f_{c_{NNs}}^{t\ [F_i]} = (f_{MLP}^{t\ [F_i]} + f_{RNN}^{t\ [F_i]} + f_{PSN}^{t\ [F_i]}) / 3 \ , i = 1, 2, 3 \qquad (5.5)$$

5.4.2 Least Absolute Shrinkage and Selection Operator (LASSO)

The LASSO Regression is also used to combine the individual forecasts from the qualifying NN committees. The exact specification of this method is explained in chapter 4. In this chapter, the best results in terms of trading performance are acquired, when the constraints take the following forms:

$$\begin{Bmatrix} \left|\beta_{MLP}\right|^{[F_1]} + \left|\beta_{RNN}\right|^{[F_1]} + \left|\beta_{PSN}\right|^{[F_1]} \leq 3.1 \\ \left|\beta_{MLP}\right|^{[F_2]} + \left|\beta_{RNN}\right|^{[F_2]} + \left|\beta_{PSN}\right|^{[F_2]} \leq 1.9 \\ \left|\beta_{MLP}\right|^{[F_3]} + \left|\beta_{RNN}\right|^{[F_3]} + \left|\beta_{PSN}\right|^{[F_3]} \leq 2.3 \end{Bmatrix} \tag{5.6}$$

Subject to the above, the final LASSO forecast combinations are given by the following set of equations:

$$\begin{Bmatrix} {f_{c_{NNs}}^{t}}^{[F_1]} = 0.125\, {f_{MLP}^{t}}^{[F_1]} + 0.723\, {f_{RNN}^{t}}^{[F_1]} + 1.534 {f_{PSN}^{t}}^{[F_1]} + \varepsilon_t^{[F_1]} \\ {f_{c_{NNs}}^{t}}^{[F_2]} = 0.021\, {f_{MLP}^{t}}^{[F_2]} + 0.218\, {f_{RNN}^{t}}^{[F_2]} + 1.452 {f_{PSN}^{t}}^{[F_2]} + \varepsilon_t^{[F_2]} \\ {f_{c_{NNs}}^{t}}^{[F_3]} = 0.095\, {f_{MLP}^{t}}^{[F_3]} + 0.314\, {f_{RNN}^{t}}^{[F_3]} + 1.684\, {f_{PSN}^{t}}^{[F_3]} + \varepsilon_t^{[F_3]} \end{Bmatrix} \tag{5.7}$$

Each constraint makes the model adaptive, since it creates a penalization balance on each estimate by leading some coefficients to zero or close to zero. In all cases, the weight of the PSN forecast is higher than the rest ones.

5.4.3 Kalman Filter

The Kalman Filter is an efficient recursive filter that is described in chapter 3 and appendix A. The time-varying coefficient combination forecast suggested in this chapter is shown below. These are the final states for the respective three exercises:

$$\left\{\begin{array}{l} {f_{c_{NNs}}^{t}}^{[F_1]} = 0.152\, {f_{MLP}^{t}}^{[F_1]} + 0.785\, {f_{RNN}^{t}}^{[F_1]} + 1.485 {f_{PSN}^{t}}^{[F_1]} + \varepsilon_t^{[F_1]} \\ {f_{c_{NNs}}^{t}}^{[F_2]} = 0.081\, {f_{MLP}^{t}}^{[F_2]} + 0.976\, {f_{RNN}^{t}}^{[F_2]} + 1.322 {f_{PSN}^{t}}^{[F_2]} + \varepsilon_t^{[F_2]} \\ {f_{c_{NNs}}^{t}}^{[F_3]} = 0.108\, {f_{MLP}^{t}}^{[F_3]} + 0.655\, {f_{RNN}^{t}}^{[F_3]} + 1.271\, {f_{PSN}^{t}}^{[F_3]} + \varepsilon_t^{[F_3]} \end{array}\right\} \tag{5.8}$$

From the above set of equations it is obvious that the Kalman filtering process, as in the case of LASSO, favors PSN forecasts regardless the period under study. This is what one would expect, since it is the model that performs best individually.

5.4.4 Genetic Programming (GP)

Genetic Programming (GP) algorithms are a class of Genetic Algorithms and their description is given in chapter 3. In this chapter the NNs' individual forecasts are used as inputs. The parameters of the GP application are defined based on which model presents optimized trading results in the in-sample sub-period. These parameters, finally, remain the same throughout exercises F1, F2 and F3 and are given in appendix C.2.

5.4.5 Support Vector Regression (SVR)

The Support Vector Regression (SVR) and its theoretical background are thoroughly explained in chapter 3. Except the utility of Kalman Filter and GP, the SVR algorithm is explored as forecasting combination techniques. As mentioned previously, the RBF kernels are the most common in similar SVR applications (see and Ince and Trafalis (2006b and 2008)). This is based on the fact that they efficiently overcome over-fitting and seem to excel in directional accuracy.

Having made that choice of Kernel, this application follows Cherkassky's and Ma's (2004) RBF application of optimal choice of *C* through a standard parameterization of the SVR solution. Based on their approach:

$$|f(x)| \le \left|\sum_{i=1}^{n_{sv}} (a_i - a_i^*) K(x_i, x)\right| \le \sum_{i=1}^{n_{sv}} \left|(a_i - a_i^*)\right| \cdot \left|K(x_i, x)\right| \le \sum_{i=1}^{n_{sv}} C \cdot \left|K(x_i, x)\right| \qquad (5.9)$$

For $K(x_i, x) = \exp(-\gamma \|x_i - x\|^2) \le 1$, the upper bound of the SVR function is obtained as:

$$|f(x)| \le C \cdot n_{sv} \qquad (5.10)$$

Thus, the estimation of *C* independently of the number of support vectors n_{sv} is given by $C \ge |f(x)|$ for all training samples. In other words, the optimal choice of *C* is equal to the range of the output values of the training data. In order to overcome outliers, the final *C* is computed as:

$$C = \max(|\bar{y} + 3\sigma_y|, |\bar{y} - 3\sigma_y|) \qquad (5.11)$$

where $\bar{y}, \sigma_y$ is the mean and the standard deviation of the training responses respectively.

Based on that the parameters for every exercise are calculated as C^{F1}=0.02, C^{F2}=0.022 and C^{F3}=0.0021. In most SVR studies, the model parameters are determined one at a time by letting each parameter taking a range of different values and then identifying the value that corresponds to the best model performance assessed by cross-validation (see Chalimourda *et al.* (2004) and Smola and Scholkopf (2004)). In this case it is applied a 5-fold cross-validation for calculating the optimal v and γ in the in-sample datasets, having set the parameter *C* for the respective exercise. During this cross-validation process, the in-sample period is partitioned into five equal subsamples. From those subsamples, a single subsample is retained as the validation data for testing the model and the remaining four subsamples are used as training data. The cross-validation process is then repeated five times with each one of the subsamples used only once as the validation data. As suggested by Duan *et al.* (2003) keeping the number of folds moderate, i.e. five, offers efficient parameter estimation with constraining substantially computational costs.

For example, regarding the exercise F1 the cross-validation is performed for the v parameter with C^{F1}=0.02 and fixed values of γ^{F1}. This selection is based on the best trading performance in the F1 in-sample dataset. Nonetheless, the value of the parameter γ^{F1} is not constrained. In order to overcome this issue, the proposed SVR model encompasses a *pseudo-R^2* criterion (Veall and Zimmermann, 1996). This criterion is calculated based on the residual sum of squared errors of each model (RSS_v) and a *'default model'* (RSS_{def}). This is the model which does not use information from the independent variables for the prediction of the dependent variable. According to the least square principle, the default model is simply the mean of the dependent variable computed in the training sample:

$$pseudo-R^2 = 1 - \frac{RSS_v}{RSS_{def}} \text{, where } RSS_{def} = \sum (y_i - \overline{y}_{train}) \tag{5.12}$$

The *pseudo-R^2* criterion allows firstly the retain of those v values that present simultaneously high trading performances and higher criterion values and secondly constrain the range of the fixed values of γ, saving a great amount of computational time. For $\gamma^{F1} \geq 1.33$ the criterion obtains values close to zero or even negative, which is evidence of over-fitting. Based on the above, the optimal v^{F1}=0.64 is calculated. The final step is to perform again the cross-validation process for γ parameter, with C^{F1}=0.02 and v^{F1}=0.64, but also with the constraint provided by the *pseudo-R^2criterion,* namely $\gamma^{F1} \leq 1.33$. Based on this procedure, the final F1 forecast combinations are derived with C^{F1}=0.02, v^{F1}=0.54 and γ^{F1}=0.63 selected as parameters for the RBF v-SVR model.

Similarly, for F2 and F3 I obtain C^{F2}=0.022, v^{F2}=0.71, γ^{F2}=1.41 and C^{F3}=0.021, v^{F3}=0.32, γ^{F3}=0.98 respectively. Small values of γ are in general welcome because they result in smoother marginal decisions. The restrictiveness of the SVR 'tube' though depends on all three parameters and therefore it is difficult to assess if the proposed model is more adaptive in one exercise than another.

5.5 Statistical Performance

As it is standard in the literature, in order to evaluate statistically the forecasts, the RMSE, the MAE, the MAPE and the Theil-U statistics are computed. For all four of the error statistics retained the lower the output, the better the forecasting accuracy of the model concerned. Their mathematical formulas are presented in Appendix B.4.

Table 5-3 summarizes the in-sample statistical performances of every model in each exercise. The results of the table suggest that the SVR presents the best in-sample statistical in all out-of-sample sub-periods. All forecast combinations are statistically more accurate than the NNs. Concerning the individual models, the PSN architecture seems superior for the statistical measures retained from the individual forecasts, having a close performance with the Simple Average. RNN and MLP are following with the second and third more statistically accurate forecasts for individual models, while the RW, ARMA and STAR strategies present the less accurate in-sample forecasts for the series and periods under study. The worse realizations of the statistics are given in F2, while the best ones are attained during F3.

The statistical performances of the models in every out-of-sample period are provided in table 5-4. The statistical accuracy ranking of the models does not change from the in-sample to the out-of-sample periods. The SVR confirms its forecasting superiority for all the statistical measures and forecast combinations retained. Similarly with the in-sample periods, the PSN is outperforming the RNN and MLP which remain the second and third best individual models in statistical terms. During 2009 – 2010 the models present the worse statistical performance. This period coincides with the start of the EU debt crisis. In the next sub-period, the models perform considerably better. This is happening despite the fact that the EMU debt crisis is in peak and the euro presents a volatile behavior.

		TRADITIONAL STRATEGIES			NEURAL NETWORKS			FORECAST COMBINATIONS				
IN-SAMPLE		**RW**	**ARMA**	**STAR**	**MLP**	**RNN**	**PSN**	**AVERAGE**	**LASSO**	**KALMAN**	**GP**	**SVR**
F1	**MAE**	0.0068	0.0053	0.0051	0.005	0.0051	0.0048	0.0047	0.0043	0.0041	0.0038	0.0036
	MAPE	207.25%	125.38%	110.27%	105.97%	101.15%	98.53%	97.44%	93.66%	91.42%	88.79%	84.61%
	RMSE	0.0089	0.0075	0.0071	0.0069	0.0068	0.0065	0.0063	0.0061	0.0058	0.0054	0.0049
	THEIL-U	0.7551	0.7494	0.7225	0.6955	0.6814	0.6629	0.6517	0.6328	0.6005	0.5718	0.5306
F2	**MAE**	0.0088	0.0064	0.0061	0.0057	0.0057	0.0055	0.0054	0.0052	0.005	0.0047	0.0044
	MAPE	215.33%	128.84%	115.39%	106.05%	102.44%	99.84%	98.42%	95.78%	93.17%	92.44%	89.27%
	RMSE	0.0095	0.0082	0.0078	0.0071	0.0067	0.0065	0.0064	0.0063	0.0061	0.0058	0.0054
	THEIL-U	0.9153	0.8715	0.8244	0.7264	0.7128	0.6925	0.6897	0.6559	0.6205	0.5847	0.5749
F3	**MAE**	0.0083	0.0061	0.0058	0.0047	0.0046	0.0044	0.0043	0.0041	0.0039	0.0037	0.0033
	MAPE	167.68%	119.52%	109.24%	98.69%	94.73%	91.38%	90.51%	89.53%	86.46%	84.37%	81.52%
	RMSE	0.0083	0.0071	0.0066	0.0062	0.0059	0.0057	0.0055	0.0052	0.0051	0.0049	0.0046
	THEIL-U	0.7484	0.7211	0.6859	0.6519	0.6367	0.6117	0.6052	0.5843	0.5602	0.5497	0.5133

Table 5-2: Summary of In-Sample Statistical Performance

OUT-OF-SAMPLE		TRADITIONAL STRATEGIES			NEURAL NETWORKS			FORECAST COMBINATIONS				
		RW	ARMA	STAR	MLP	RNN	PSN	AVERAGE	LASSO	KALMAN	GP	SVR
F1	**MAE**	0.0081	0.0065	0.006	0.0058	0.0056	0.0053	0.0052	0.0047	0.0046	0.0043	0.0039
	MAPE	221.18%	129.58%	116.23%	106.87%	104.25%	101.28%	98.37%	95.71%	92.49%	89.54%	86.67%
	RMSE	0.0094	0.0083	0.0075	0.0074	0.0072	0.0069	0.0066	0.0063	0.0061	0.0057	0.0053
	THEIL-U	0.8867	0.8355	0.7854	0.7578	0.7519	0.7226	0.6951	0.6795	0.6732	0.6429	0.6117
F2	**MAE**	0.0096	0.0079	0.0073	0.0063	0.0061	0.0059	0.0059	0.0056	0.0055	0.0052	0.0048
	MAPE	234.17%	131.22%	121.76%	107.48%	105.37%	103.72%	101.56%	99.27%	98.13%	95.27%	92.84%
	RMSE	0.0152	0.0094	0.0081	0.0074	0.0072	0.007	0.0069	0.0066	0.0064	0.0061	0.0058
	THEIL-U	0.9815	0.9125	0.8654	0.7972	0.7895	0.7664	0.7351	0.7005	0.6886	0.6758	0.6328
F3	**MAE**	0.0079	0.0063	0.0059	0.0051	0.0049	0.0048	0.0047	0.0045	0.0043	0.0041	0.0037
	MAPE	186.21%	123.68%	114.78%	99.52%	98.06%	96.84%	95.73%	93.12%	89.57%	87.33%	85.27%
	RMSE	0.0086	0.0077	0.0074	0.0066	0.0065	0.0064	0.0061	0.0058	0.0055	0.0053	0.0051
	THEIL-U	0.8358	0.7841	0.7059	0.6529	0.6458	0.6297	0.6218	0.6014	0.5788	0.5617	0.5419

Table 5-3: Summary of Out-of-Sample Statistical Performance

		RW	ARMA	STAR	MLP	RNN	PSN	AVERAGE	LASSO	KALMAN	GP
F1	**MDM_1**	-12.71	-11.24	-10.97	-9.37	-9.13	-8.08	-7.95	-6.25	-5.15	-4.26
	MDM_2	-15.85	-14.37	-13.49	-12.64	-11.97	-10.05	-8.57	-7.06	-6.53	-5.56
F2	**MDM_1**	-14.08	-13.19	-12.91	-11.18	-10.27	-8.57	-8.16	-7.59	-6.87	-6.31
	MDM_2	-17.28	-15.21	-14.08	-13.57	-12.37	-10.58	-9.18	-8.17	-9.25	-8.19
F3	**MDM_1**	-11.39	-10.23	-9.25	-7.69	-7.81	-6.28	-5.24	-4.38	-4.09	-3.67
	MDM_2	-13.77	-12.19	-10.88	-10.32	-10.11	-9.84	-7.93	-6.81	-5.48	-4.39

Note: MDM_1 and MDM_2 are the statistics computed for the MSE and MAE loss function respectively.

Table 5-4: Summary results of Modified Diebold-Mariano statistics for MSE and MAE loss function

In order to further verify the statistical superiority of the best proposed architecture, the Modified Diebold-Mariano (MDM) statistic for forecast encompassing is computed, as proposed by Harvey *et al.* (1997). The null hypothesis of the test is the equivalence in forecasting accuracy between a couple of forecasting models. The MDM statistic is an extension of the Diebold-Mariano (1995) test (see appendix B.5.) and its statistic is presented below:

$$MDM = T^{-1/2}\left[T + 1 - 2k + T^{-1}k\left(k-1\right)\right]^{1/2} DM \tag{5.13}$$

where T the number of the out-of-sample observations and k the number of the step-ahead forecasts. In this case the MDM test is applied to couples of forecasts (SVR vs. another forecasting model). A negative realization of the MDM test statistic indicates that the first forecast (SVR) is more accurate than the second forecast. The lower the negative value, the more accurate are the SVR forecasts. The MDM test follows the student distribution with $T-1$ degrees of freedom.

The use of MDM is common practice in forecasting because it is found to be robust in assessing the significance of observed differences between the performances of two forecasts (Barhoumi *et al.*, 2010). MDM also overcomes the problem of over-sized DMs in moderate samples (Dreger and Kholodilin, 2013). The statistic is measured in each out-of-sample period, while MSE and MAE are used as loss functions. Table 5-5 given previously presents the values of the statistics, comparing the GA-SVR with its benchmarks. The MDM null hypothesis of forecast encompassing is rejected for all comparisons and for both loss functions at the 1% confidence interval. The table results confirm the statistical superiority of the SVR forecasts as the realizations of the MDM statistic are all negative for both loss functions.

5.6 Trading Performance

Further to a statistical evaluation, the proposed models are evaluated also in terms of trading efficiency. It is indeed interesting to see if their trading performance is consistent with their statistical accuracy. The trading performance of the models and the effect of the proposed fitness function are analysed in section 5.6.1. below. In section 5.6.2 a more sophisticated trading strategy is introduced and the results test if its application can increase the models' profitability.

5.6.1 Trading Performance without Leverage

The trading strategy is to go or stay 'long' when the forecast return is above zero and go or stay 'short' when the forecast return is below zero. The 'long' and 'short' EUR/USD position is defined as buying and selling Euros at the current price respectively. The transaction costs for a tradable amount, say USD 5-10 million, are about 1 pip (0.0001 EUR/USD) per trade (one way) between market makers. The EUR/USD time series is considered as a series of middle rates, so the transaction costs are one spread per round trip. The average of EUR/USD is 1.421, 1.36 and 1.338 for the F1, F2 and F3 out-of-sample period respectively. Therefore, the respective costs of 1 pip are equivalent to an average cost of 0.007%, 0.0074% and 0.0075% per position.

The trading performance measures and their calculation are presented in appendix B.4. Table 5-6 that follows presents the in-sample trading performances of the models and forecast combinations after transaction costs for each exercise. These results show that all the NN and forecast combination models present a positive trading performance after transaction costs. From the single forecasts, the PSN outperforms each NN and statistical benchmark in terms of annualised return and information ratio. The other two NNs architectures, the RNN and the MLP, present the second and third best trading performance respectively. This ranking is consistent in all three exercises. Concerning the forecast combinations, it is obvious that the SVR model is superior in all periods with an average annualised return of 28.71% and an information ratio of 2.89 after transaction costs. It is also worth noting that all the forecast combinations outperform the best single forecast, the PSN, in terms of trading performance.

The out-of-sample trading performances of the models are summarized in table 5-7 that also follows. The results indicate that the PSN continues to outperform all other single forecasts in terms of trading efficiency. For the three out-of-sample periods the PSN presents on average 2.59 % higher annualised return and 0.25 higher information ratio compared to the second best single model, the RNN. On the other hand, all forecast combination models present improved out-of-sample trading performance, verifying a *'combining for improvement'* trend. The SVR forecast combination continues to outperform its benchmarks achieving on average 4.12% and 2.42% higher annualized return compared to the Kalman Filter and GP model respectively. The trading performance of the models in F1, F2 and F3 sub-period coincides with the statistical one. The best trading results are obtained during F3 and the worst during F2. In addition to the above, it is noted that combining forecasts decreases the maximum drawdown, the essence of risk for an investor in financial markets.

Concerning the proposed fitness function in equation 5.4, the results from the statistical and trading evaluation of the individual and combining forecasts seem promising. Firstly, all the NNs present significant profits after transaction costs in all out-of-sample sub-periods. Moreover, there are not large inconsistencies in the statistical and trading performance of the NNs models between the in-sample and out-of-sample. Large inconsistencies could indicate that the training of the NNs is biased to either statistical accuracy or trading efficiency. This could possibly lead to promising in-sample forecasts but disastrous out-of-sample results. In the next section, a trading strategy is introduced to further improve the trading performance of the models.

		TRADITIONAL STRATEGIES			NEURAL NETWORKS			FORECAST COMBINATIONS				
IN-SAMPLE		**RW**	**ARMA**	**STAR**	**MLP**	**RNN**	**PSN**	**AVERAGE**	**LASSO**	**KALMAN**	**GP**	**SVR**
F1	**Information Ratio (including costs)**	-0.25	0.42	0.60	1.57	1.71	1.98	2.12	2.38	2.84	2.71	**2.90**
	Annualised Return (including costs)	-2.59%	4.57%	6.28%	15.41%	16.86%	19.39%	21.27%	23.18%	25.86%	26.95%	**29.51%**
	Annualised Volatility	10.27%	10.79%	10.44%	9.82%	9.84%	9.77%	10.05%	9.75%	9.12%	9.96%	**10.17%**
	Maximum Drawdown	-25.78%	-19.15%	-15.37%	-13.41%	-15.55%	-16.17%	-13.25%	-11.28%	-10.94%	-10.71%	**-10.06%**
F2	**Information Ratio (including costs)**	-0.28	0.33	0.53	1.23	1.44	1.65	1.66	1.81	2.06	2.16	**2.35**
	Annualised Return (including costs)	-3.18%	3.89%	5.89%	13.27%	14.75%	16.42%	17.56%	18.25%	20.29%	22.17%	**25.11%**
	Annualised Volatility	11.32%	11.79%	11.07%	10.78%	10.23%	9.95%	10.59%	10.07%	9.87%	10.25%	**10.67%**
	Maximum Drawdown	-32.45%	-22.21%	-17.52%	-15.68%	-16.32%	-16.75%	-14.33%	-11.96%	-11.27%	-10.98%	**-10.85%**
F3	**Information Ratio (including costs)**	-0.12	0.52	0.82	1.79	1.99	2.22	2.47	2.79	2.92	3.11	**3.42**
	Annualised Return (including costs)	-1.22%	5.67%	8.26%	17.33%	19.49%	21.37%	23.68%	25.64%	26.03%	27.58%	**31.52%**
	Annualised Volatility	10.32%	10.89%	10.13%	9.67%	9.78%	9.61%	9.59%	9.18%	8.92%	8.87%	**9.22%**
	Maximum Drawdown	-22.18%	-15.43%	-13.48%	-12.39%	-14.78%	-13.88%	-11.26%	-10.83%	-10.71%	-10.57%	**-9.84%**

Table 5-5: Summary of In-Sample Trading Performance

		TRADITIONAL STRATEGIES			NEURAL NETWORKS			FORECAST COMBINATIONS				
OUT-OF-SAMPLE		**RW**	**ARMA**	**STAR**	**MLP**	**RNN**	**PSN**	**AVERAGE**	**LASSO**	**KALMAN**	**GP**	**SVR**
F1	**Information Ratio (including costs)**	-0.11	0.21	0.32	1.03	1.35	1.58	1.46	1.68	1.93	2.05	2.10
	Annualised Return (including costs)	-1.18%	2.29%	3.41%	9.15%	12.08%	14.49%	14.68%	16.23%	18.05%	19.94%	22.18%
	Annualised Volatility	10.35%	11.05%	10.67%	8.92%	8.94%	9.19%	10.08%	9.68%	9.35%	9.74%	10.55%
	Maximum Drawdown	-15.57%	-17.26%	-16.55%	-15.18%	-14.73%	-13.25%	-12.37%	-11.79%	-11.81%	-10.91%	-10.82%
F2	**Information Ratio (including costs)**	-0.37	0.18	0.27	0.80	0.83	1.14	1.32	1.56	1.66	1.68	1.73
	Annualised Return (including costs)	-4.52%	1.86%	3.02%	7.81%	8.22%	11.26%	12.08%	14.14%	15.37%	16.17%	18.43%
	Annualised Volatility	12.22%	10.51%	11.12%	9.78%	9.96%	9.84%	9.15%	9.06%	9.25%	9.65%	10.67%
	Maximum Drawdown	-21.42%	-19.58%	-18.49%	-13.73%	-14.21%	-12.88%	-12.44%	-12.03%	-11.95%	-12.15%	-11.94%
F3	**Information Ratio (including costs)**	0.02	0.41	0.51	1.14	1.46	1.68	1.81	2.00	2.01	2.28	2.77
	Annualised Return (including costs)	0.27%	4.33%	5.51%	11.26%	14.08%	16.41%	17.32%	19.91%	20.19%	22.62%	25.37%
	Annualised Volatility	11.55%	10.67%	10.92%	9.88%	9.64%	9.78%	9.56%	9.97%	10.02%	9.92%	9.17%
	Maximum Drawdown	-19.45%	-13.67%	-13.88%	-11.76%	-11.23%	-11.65%	-10.83%	-10.67%	-10.83%	-10.84%	-10.13%

Table 5-6: Summary of Out-of-Sample Trading Performance

5.6.2 Trading Performance exploiting Hybrid Leverage

In order to further improve the trading performance of the models, this section introduces a hybrid leverage based on two time-varying factors, a leverage based on daily volatility forecasts (L1) and a leverage based on market shocks (L2). The proposed leverage for every trading day is simply the average of L1 and L2. In the next sections it is explained how L1 and L2 are assigned.

5.6.2.1 Volatility Leverage (L1)

The intuition of the Volatility Leverage (L1) is to avoid trading when volatility of the exchange rate returns is very high, while at the same time exploiting days with relatively low volatility. Firstly, I forecast with a GJR (1, 1)[9] the one day ahead realised volatility of the EUR/USD exchange rate in the test and validation sub-periods. Then, I split these two periods into six sub-periods, ranging from periods with extremely low volatility to periods experiencing extremely high volatility. The process of forming these six periods is the same as in chapter 4. For each sub-period a daily leverage factor L1 is assigned starting with *0* for periods of extremely high volatility to a L1of *2* for periods of extremely low volatility. Table 5-8 below presents the sub-periods and their relevant L1s.

	Extremely Low Vol.	**Medium Low Vol.**	**Lower Low Vol.**	**Lower High Vol.**	**Medium High Vol.**	**Extremely High Vol.**
L1	2	1.5	1	1	0.5	0

Table 5-7: Classification of Volatility Leverage (L1) in sub-periods

[9] It is also explored the RiskMetrics, GARCH (1, 1) and GARCH-M models for forecasting volatility. Their statistical accuracy in all three test sub-periods is slightly worse compared with the GJR (1, 1) daily volatility forecasts. Moreover, when their utility is measured in terms of trading efficiency for our models within the context of our strategy in the test sub-period, the results in terms of annualised returns are slightly better with GJR (1, 1) for most of the models. The ranking of the models in terms of information ratio and annualised return is the same whether I use GJR (1, 1) or the other explored alternatives.

The parameters of the strategy (μ and σ) are updated every three months by rolling forward the estimation period, similarly to the update of chapter 4.

5.6.2.2 Index Leverage (L2)

The L1 measure presented above exploits periods of low volatility, but it does not take into account the effects on the EUR/USD exchange rate deriving from possible daily shocks in the EU and USA stock markets. For that reason, this section introduces an Index Leverage (L2), based on two representative indices, the Dow Jones Industrial Average Index (DJIA) and the Dow Jones EuroStoxx 50 Index (SX5E). These indices efficiently reflect any shocks in the USA and EMU economies and are used as their proxies in a wealth of relevant studies (see amongst others Charles and Darne (2006), Tastan (2006), Hemminki and Puttonen (2008) and Awartani et *al.* (2009)).

The intuition of this leverage is to capture the shocks that the models are unable to incorporate in the short-run (for example the devaluation from a rating agency of an EMU country or a change in US interest rates). These changes will be instantly reflected in the affected stock market and the next day in the ECB EUR/USD fixing. However, the models will need some period to adjust to these shocks and are certainly unable to reflect them in the short-run.

The methodology is similar to the one followed for L1. Firstly, it is defined the daily difference $\delta_{E\text{-}U}$ as:

$$\delta_{E-U} = R_{SX5E} - R_{DJIA} \tag{5.14}$$

where R_{SX5E} and R_{DJIA} are the daily SX5E and DJIA stock index returns respectively.[10] The mean of that difference (μ') and its standard deviation (σ') are calculated. Then based on $\delta_{E\text{-}U}$, μ' and σ', I split again every three months of the test and the out-of-sample into six sub-periods. The parameters of the strategy (μ' and σ') are updated every three months by rolling forward the estimation period. The sub-periods are generated as in L1. Namely, the periods where the difference $\delta_{E\text{-}U}$ is between μ' and one σ' are classified as *'Lower High* $\delta_{E\text{-}}$

[10] DJIA's closing time is at 4:30 a.m. (ECT), while SX5E is closing at 6:00 p.m. (ECT). Since ECB's daily fixing is available at 2.15 p.m. (ECT), I calculate today's $\delta_{E\text{-}U}$ with the first lags of the stock index returns R_{SX5E} and R_{DJIA}. Both R_{SX5E} and R_{DJIA} are calculated as in equation (1).

$_U$ *Periods*'. Similarly, '*Medium High* $\delta_{E\text{-}U}$' (between $\mu'+\sigma'$ and $\mu'+2\sigma'$) and '*Extremely High* $\delta_{E\text{-}U}$' (above $\mu'+2\sigma'$) periods can be defined. Periods with low difference $\delta_{E\text{-}U}$ are also defined following the same $1\sigma'$ and $2\sigma'$ approach, but with a minus sign. When $\delta_{E\text{-}U}$ is considerably higher than the average (a positive shock in the euro zone), the EUR is expected to appreciate.

In order to justify the application of this leverage, though, the trading days must be further separated based on the sign of the daily forecast. Thus, the following two scenarios are possible:

- If the sign of the forecast is positive ('long' position), a leverage ($L2^+$) of more than 1 is applied.
- If the sign of the forecast is negative ('short' position), a leverage ($L2^-$) of less than 1 is applied.

When the $\delta_{E\text{-}U}$ is considerably lower than the average (a negative shock in the euro zone), a depreciation of the euro should be expected. Thus, the assigned leverage has the opposite trend in the corresponding scenario. The final classification of L2 is shown in the following table.

	Extremely Low $\delta_{E\text{-}U}$	**Medium Low** $\delta_{E\text{-}U}$	**Lower Low** $\delta_{E\text{-}U}$	**Lower High** $\delta_{E\text{-}U}$	**Medium High** $\delta_{E\text{-}U}$	**Extremely High** $\delta_{E\text{-}U}$
$L2^+$	0	0.5	1	1	1.5	2
$L2^-$	2	1.5	1	1	0.5	0

Table 5-8: Classification of Index Leverage (L2+ and L2-) in sub-periods

5.6.2.3 Hybrid Leverage Performance

From the above, the L1 and L2 (depending on the scenario, $L2^+$ or $L2^-$) factors are available for each trading day. The daily hybrid leverage applied is equal to the simple average of L1 and L2. The next step is to examine if this trading strategy improves the profitability of the models. For the model with the best statistical and trading performance, the SVR NN forecast combination, the L1 and L2 factors for F1, F2 and F3 exercises are presented in figure 5-2.

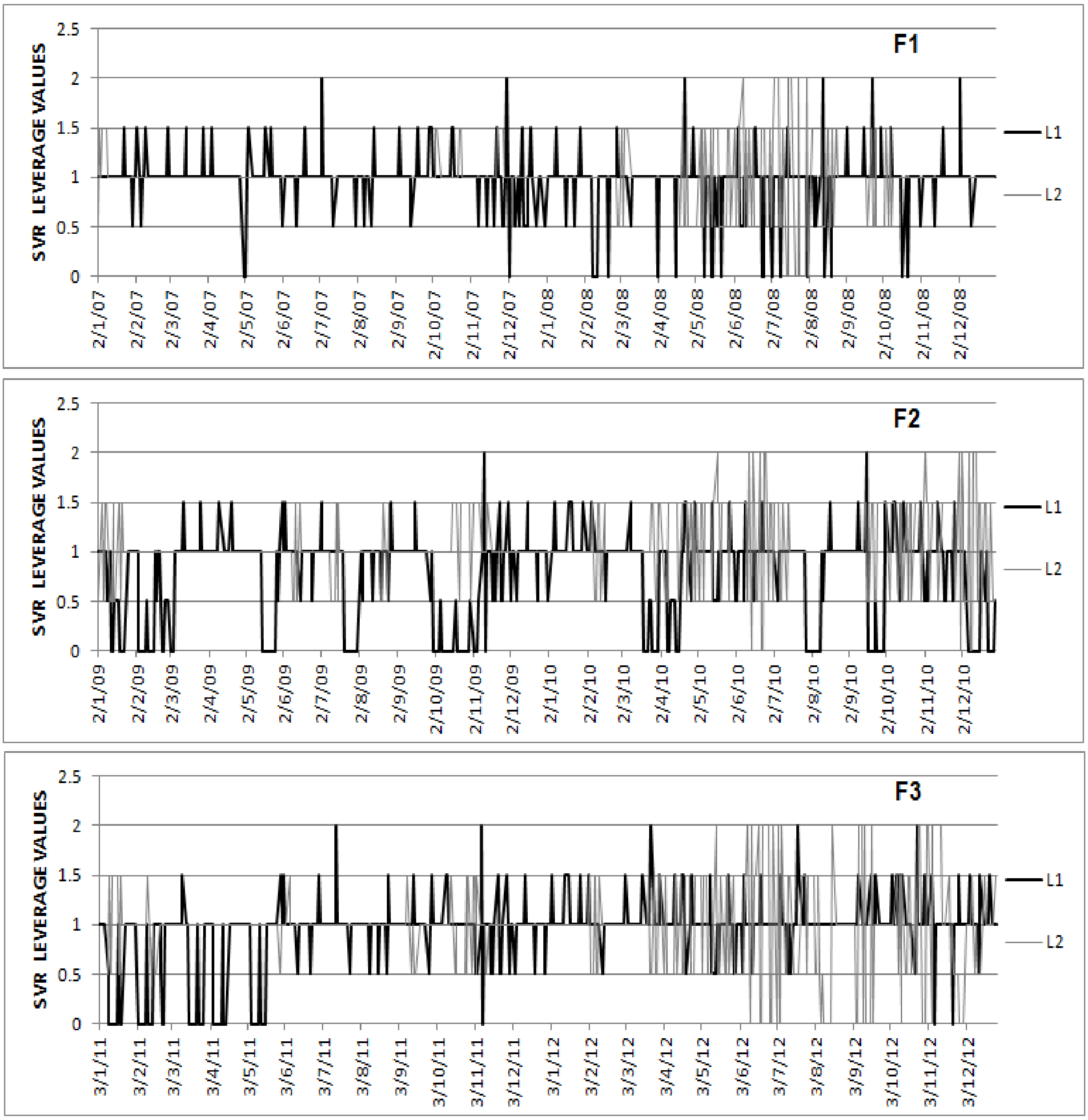


Figure 5-2: The Volatility Leverage (L1) and Index Leverage (L2) values assigned to the SVR model for each period under study

From the figure above it is noted that the volatility based leverage (L1) takes mainly low values during 2008, through the F2 and the first semester of the F3 sub-period. Regarding L2, the trend is more irregular and in general more extreme, going from very low values to high ones in short period intervals. This can be attributed to the economic turbulence that dominates the out-of-sample periods and the shocks in the two benchmark markets. The L1 and L2 graphs for the other NN and forecast combination models present similar behaviors for the three periods.

The cost of leverage (interest payments for the additional capital) is calculated at 0.504% p.a. (that is 0.002% per trading day[11]). The final results are presented in table 5-10 that follows. Based on these results, it is obvious that the hybrid trading strategy is successful for all the models and periods. The SVR forecast combination seems to exploit the trading strategy well and achieves on average an annualized return of 25.08% after costs, increasing its profitability by 3.05%, 4.16% and 2.05% during F1, F2 and F3 sub-periods respectively. GP and Kalman Filter remain the second and the third most profitable models, achieving both on average annualised returns over 20%, regardless the period under study. In general all forecasting models increase their trading performance by 1.69% on average, while their maximum drawdown is decreased on average by 1.01%. In all three sub-periods, the EUR/USD exchange rate is dominated by shocks and high volatility. The proposed leverage factors manage to exploit this environment and increase the trading performance of all the models, in a period where uncertainty is present in the market.

[11] The interest costs are calculated by considering a 0.504% interest rate p.a. (the Euribor rate at the time of calculation) divided by 252 trading days. In reality, leverage costs also apply during non-trading days. Hence, the interest costs should be calculated using 360 days per year. But for the sake of simplicity, the approximation of 252 trading days is used to spread the leverage costs of non-trading days equally over the trading days. This approximation allows the practitioner not to keep track of how many non-trading days a position is hold.

		TRADITIONAL STRATEGIES			NEURAL NETWORKS			FORECAST COMBINATIONS				
OUT-OF-SAMPLE		**RW**	**ARMA**	**STAR**	**MLP**	**RNN**	**PSN**	**AVERAGE**	**LASSO**	**KALMAN**	**GP**	**SVR**
F1	**Information Ratio (including costs)**	-0.06	0.21	0.46	1.32	1.43	1.71	1.68	1.92	2.04	2.30	2.60
	Annualised Return (including costs)	-0.58%	2.33%	4.54%	12.33%	13.26%	15.67%	15.78%	18.35%	19.37%	21.58%	25.23%
	Annualised Volatility	10.41%	10.95%	9.87%	9.32%	9.25%	9.18%	9.37%	9.55%	9.48%	9.39%	9.71%
	Maximum Drawdown	-14.66%	-14.59%	-13.85%	-14.08%	-14.13%	-13.03%	-11.18%	-10.43%	-10.17%	-10.07%	-9.86%
F2	**Information Ratio (including costs)**	-0.10	0.29	0.27	1.00	1.11	1.33	1.35	1.71	1.82	2.04	2.42
	Annualised Return (including costs)	-1.29%	3.17%	3.96%	9.95%	10.97%	12.87%	13.43%	16.26%	17.15%	18.67%	22.59%
	Annualised Volatility	13.12%	11.03%	10.05%	9.94%	9.84%	9.71%	9.96%	9.51%	9.44%	9.17%	9.33%
	Maximum Drawdown	-20.56%	-19.17%	-17.88%	-13.27%	-13.57%	-12.41%	-11.89%	-11.57%	-11.04%	-10.85%	-10.21%
F3	**Information Ratio (including costs)**	0.04	0.46	0.79	1.38	1.71	1.95	1.92	2.08	2.29	2.47	2.80
	Annualised Return (including costs)	0.44%	4.68%	7.84%	12.98%	16.44%	18.25%	18.74%	20.57%	21.94%	23.28%	27.42%
	Annualised Volatility	10.95%	10.12%	9.93%	9.42%	9.59%	9.35%	9.74%	9.88%	9.56%	9.43%	9.81%
	Maximum Drawdown	-15.54%	-13.04%	-13.15%	-11.12%	-10.92%	-10.97%	-10.41%	-10.08%	-9.76%	-9.57%	-9.48%

Note: Not taken into account the interest that could be earned during times where the capital is not traded (non-trading days) or not fully invested and could therefore be invested.

Table 5-9: Summary of Out-of-Sample Trading Performance - final results

5.7 Conclusions

The aim of this chapter is to examine the performance of a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN) and a Psi-Sigma Network (PSN) architecture in forecasting and trading the Euro/Dollar (EUR/USD) exchange rate and explore the utility of Kalman Filter, Genetic Programming (GP) and Support Vector Regression (SVR) algorithms as forecasting combination techniques. As benchmarks for the NNs I use a RW, an ARMA and a STAR, while for the forecast combination techniques a Simple Average and a Least Absolute Shrinkage and Selection Operator (LASSO). A new fitness function is also introduced for NNs in trading applications and a hybrid leverage trading strategy, in order to evaluate if their application can improve the trading performance of the models.

In terms of the results, the PSN from the individual forecasts and the SVR from the forecasting combination techniques outperform their benchmarks in terms of statistical accuracy and trading efficiency. All NN forecast combinations achieve higher annualised returns and information ratios, presenting a “combining for improvement” pattern. Concerning the hybrid leverage strategy, it is noted that all models exploit it by increasing annualised returns and decreasing maximum drawdowns. The hybrid leverage factors applied serve their purpose, since they are more effective in periods of increased market volatility and risk. Moreover, the proposed fitness function for NNs is promising as all networks produce high profitability in both in- and out-of-sample periods and present a consistency between their statistical and trading ranking. Finally, it is observed that the ranking of all models is consistent in statistical and trading terms.

The remarkable trading performance of the SVR indicates that it can be considered as the optimal forecasting combination for the models and time-series under study. The successful application of the proposed hybrid trading strategy and fitness function demonstrates the necessity for a shift from purely statistically based models to models that are optimized in a hybrid trading and statistical approach. In general, the results should go some way towards convincing scientists and investment managers to experiment beyond the bounds of traditional models and trading strategies.

Chapter 6

Modeling and Trading the EUR Exchange Rates with Hybrid Genetic Algorithms – Support Vector Regression Forecast Combinations

6.1 Introduction

Forecasting financial time series appears to be a challenging task for the scientific community because of its non-linear and non-stationary structural nature. On one hand, traditional statistical methods fail to capture this complexity while on the other hand, non-linear techniques present promising empirical evidence. However, their practical limitations and the expertise required to optimize their parameters are creating skepticism on their utility.

The motivation for this chapter is to introduce a novel hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) algorithm for optimal parameter selection and feature subset combination, when applied to the task of forecasting and trading the EUR/USD, EUR/GBP and EUR/JPY exchange rates. The proposed model genetically searches over a feature space (pool of individual forecasts) and then combines the optimal feature subsets (SVR forecast combinations) for each exchange rate. This is achieved by applying a fitness function specialized for financial purposes. This function not only minimizes the error of the forecasts, but also increases the profitability of the final forecast combinations. This is crucial in financial applications where statistical accuracy is not always synonymous with the financial profitability of the deriving forecasts. The GA-SVR algorithm is benchmarked with SVR models with non-genetically optimized parameters, such as ε-SVR and ν-SVR. The statistical and trading performance of all models is investigated during the period of 1999-2012, using the last two years for out-of-sample testing.

To the best of my knowledge, the proposed methodology has not been applied in relevant applications. In the literature there are similar hybrid applications which are either limited in classification problems (Min *et al.* (2006), Huang and Wang (2006), Wu *et al.* (2007) and Dunis *et al.* (2013)) or the GA does not extend to optimal feature subset selection (Pai *et al.* (2006), Chen and Wang (2007), Yuang (2012)). The novelty of the model lies in its ability to genetically optimize the SVR parameters, combine the optimal feature subsets and apply a fitness function, which aims to maximize not only the statistically accuracy of the forecasts but also their financial profitability. Compared to non-adaptive algorithms presented in the literature, this proposed architecture does not require from the practitioner to follow any time consuming optimization approach (such as cross validation or grid search) and is free from the data snooping bias. The latter is achieved because all parameters of the GA-SVR model are optimized in a single optimization procedure.

From this analysis it emerges that the GA-SVR presents the best performance in terms of statistical accuracy and trading efficiency for all exchange rates under study. GA-SVR's trading performance and forecasting superiority not only confirms the success of the implemented fitness function. In additions it is validated from the results that applying GAs in this hybrid model to optimize the SVR parameters is more efficient compared to the optimization approaches (cross validation and grid search algorithms) that dominate the relevant literature.

The rest of the chapter is organized as follows. Section 6-2 describes the EUR/USD, EUR/GBP and EUR/JPY ECB fixing series, used as dataset, while section 6-3 summarizes the theoretical background needed for the complete understanding of the proposed methodology. In section 6-4 follows the complete description of the hybrid GA-SVR model. The statistical and trading performance of the models is presented in sections 6-5 and 6-6 respectively. Finally, some concluding remarks are provided in section 6-7.

6.2 The EUR/USD, EUR/GBP and EUR/JPY Exchange Rates and Related Financial Data

The European Central Bank (ECB) publishes a daily fixing for selected EUR exchange rates. These reference mid-rates are based on a daily concentration procedure between central banks within and outside the European System of Central Banks. The rational of the selection of the ECB daily fixings is explained in previous chapters. The main intuition is that many financial institutions are ready to trade at the EUR fixing, leaving orders with a bank for business to be transacted at this level. Thus, the ECB daily fixings of the EUR exchange rate are tradable levels and using them is a realistic choice.

This chapter examines the ECB daily fixings of EUR/USD, EUR/GBP and EUR/JPY exchange rates over the period of 1999-2012, as described in Table 1 below.

PERIODS	TRADING DAYS	START DATE	END DATE
Total Dataset	3395	01/02/1999	30/04/2012
In-sample Dataset	2878	01/02/1999	29/04/2010
Out-of-sample Dataset	517	30/04/2010	30/04/2012

Table 6-1: The Total Dataset - Neural Networks' Training Datasets

The graph below shows the total dataset for the three exchange rates under study.

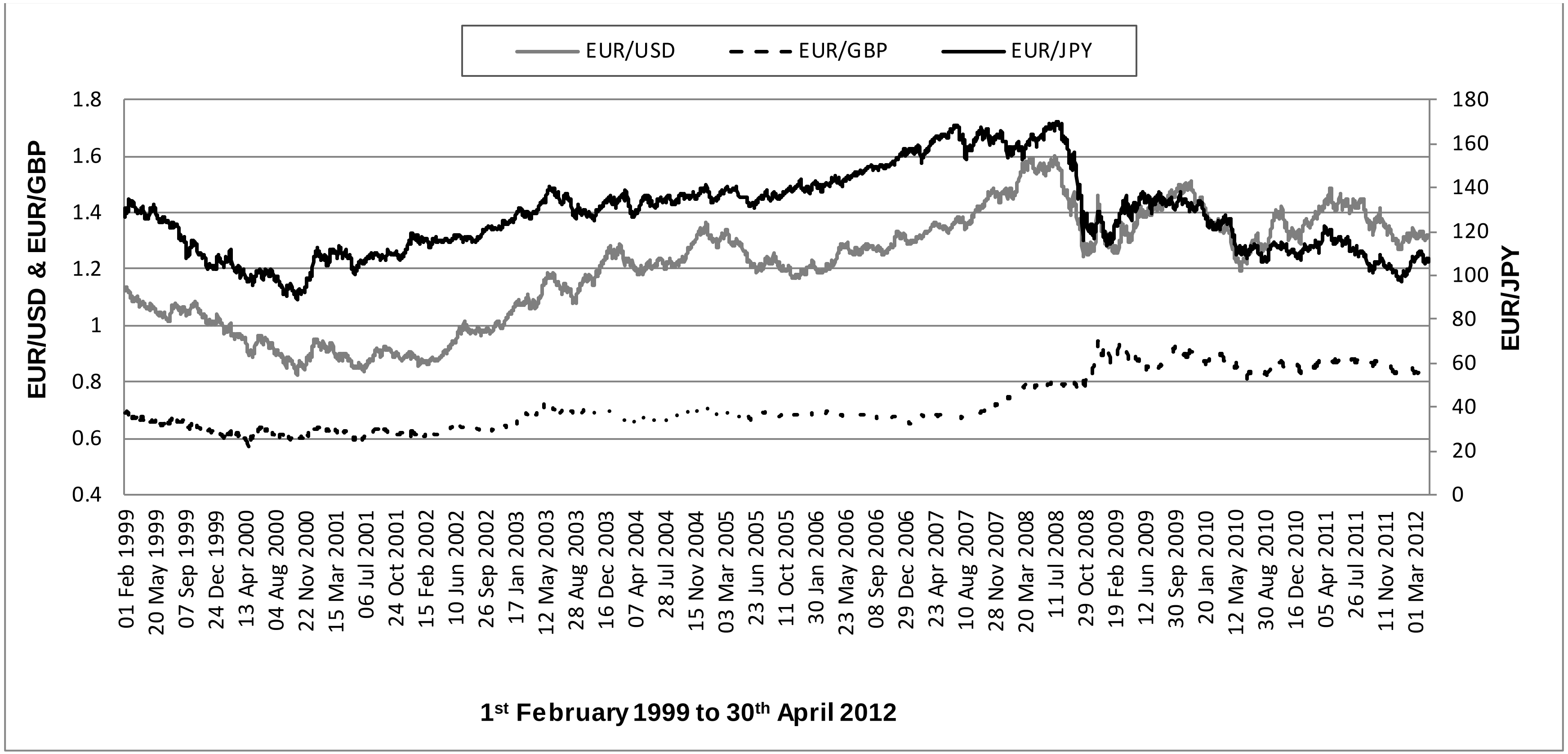


Figure 6-1: The EUR/USD, EUR/GBP and EUR/JPY total dataset

The three observed time series are non-normal (Jarque-Bera statistics (1980) confirm their non-normality at the 99% confidence interval) containing slight skewness and high kurtosis. They are also non-stationary and hence I transform them into three daily series of rate returns[12] using the following formula:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{6.1}$$

Where R_t is the rate of return and P_t is the price level at time t.

The summary statistics of the EUR/USD, EUR/GBP and EUR/JPY return series reveal that the slight skewness and high kurtosis remain. In addition, the Jarque-Bera statistic confirms again their non-normality at the 99% confidence interval. The aim is to forecast and trade the one day ahead return (E (R_t)) of the three exchange rates. As a first step, the three return series are estimated with several linear and non-linear models. Then these estimations are used as potential inputs to the proposed GA-SVR algorithm.

6.3 Theoretical Background

As mentioned before, the intention of this chapter combine and integrate the virtues of GAs to an SVR process. The reason is to face and efficiently cope with issues of optimal parameter tuning and feature selection. For that reason, a short theoretical background on all these issue is crucial to fully understand the attributes of the GA-SVR and identify its novelty. The explanation of the SVR process and the optimization of its parameters are given in detail in chapter 3. Feature selection is an optimization problem that refers to the search over a space of possible feature subsets in order to find those that are optimal with respect to specific criteria. Chapter 3 is also engaged with this issue in detail. Therefore, these issues are not further elaborated in this chapter, relieving the reader from unnecessary repetitions.

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[12] Confirmation of their stationary property is obtained at the 1% significance level by both the Augmented Dickey Fuller (ADF) and Phillips-Perron (PP) test statistics.

6.4 Hybrid Genetic Algorithm – Support Vector Regression (GA-SVR)

The hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model for optimal parameter selection and feature subset combination is presented in this section. Initially, the generic architecture of the methodology is described. Then the feature space, in which the model searches for the optimal subsets and combinations, is identified along with the models that are going to be used as benchmarks.

6.4.1 Architecture

The proposed model genetically searches over a feature space (pool of individual forecasts) and then combines the optimal feature subsets (SVR forecast combinations) for each exchange rate. In order to achieve this, a simple GA is used. Each chromosome includes *feature genes* that encode the best feature subsets and *parameter genes* that encode the best choice of parameters. The model is explained in detail in chapter 3.

A two-objective fitness function is applied to the hybrid approach in order to achieve the optimal selection of the feature subsets (individual forecasts). Firstly the annualised return of the SVR forecast combinations should be maximized and secondly the Root Mean Square Error (RMSE) of the output should be minimized in the test sub-period. Based on the above, the fitness function takes the form of equation 6.2.:

$$Fitness = Annualised\_Return - 10*RMSE \qquad (6.2)$$

The aim is to maximize the previous equation[13], since in genetic modelling the fitness function have to be increasing functions. This function aims to bring a balance between trading profitability (first factor of equation) and statistical accuracy (second factor of the equation). In trading applications this is a very important virtue, because the statistical accuracy does not always imply financial profitability.

[13] The RMSE is multiplied by 10 so the two factors in our equation are more or less equal in levels.

The size of the initial population is set to 40 chromosomes while the maximum number of generations is set to 200. The algorithm, though, terminates when the number of generations is 60 on average, regardless the series under study. This number must be reached in combination with a termination method that stops the evolution, when the population is deemed as converged. As mentioned in chapter 3, the population is deemed as converged when the average fitness across the current population is less than 5% away from the best fitness of the current population. The summary of the GA's characteristics is presented in table 6-2 below. Finally, the detailed flowchart of the proposed methodology is depicted in figure 3-6 in chapter 3.

Population Size	40
Maximum Generations	200
Selection Type	Roulette Wheel Selection
Elitism	Best member of every population is maintained in the next generation.
Crossover Probability	0.9
Mutation Probability	0.1
Fitness Function	*Annualised_Return – 10*RMSE*

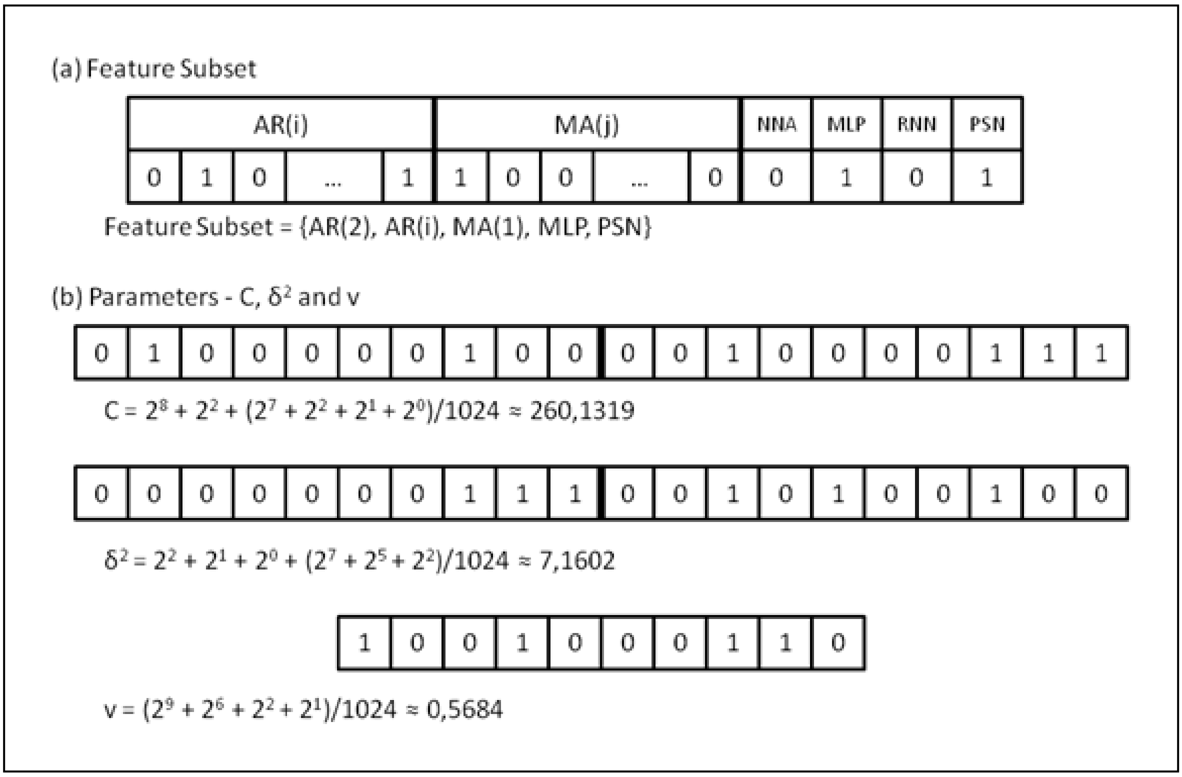
Table 6-2: GA Characteristics and Parameters

6.4.2 Feature Space, Feature Subset Selection and Benchmark Models

The forecasting ability of the proposed methodology is evaluated over a feature space (pool of individual forecasts) that is synthesized by individual linear and non-linear forecasts of each exchange rate. More specifically, the pool comprises of a series of Autoregressive (AR), Moving Average (MA), Autoregressive Moving Average (ARMA) linear models and five non-linear algorithms, namely a Nearest Neighbours Algorithm (*k*-NN) a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN), a Higher Order Neural Network (HONN) and a Psi-Sigma Neural Network (PSN). A summary of the linear models is presented in table 6-3 below, while the non-linear models are explained in Appendix D.

LINEAR MODELS	DESCRIPTION
RW	$E(R_t) = \mu + e_t, e_t \sim N(0,1)$ *where μ the in-sample mean*
AR (*p*)	$E(R_t) = \beta_0 + \sum_{i=1}^{p} \beta_i R_{t-i}$ *where p=1,…,20 and* β_0, β_i *the regression coefficients*
MA (*q*)	$E(R_t) = (R_{t-1} + ... + R_{t-q+1}) / q$ *, where q=3…25*
ARMA (*m, n*)	$E(R_t) = \varphi_0 + \sum_{j=1}^{m} \varphi_j R_{t-j} + a_0 + \sum_{k=1}^{n} w_k a_{t-k}$ *,where m, n=1,..,15,* φ_0,φ_j *are the regression coefficients,* a_0, a_{t-k} *the residual terms and* w_k *the weights of the residual terms*

Table 6-3: The summary description of the linear models



Note: (a) shows a possible selected feature subset. This subset gene includes the forecasts of AR (2), AR (i), MA(1), MLP and PSN. (b) refers to the parameters gene which includes the three parameters C, δ^2*, ν (*$\delta^2=\gamma$*). The two genes together comprise the output chromosome, while the three encoded parameters are used to provide the final SVR forecast for the given example.*

Figure 6-2: The GA-SVR chromosome

In this chapter, the algorithm genetically searches the above feature space and finally selects as optimal feature subsets the MLP, RNN and PSN individual forecasts for all three exchange rates under study. This means that the proposed methodology rejects all linear approaches, the k-NN and the HONN models over the MLP, RNN and PSN. Regarding the linear models, that is expected because of the non-linearity that dominates financial time series. Concerning the k-NN and HONNs models, the algorithm identifies that their individuals forecasts are either not adding any value as inputs to the GA-SVR algorithms or their forecasts are encompassed to the ones selected. Knowing the feature subsets that qualify from the feature space, the final stage of this methodology can be reached. This is the combination of the individual forecasts of MLP, RNN and PSN with SVR to produce the final forecasts. In this final step, the optimized parameters are used, as the GA produced for the specific set of inputs during the previous selection process (see figure 6-2 above).

The statistical and trading efficiency of the hybrid model is evaluated by benchmarking GA-SVR with more traditional SVRs, such as ε-SVR and v-SVR, whose parameters are not genetically optimized. The ε-SVR and v-SVR alternatives are described in detail in chapter 3. The RBF kernel and the optimal selected inputs (MLP, RNN and PSN individual forecasts) are used in all SVR benchmarks in order to achieve a fair comparison with the proposed model. Based on this research background, the following benchmark alternatives are identified:

- An ε-SVR model that implements a 5-fold cross-validation and a simple data-driven calculation on the in-sample dataset to calculate parameters ε, γ and C respectively (ε-SVR_1) (see SVR process of chapter 5).
- A v-SVR model that calculates its parameters v, γ and C as the ε-SVR_1 (v-SVR_1).
- An ε-SVR and v-SVR model that all parameters are selected based on a grid-search algorithm in the in-sample dataset (ε-SVR_2 and v-SVR_2).

For more on the ε-SVR_1 and v-SVR_1 approaches see Duan *et al.* (2003) and Cherkassky and Ma (2004), while for the ε-SVR_2 and v-SVR_2 see Scholkopf and Smola (2002). The parameters of the benchmark SVRs and the proposed GA-SVR are shown in the following table:

	PARAMETERS	ε-SVR$_1$	ε-SVR$_2$	v-SVR$_1$	v-SVR$_2$	GA-SVR
EUR/USD	**C**	3.15	10.75	4.68	8.28	6.23
	ε	10.91	4.12	-	-	-
	v	-	-	0.87	0.53	0.75
	γ	5.28	17.69	8.51	10.25	14.78
EUR/GBP	**C**	2.55	9.83	5.57	11.84	8.19
	ε	8.17	2.47	-	-	-
	v	-	-	0.57	0.81	0.64
	γ	7.42	12.16	9.41	19.93	17.12
EUR/JPY	**C**	1.98	6.88	4.42	5.75	4.33
	ε	12.66	3.46	-	-	-
	v	-	-	0.34	0.59	0.41
	γ	11.23	15.24	13.67	12.51	11.47

Table 6-4: The parameters of the SVR model for each exchange rate under study

6.5 Statistical Performance

As it is standard in the literature, in order to evaluate statistically of the forecasts, the Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil-U statistics are computed. The mathematical formulas of these statistics are presented in Appendix B.4. For all four statistical measures retained, the lower the output the better the forecasting accuracy of the model concerned. The Pesaran-Timmermann (PT) test (1992) examines whether the directional movements of the real and forecast values are in step with one another. In other words, it checks how well rises and falls in the forecasted value follow the actual rises and falls of the time series. The null hypothesis is that the model under study has no power on forecasting the relevant exchange rate.

The in-sample statistical performance of the models for the EUR/USD, EUR/GBP and EUR/JPY exchange rates is presented in table 6-5 below.

	IN-SAMPLE	ε-SVR$_1$	ε-SVR$_2$	v-SVR$_1$	v-SVR$_2$	GA-SVR
EUR/USD	MAE	0.00445	0.00428	0.00399	0.00364	**0.00328**
	MAPE	90.41%	89.94%	86.22%	81.66%	**75.27%**
	RMSE	0.00613	0.00569	0.00561	0.00529	**0.00488**
	Theil-U	0.58874	0.56416	0.53672	0.51407	**0.46310**
	PT-statistic	8.34	9.55	10.89	11.95	**14.82**
EUR/GBP	MAE	0.00436	0.00402	0.00388	0.00356	**0.00317**
	MAPE	89.59%	88.67%	86.22%	82.29%	**78.14%**
	RMSE	0.00568	0.00537	0.00514	0.00483	**0.00443**
	Theil-U	0.59148	0.56416	0.53472	0.50526	**0.47538**
	PT-statistic	7.86	9.15	10.66	11.55	**14.21**
EUR/JPY	MAE	0.00485	0.00453	0.00433	0.00401	**0.00358**
	MAPE	92.47%	91.68%	89.41%	86.28%	**81.79%**
	RMSE	0.00627	0.00598	0.00561	0.00522	**0.00478**
	Theil-U	0.52338	0.49954	0.47852	0.44771	**0.40659**
	PT-statistic	9.17	10.21	11.51	13.21	**15.07**

Table 6-5: Summary of In-Sample Statistical Performance

From the results above it is suggested that the GA-SVR presents the best in-sample statistical performance for every exchange rate under study and for all four statistical measures retained. The PT-statistics rejects the null hypothesis of no forecasting power at the 1% confidence interval for all models and series under study. It seems that none of the SVR approaches projects poor directional change forecasts in the in-sample period. Moreover, it is noted that the v-SVR models (v-SVR$_1$ and v-SVR$_2$) seem to have better realizations of the statistical measures than the ε-SVR ones (ε-SVR$_1$ and ε-SVR$_2$). Table 6-6 summarizes the statistical performance of the models in the out-of-sample period.

	OUT-OF-SAMPLE	ε-SVR$_1$	ε-SVR$_2$	v-SVR$_1$	v-SVR$_2$	GA-SVR
EUR/USD	MAE	0.00491	0.00475	0.00437	0.00404	**0.00358**
	MAPE	95.51%	93.69%	90.78%	85.74%	**80.68%**
	RMSE	0.00653	0.00637	0.00593	0.00568	**0.00519**
	Theil-U	0.63415	0.62478	0.57038	0.53874	**0.48994**
	PT-statistic	7.89	8.01	9.14	10.21	**12.77**
EUR/GBP	MAE	0.00474	0.00428	0.00408	0.00386	**0.00344**
	MAPE	94.25%	91.95%	88.61%	86.11%	**81.95%**
	RMSE	0.00571	0.00542	0.00522	0.00507	**0.00555**
	Theil-U	0.63914	0.60144	0.58194	0.65276	**0.62334**
	PT-statistic	6.38	7.15	8.41	9.27	**12.15**
EUR/JPY	MAE	0.00525	0.00507	0.00480	0.00448	**0.00394**
	MAPE	97.17%	94.53%	91.22%	87.16%	**82.19%**
	RMSE	0.006825	0.00649	0.00618	0.00579	**0.00583**
	Theil-U	0.60571	0.59341	0.55948	0.50489	**0.48921**
	PT-statistic	7.42	8.23	9.21	11.26	**13.75**

Table 6-6: Summary of Out-of-Sample Statistical Performance

From the results of table 6-6 it is obvious that the proposed methodology retains its forecasting superiority for the statistical measures applied in the out-of-sample period. Once more, the v-SVR approaches outperform the ε-SVR models and the PT-statistics indicate that all models forecast accurately the directional change of the exchange rates under study. Finally, it also obvious that the v-SVR model that optimizes its parameters with the grid-search algorithm (v-SVR_2) retains the second more accurate statistical performance after the hybrid proposed methodology.

Similarly to previous chapters, the statistical superiority of the best proposed architecture, the GA-SVR, is evaluated also by computing the Diebold-Mariano (1995) DM statistic for predictive accuracy (see appendix B.5.). In this study, both MSE and MAE are considered as loss functions. Table 6-7 below presents the DM statistic comparing the GA-SVR with its benchmarks.

	Loss Functions	ε-SVR_1	ε-SVR_2	v-SVR_1	v-SVR_2
EUR/USD	s_{MSE}	-6.258	-5.997	-4.841	-3.957
	s_{MAE}	-11.539	-10.165	-8.412	-5.331
EUR/GBP	s_{MSE}	-5.894	-5.233	-4.014	-3.108
	s_{MAE}	-9.568	-7.129	-5.743	-4.157
EUR/JPY	s_{MSE}	-8.027	-7.549	-6.138	-4.147
	s_{MAE}	-11.622	-12.057	-10.619	-7.219

Table 6-7: The Diebold-Mariano statistics of MSE and MAE loss functions

The table validates that the null hypothesis of equal predictive accuracy is rejected for all comparisons and for both loss functions at the 1% confidence interval (absolute values higher than the critical value of 2.33). Moreover, the statistical superiority of the GA-SVR forecasts is confirmed as the realizations of the DM statistic are negative for both loss functions[14]. It is also found that the second best model in statistical terms, the v-SVR_2, has the closest forecasts with the GA-SVR model.

Under the above given computational and statistical context, it is worth repeating that the proposed GA-SVR methodology is fully adaptive. The practitioner does not need to experiment with the parameters of the algorithm in order to optimize the forecasts. The GA-SVR structure and parameters are generated in a single optimization procedure, a procedure which prevents the data snooping effect.

[14] In this chapter the Diebold-Mariano test is applied to couples of forecasts (GA-SVR vs. another forecasting model). A negative realization of the Diebold-Mariano test statistic indicates that the first forecast (GA-SVR) is more accurate than the second forecast. The lower the negative value, the more accurate are the GA-SVR forecasts.

6.6 Trading Performance

In the previous section the forecasts are evaluated through a series of statistical accuracy measures and tests. However, statistical accuracy is not always synonymous with financial profitability. In financial applications, the practitioner's utmost interest is to produce models that can be translated to profitable trades. It is therefore crucial to further examine the proposed model and evaluate its utility through a trading strategy. The trading strategy applied is simple. The trading signals are 'long' when the forecast return is above zero and 'short' when the forecast return is below zero. The 'long' and 'short' EUR/USD, EUR/GBP or EUR/JPY position is defined as buying and selling Euros at the current price respectively. Appendix B.4 includes the specification of the trading performance measures used in this chapter.

Based on the trading rational of chapters 4 and 5, the transaction costs for a tradable amount are about 1 pip per trade (one way) between market makers. The EUR/USD, EUR/GBP and EUR/JPY time series are considered a series of middle rates, the transaction cost is one spread per round trip. For the given dataset a cost of 1 pip is equivalent to an average cost of 0.0074%, 0.0117% and 0.0091% per position for the EUR/USD, the EUR/GBP and the EUR/JPY respectively.

Table 6.8 that follows presents the summary of the out-of-sample trading performance of the models for each exchange rate under study. From the results of this table it is suggested that the GA-SVR demonstrates the superior trading performance in terms of annualised return and information ratio for all exchange rates in the in-sample period. The GA-SVR yields on average 4.13% higher annualised returns than v-SVR_2, which is the second most profitable SVR approach. Referring to the statistical performance of the models during the same period (see table 6-5), the statistical ranking of the models is similar to their ranking in trading terms.

	IN-SAMPLE	ε-SVR$_1$	ε-SVR$_2$	ν-SVR$_1$	ν-SVR$_2$	GA-SVR
EUR/USD	**Annualised Return (excluding costs)**	30.22%	32.94%	35.30%	38.53%	41.83%
	Annualised Volatility	10.39%	10.34%	10.31%	10.26%	10.21%
	Information Ratio (excluding costs)	2.91	3.19	3.42	3.76	4.10
	Maximum Drawdown	-11.25%	-11.35%	-10.52%	-10.30%	-11.17%
	Annualized Transactions	120	114	106	116	113
	Transaction Costs	0.89%	0.84%	0.78%	0.86%	0.84%
	Annualised Return (including costs)	**29.33%**	**32.10%**	**34.52%**	**37.67%**	**40.99%**
	Information Ratio (including costs)	**2.82**	**3.10**	**3.35**	**3.67**	**4.01**
EUR/GBP	**Annualised Return (excluding costs)**	28.57%	31.10%	32.77%	35.82%	40.61%
	Annualised Volatility	8.03%	7.88%	7.85%	7.80%	7.78%
	Information Ratio(excluding costs)	3.56	3.95	4.17	4.59	5.22
	Maximum Drawdown	-7.92%	-7.64%	-7.34%	-7.83%	-8.33%
	Annualized Transactions	132	156	136	153	150
	Transaction Costs	1.54%	1.83%	1.59%	1.79%	1.76%
	Annualised Return (including costs)	**27.03%**	**29.27%**	**31.18%**	**34.03%**	**38.85%**
	Information Ratio (including costs)	**3.37**	**3.71**	**3.97**	**4.36**	**4.99**
EUR/JPY	**Annualised Return (excluding costs)**	29.45%	32.31%	34.81%	37.98%	42.25%
	Annualised Volatility	11.55%	12.08%	12.47%	12.22%	12.04%
	Information Ratio (excluding costs)	2.55	2.67	2.79	3.11	3.51
	Maximum Drawdown	-14.29%	-13.93%	-13.28%	-12.21%	-12.19%
	Annualized Transactions	122	120	127	120	122
	Transaction Costs	1.11%	1.09%	1.16%	1.10%	1.11%
	Annualised Return (including costs)	**28.34%**	**31.22%**	**33.65%**	**36.88%**	**41.14%**
	Information Ratio(including costs)	**2.45**	**2.58**	**2.70**	**3.02**	**3.42**

Table 6-8: Summary of In-Sample Trading Performance

The trading performance of the models in the out-of-sample period is presented in table 6-9. The GA-SVR continues to outperform all other SVR forecast combination models in terms of trading efficiency. On average, it presents a 3.53% higher annualised return and 0.32 higher information ratio compared to the second best model, the ν-SVR$_2$. The proposed methodology clearly outperforms its benchmarks in terms of statistical accuracy and financial profitability. It is interesting to extrapolate that the profitability divergence between the different SVR models. For instance, between GA-SVR and ε-SVR$_1$ there is an average difference of 12.37% in annualised return after transaction costs for the three exchange rates. Smaller differences are also evident in the other SVR approaches. In general, the above results indicate that SVR's trading performance is very sensitive to the parameters optimization process.

Regarding the fitness function integrated in the GA, the results are extremely promising, since the selection of MLP, RNN and PSN as optimal feature subsets leads to genetic (GA-SVR) or non-genetic (ε-SVR_1, ε-SVR_2, v-SVR_1 and v-SVR_2) forecast combinations with high annualised returns and information ratios after transaction costs. Finally, it is interesting that the statistical ranking of the proposed models coincides with their trading performance for all exchange rates and sub periods.

	OUT-OF-SAMPLE	ε-SVR_1	ε-SVR_2	v-SVR_1	v-SVR_2	GA-SVR
EUR/USD	**Annualised Return (excluding costs)**	20.17%	23.35%	26.82%	29.78%	33.75%
	Annualised Volatility	10.81%	11.08%	11.05%	11.02%	10.97%
	Information Ratio (excluding costs)	1.87	2.11	2.43	2.70	3.08
	Maximum Drawdown	-11.04%	-10.85%	-10.65%	-11.35%	-13.74%
	Annualized Transactions	152	146	140	144	144
	Transaction Costs	1.13%	1.08%	1.04%	1.07%	1.07%
	Annualised Return (including costs)	**19.04%**	**22.27%**	**25.78%**	**28.71%**	**32.68%**
	Information Ratio (including costs)	**1.76**	**2.01**	**2.33**	**2.61**	**2.98**
EUR/GBP	**Annualised Return (excluding costs)**	19.97%	22.11%	24.91%	28.64%	30.49%
	Annualised Volatility	8.45%	8.24%	8.21%	8.16%	8.13%
	Information Ratio(excluding costs)	2.36	2.68	3.03	3.51	3.75
	Maximum Drawdown	-12.11%	-14.90%	-12.60%	-13.03%	-14.90%
	Annualized Transactions	105	154	103	153	152
	Transaction Costs	1.23%	1.80%	1.21%	1.79%	1.78%
	Annualised Return (including costs)	**18.74%**	**20.31%**	**23.70%**	**26.85%**	**28.71%**
	Information Ratio (including costs)	**2.22**	**2.46**	**2.89**	**3.29**	**3.53**
EUR/JPY	**Annualised Return (excluding costs)**	20.79%	23.56%	26.39%	29.66%	34.33%
	Annualised Volatility	13.18%	13.47%	13.45%	13.42%	13.37%
	Information Ratio (excluding costs)	1.58	1.75	1.96	2.21	2.57
	Maximum Drawdown	-13.21%	-14.18%	-12.90%	-13.05%	-10.20%
	Annualized Transactions	130	138	121	142	132
	Transaction Costs	1.18%	1.26%	1.10%	1.29%	1.20%
	Annualised Return (including costs)	**19.61%**	**22.30%**	**25.29%**	**28.37%**	**33.13%**
	Information Ratio(including costs)	**1.49**	**1.66**	**1.88**	**2.11**	**2.48**

Table 6-9: Summary of Out-of-Sample Trading Performance - final results

6.7 Conclusions

In this chapter the hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model for optimal parameter selection and feature subset combination is introduced. It is applied to the task of forecasting and trading the EUR/USD, EUR/GBP and EUR/JPY exchange rates. The proposed model genetically searches over a feature space and then combines the optimal feature subsets for each exchange rate. This is achieved by applying a fitness function specialized for financial purposes. The individual forecasts are derived from several linear and non-linear models. Finally, the GA-SVR is benchmarked with non-genetically optimized SVRs, such as ε-SVR and ν-SVR.

The GA-SVR model presents the best performance in terms of statistical accuracy and trading efficiency for all the exchange rates under study. GA-SVR's superiority not only confirms the success of the implemented fitness function, but also validates the benefits of applying GAs to SVR models. Regarding the fitness function integrated to the GA, the results are interesting. The selection of MLP, RNN and PSN as optimal feature subsets leads to genetic (GA-SVR) or non-genetic (ε-SVR_1, ε-SVR_2, ν-SVR_1 and ν-SVR_2) forecast combinations with high annualised returns and information ratios after transaction costs. Finally, it is interesting that the statistical ranking of the proposed models coincides with their trading performance for all exchange rates and sub periods.

The large differences in the trading performance of the models under study, indicates the sensitivity of SVRs to their parameters optimization processes. Consequently, with the empirical evidence of this chapter a contribution is made to the extensive literature that covers the issues of parameter tuning. In conclusion, the results point out that the SVR practitioners should experiment beyond the bounds of traditional SVRs.

Chapter 7

Inflation and Unemployment Forecasting with Genetic Support Vector Regression

7.1 Introduction

Developing highly accurate techniques for predicting the inflation and the unemployment is a crucial problem for economists and bankers. The forecasts for the unemployment and inflation play a crucial role in almost any monetary and policy decision process. As a result the empirical literature on forecasting macroeconomic variables is wealthy and extensive. Several statistical, technical and econometrical techniques have been applied to the problem with ambiguous results. Although researchers seem able to capture the pattern of the macroeconomic variables under normal market conditions, these models fail to provide accurate results during periods of recessions and economy shocks (Ager *et al.* (2009), Cogley *et al.* (2010) and Li (2012)). This can be explained by the fact that the relevant literature is dominated by linear models and/or models based on a fixed set of predictors. Inflation and unemployment though are affected by a number of different macroeconomic indicators and the underlying relation is likely to be changing depending on the state of the economy (D'Agostino *et al.*, 2013).

In this chapter a hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model in economic forecasting and macroeconomic variable selection is introduced. Extending the GA-SVR model of chapter 6, in this application the GA-SVR does not perform genetic SVR forecast combinations. The proposed algorithm is applied to the task of forecasting the US inflation and unemployment. The GA-SVR genetically optimizes the SVR parameters and adapts to the optimal feature subset from a feature space of potential inputs. The feature space includes a wide pool of macroeconomic variables that might affect the two series under study. The forecasting performance of the GA-SVR is benchmarked with a random walk model (RW), an Autoregressive Moving Average model (ARMA), a Moving Average Convergence/Divergence model (MACD), a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN) and a Genetic Programming (GP) algorithm. In terms of the results, GA-SVR outperforms all benchmark models and provides evidence on what macroeconomic variables can be relevant predictors of US inflation and unemployment in the specific period under study.

The novelty of this model lies in its ability to capture the asymmetries and nonlinearities in the given sample of predictors, select the optimal feature subsets and provide a single robust SVR. In that way, the GA-SVR sheds more light on the quest of nonlinear mapping of macroeconomic variables. From a technical point of view, the proposed model is superior to non-adaptive algorithms presented in the literature. It does not require analytic parameter calculation as Cherkassky and Ma (2004) propose, but also avoids time consuming optimization approaches (cross validation or grid search) that are used in similar applications (Lu *et al.* (2009) and Kim and Sohn (2010)). Additionally it is free from the data snooping bias, since all parameters of the GA-SVR model are optimized in a single optimization procedure.

The GA-SVR is applied to the task of forecasting the US inflation and unemployment and attempts to capture the complex and non-linear behavior that dominates the two series. As potential inputs, the proposed algorithm uses a pool of 110 potential predictors. This increases the model's flexibility and allows it to explore a large universe of potential relationships between the 110 predictors and the US inflation and unemployment. The selection of the proposed model's inputs and parameters is based on a GA algorithm, while the pool of potential inputs is only limited by the data availability. All models present forecasts for the periods from January 1974 to December 2012. The periods from January 1997 to December 2000, January 2001 to December 2004, January 2005 to December 2008 and January 2009 to December 2012 act as out-of-samples by rolling forward the estimation by four years. From an econometric perspective the rolling forward estimation adds validity to the results of the forecasting exercise. From an economic perspective, the unique architecture of the GA-SVR model will allow to study if variables that are significant in forecasting the inflation and the unemployment in the pro-crisis period (1997-2004) remain significant in crisis and after crisis period (2005-2012). The above selection of the out-of-sample periods tests if the forecasting power of the models is reduced during the recession period, as it is repeatedly reported in the recent relevant literature.

During the last decades the dynamics of US inflation have changed considerably. Inflation forecasters have implemented a wide variety of multivariate models, such as Cogley and Sargent (2005) and Cogley *et al.* (2010). These models attempt to outperform simple univariate models like the Atkeson-Ohanian's (2001) random walk model or time varying models with unobserved components as presented by Stock and Watson (2007). Their success though is inconsistent and their inflation forecasts are unstable. A concise survey of the instability of these models is given by Stock and Watson (2009). Stock and Watson (2003, 2004) also propose that the best predictive performance is attained through simple averaging of inflation forecasts derived from a very large number of models. McAdam and McNelis (2005) perform an inflation forecasting exercise in US, Japan and Euro area, where GAs are combined with NNs in order to achieve optimal non-linear Phillips curve specifications. Based on their results, the authors conclude that the payoff of the NN strategy comes in periods of structural change and uncertainty. Ang *et al.* (2007) compare and combine the forecasting power of several linear and non-linear models of forecasting U.S. inflation with survey-based measures. Their study shows that the use of surveys' information can lead to superior individual forecasts. Furthermore, Inoue and Kilian (2008) apply the method of bootstrap forecast aggregation to the task of forecasting the US CPI inflation, also known as bagging. The empirical evidence confirms the superiority of this method to the Bayesian model averaging or Bayesian shrinkage estimators used by other researchers (see amongst others Groen *et al.* (2010), Koop and Korobilis (2012) and Stock and Watson (2012)). The authors, though, note that the utility of the bagging method should be further explored in other empirical cases. All these approaches attempt to pool forecasts from many macroeconomic predictors, but they are highly demanding computational tasks. The proposed GA-SVR algorithm is able to exploit a large pool of potential inputs computationally efficiently, since it can be implemented with the help of any modern laptop in a couple of hours.

Forecasting unemployment rates is also a well-documented case study in the literature (Rothman (1998), Montgomery *et al.* (1998)). Swanson and White (1998) forecast several macroeconomic time series, including US unemployment, with linear models and Neural Networks (NNs). In their approach, NNs present promising empirical evidence against the linear VAR models. Moshiri and Brown (2004) apply a back-propagation model and a generalized regression NN model to estimate post-war aggregate unemployment rates in the USA, Canada, UK, France and Japan. The out-of-sample results confirm the forecasting superiority of the NN approaches against traditional linear and non-linear autoregressive models. Smooth transition vector error-correction models are also used to forecast the unemployment rates, as in the non-Euro G7 countries' study of

Milas and Rothman (2008). The proposed model outperforms the linear autoregressive benchmark and improves significantly the forecasts of the US and UK unemployment rate during business cycle expansions. Wang (2010) combines several rival individual US unemployment forecasts with directed acyclical graphs. The results indicate that models that are not directly causally linked can be combined to project a more accurate composite forecast. Chua *et al.* (2012) present a latent variable approach to the same forecasting task. Their model exploits the time series properties of US unemployment, while satisfying the economic relationships specified by Okun's law and the Phillips curve. The specification is advantageous since it provides an unemployment forecast consistent with both theories, but at the same time is less computational demanding than equivalent atheoretical models like VAR and BVAR. Finally, Olmedo (2013) performs a competition between non-linear models to forecast different European unemployment rate time series. The best results are provided by a vector autoregressive and baricentric predictor, but as the forecasting horizon lengthens the performance deteriorates.

The rest of the chapter is organized as follows. Section 7-2 describes the dataset used for this study, while a brief description of the benchmark models is given in section 7-3. In Section 7-4 follows the description of the hybrid GA-SVR model. The empirical results are presented in sections 7-5. The final section 7-6 includes the concluding remarks of this chapter.

7.2 Data Description

This chapter implements two forecasting exercises with monthly data over the period of January 1974 to December 2012. The first exercise attempts to forecast the percentage change in the US inflation. As a proxy for the US inflation, the US Consumer Price Index (CPI) is employed. The second one focuses on predicting the percentage change of the US unemployment rate (UNEMP). Figure 7-1 below presents the two series under study in levels.

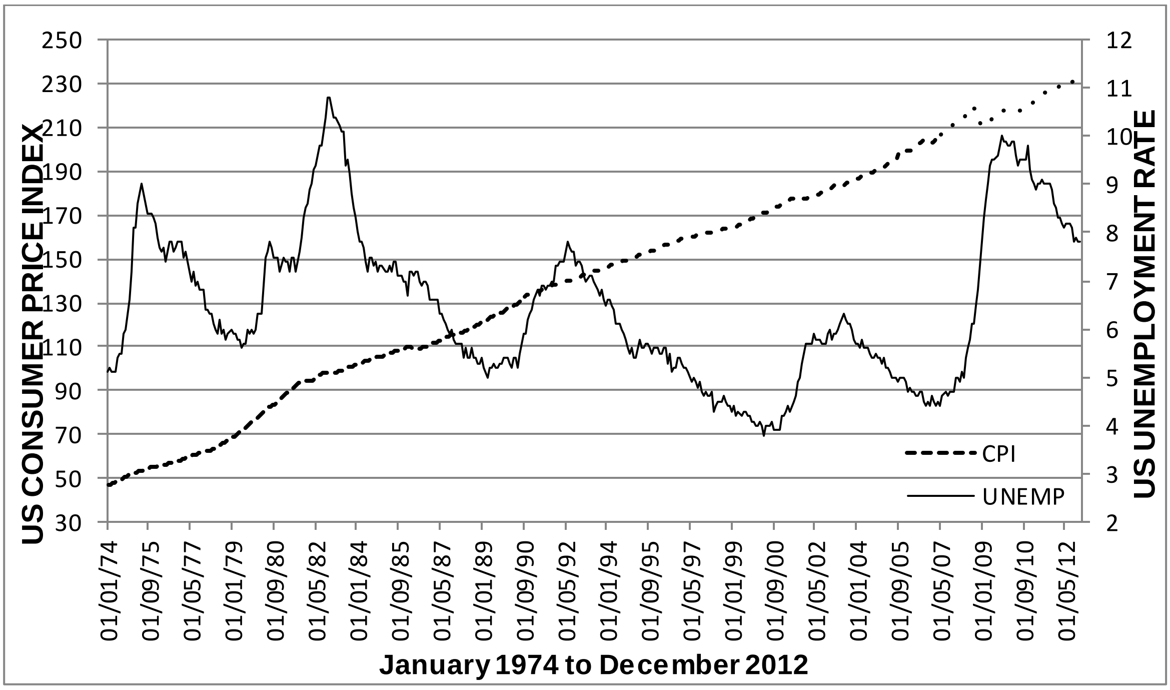


Figure 7-1: The historical monthly series of US CPI and Unemployment Rate in levels

Following similar studies (Wright (2009) and Koop and Korobilis (2012)), eleven predictors are selected that can explain the economic premises of inflation and unemployment or are found to be useful in forecasting them. The pool of the potential inputs includes the first ten autoregressive terms of these predictors. Thus, the feature space consists of hundred ten series of monthly percentage changes. All series are seasonally adjusted, where applicable. The sources of the data are the Federal Reserve Bank of St. Louis (FRED) and Bloomberg (BLOOM). Table 7-1 below summarizes the variables used for the purpose of this forecasting exercise.

No	MNEMONIC	DESCRIPTION	SOURCE
1	CPI	US Consumer Price Index for All Urban Consumers: All Items (SA)	FRED
2	UNEMP	US Civilian Unemployment Rate (SA)	FRED
3	JPY	JPY/USD Exchange Rate (NSA)	FRED
4	GBP	GBP/USD Exchange Rate (NSA)	BLOOM
5	HOUSE	US Housing Starts Total: New Privately Owned Housing Units Started (SA)	FRED
6	INDP	US Industrial Production Index (SA)	FRED
7	M1	US M1 Money Stock (SA)	FRED
8	EMPL	US All Employees: Total nonfarm (SA)	FRED
9	PCE	US Personal Consumption Expenditures (SA)	FRED
10	PI	US Personal Income (SA)	FRED
11	TBILL	US 3-Month Treasury Bill: Secondary Market Rate (NSA)	FRED
12	WAGE	US Average Hourly Earnings of Production and Nonsupervisory Employees: Manufacturing (SA)	FRED
13	DJIA	Dow Jones Industrial Average (NSA)	BLOOM

Note: CPI and UNEMP2 are observed variables. The pool of predictors consists of the first ten autoregressive terms of variables 3-13 (110 series in total). FRED refers to the FRED database of the St. Louis Federal Reserve Bank, while BLOOM stands for Bloomberg. All series are in monthly percentage changes.SA and NSA means that the series is seasonally adjusted and not seasonally adjusted respectively.

Table 7-1: List of all the variables

7.3 Benchmark Forecasting Models

The proposed GA-SVR model is benchmarked with a Random Walk model (RW), an Autoregressive Moving Average model (ARMA), a Moving Average Convergence/Divergence Model (MACD), a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN) and a Genetic Programming (GP) algorithm. This section provides a brief description of these models.

7.3.1 Random Walk Model (RW)

The RW is a process where the current value of a variable is calculated from the past value plus an error term. The error term follows the standard normal distribution. The specification of the model is:

$$\hat{Y}_t = Y_{t-1} + e_t,\ e_t \sim N(0,1) \tag{7.1}$$

where $\hat{Y}_t$ is the forecasted inflation/unemployment for period t and Y_{t-1} is the actual inflation/unemployment of period *t-1*. The RW is a non-stationary process with a constant mean, but not a constant variance.

7.3.2 Auto-Regressive Moving Average Model (ARMA)

An ARMA model embodies autoregressive and moving average components. The exact specification of the model is given in chapter 4. The ARMA models are selected using the correlogram and the information criteria in the in-sample period as a guide, as described in previous chapters. The back-casting technique is used to obtain pre-sample estimates of the error terms (Box and Jenkins, 1976). The null hypotheses that all coefficients (except the constant) are not significantly different from zero and that the error terms are normally distributed are rejected at the 95% confidence interval.

7.3.3 Moving Average Convergence/Divergence Model (MACD)

A moving average model is defined as:

$$M_t = \left(Y_{t-1} + Y_{t-2} + ... + Y_{t-n+1}\right) / n \tag{7.2}$$

Where:

- M_t : moving average at time t
- n: the number of terms in the moving average
- $Y_{t-1,\ldots,} Y_{t-n+1}$: the actual inflation/unemployment at periods $t-1,\ldots,t-n+1$

The MACD line derived by two moving average series with different lengths (short and long) is used to forecast the two series under study. The short and long terms used in the estimation of the moving averages are commonly determined based on the forecaster's judgment and practical previous knowledge. In this case, the combinations that perform best over the in-sample sub-period are retained for out-of-sample evaluation.

7.3.4 Neural Networks (NNs)

The Multi-Layer Perceptron (MLP) and the Recurrent Neural Network (RNN) are the two traditional NNs used as benchmarks for this forecasting application. Their specifications are presented in chapter 3. Here it should be noted that the specialized function that trained the NNs in chapters 5 and 6 it has no practical use in the forecasting exercised implemented in this chapter. The obvious reason for that is that there is no trading application. The rationale behind the selection of the inputs of NNs is explained thoroughly in the applications of previous chapters. The aim is to select as inputs those sets of variables that provide the best statistical performance for each network in the in-sample period. Based on the guidelines (Lisboa and Vellido (2000) and Zhang (2009)) of NN modelling, I experiment with the first fifteen autoregressive terms of each forecasted series in all in-sample periods. More details about the design and training characteristics the NNs are included in appendix E.

7.3.5 Genetic Programming (GP)

Genetic Programming (GP) algorithms are a class of Genetic Algorithms and their description is given in chapter 3. In chapter 5, the GP is applied in a forecasting combination scheme. The inputs in that case are individual forecasts. I include the GP in these forecasting exercises in order to give a viable 'genetic opponent' to the GA-SVR approach. The large pool of relevant predictors is given as input to the algorithm and through its genetic adaptive nature (see chapter 3) it achieves the final forecast. The parameters of the GP in this application are defined based on which model presents the best statistical performance in the in-sample sub-period and are presented in appendix E.

7.4 Hybrid Genetic Algorithm – Support Vector Regression (GA-SVR)

The proposed hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model is provided in this section. The theoretical background needed for the deeper understanding of the methodology is the same as in chapter 6. In addition, the extensive description of the model is given in chapter 3. The algorithm genetically searches over the feature space. Differently from the previous chapter, the pool of inputs described by table 7-1 does not include individual forecasts of inflation or unemployment, but indicators that considered relevant to these two series.

Extending the GA-SVR model of chapter 6, in this application the GA-SVR is able to capture the asymmetries and nonlinearities in the given sample of predictors, select the optimal feature subsets and provide a single robust SVR. In order to achieve this, a GA is used which evaluates chromosomes, similar to figure 6-2 in the previous chapter. The chromosome again consists of feature genes and parameter genes. But in this case, the feature gene encodes the selected autoregressive terms of the inflation or unemployment series. The parameter genes include the optimal parameters for this feature gene and are used to give the final SVR forecast. This forecast is evaluated over the out-of-sample period. The function used to evaluate the fitness of each chromosome is specified as:

$$\text{Fitness} = 1/(1+\text{MSE}) \tag{7.3}$$

The function is maximized. The size of the initial population is set to 400 chromosomes while the maximum number of generations is set to 5000. The algorithm terminates at 3000 generations on average. This number must be achieved, as long as convergence of the population has not already happened (see chapter 3). The flowchart of the GA-SVR methodology is depicted in detail in figure 3-6 of chapter 3. The summary of the GA's characteristics is presented in the following table.

Population Size	400
Maximum Generations	5000
Selection Type	Roulette Wheel Selection
Elitism	Best member of every population is maintained in the next generation.
Crossover Probability	0.85
Mutation Probability	0.15
Fitness Function	1/(1+MSE)

Table 7-2: GA Characteristics and Parameters

7.5 Empirical results

The empirical results of the proposed methodology are presented in this section. Here the adaptive selection of the macroeconomic variables is described for each forecasting exercise. Then, the statistical evaluation of the optimized GA-SVR forecasts follows in regard to its benchmarks and a robustness test.

7.5.1 Selection of Predictors

The macroeconomic contribution of this chapter is based on the fact that GA-SVR algorithm is able to genetically adapt in the most relevant predictors for the US inflation and unemployment. The selected variables for both forecasting exercises and all out-of-sample periods are presented Table 7-3. This selection corresponds to the chromosomes that provide the best forecasts of CPI and UNEMP.

OUT-OF-SAMPLE PERIODS	ALL PREDICTORS	CPI PREDICTORS	SELECTED LAGS	UNEMP PREDICTORS	SELECTED LAGS
01/1997 – 12/2000*	JPY	-	-	-	-
	GBP	-	-	-	-
	HOUSE	HOUSE	1,2	HOUSE	2,3,4
	INDP	INDP	**1,2,3**	INDP	**1,2,3**,4
	M1	M1	2,**3**	M1	**3**,4
	EMPL	EMPL	1,4	EMPL	2,3
	PCE	PCE	**4**	PCE	**4**
	PI	PI	3,4	PI	1,3,5
	TBILL	-		TBILL	2,3
	WAGE	WAGE	1,2,3	WAGE	2,4,5
	DJIA	DJIA	5	DJIA	3
	TOTAL	8	16	9	21
01/2001 – 12/2004**	JPY	-	-	-	-
	GBP	-	-	-	-
	HOUSE	HOUSE	2,3,4	HOUSE	1,2
	INDP	INDP	**3,4**,5	INDP	1,2,**3,4**
	M1	M1	**2**	M1	**2**,3
	EMPL	EMPL	1,3,4	EMPL	3
	PCE	PCE	1,**4**	PCE	2,3,**4**
	PI	PI	4	PI	4,5
	TBILL	-	-	TBILL	1
	WAGE	WAGE	2,3	WAGE	1,2,4
	DJIA	DJIA	4,5	DJIA	2,5
	TOTAL	8	17	9	20
01/2005 – 12/2008***	JPY	-	-	-	-
	GBP	-	-	-	-
	HOUSE	-	-	-	-
	INDP	INDP	**1,2**	INDP	**1,2**,3,4
	M1	M1	2,**3**	M1	**3**
	EMPL	-	-	EMPL	2,3
	PCE	PCE	**1**,2	PCE	**1**,3
	PI	-	-	PI	1,2
	TBILL	TBILL	1,2	-	-
	WAGE	WAGE	1,2,3	WAGE	2,4
	DJIA	-	-	-	-
	TOTAL	5	11	6	13
01/2009 – 12/2012****	JPY	-	-	-	-
	GBP	-	-	-	-
	HOUSE	-	-	-	-
	INDP	INDP	**1**	INDP	**1**,2,3,4
	M1	M1	1,**2**	M1	**2**
	EMPL	-	-	EMPL	1
	PCE	PCE	1,**2**	PCE	**2**
	PI	PI	1,2,3	-	-
	TBILL	-	-	-	-
	WAGE	-	-	WAGE	2,3
	DJIA	-	-	-	-
	TOTAL	4	8	5	9

*Note: The bold predictors in the second column represent the commonly selected variables for both exercises regardless the out-of-sample period. The bold values in the fourth and sixth column are the common predictors for both forecasting exercises in the respective out-of-sample sub-periods. * CPI: Population=60, Generations=440, C=61.5, γ=0.015, v=0.47, UNEMP: Population=200, Generations=500, C=143.8, γ=0.91, v=0.54. **CPI: Population=110, Generations=280, C=54.3, γ=0.03, v=0.55, UNEMP: Population=300, Generations=400, C=121.4, γ=0.75, v=0.63. *** CPI: Population=80, Generations=220, C=37.8, γ=0.042, v=0.31, UNEMP: Population=140, Generations=250, C=94.6, γ=0.88, v=0.77. **** CPI: Population=75, Generations=550, C=51.5, γ=0.025, v=0.59, UNEMP: Population=130, Generations=430, C=135.3, γ=0.56, v=0.37.*

Table 7-3: The selected predictors for US inflation and unemployment (best CPI and UNEMP chromosome)

Concerning the inflation exercise, the results show that the algorithm retains maximum seventeen time series from the overall one hundred ten as inputs. During the 1997-2000 and 2001-2004 those series are autoregressive terms up to the order of five of eight variables, the HOUSE, INDP, M1, EMPL, PCE, PI, WAGE and DJIA. For the 2005-2008 sub-period, the GA-SVR discards the HOUSE, EMPL, PI, DJIA variables and adds the TBILL. It seems that in this period, there is a structural break for inflation and the set of variables that have explanatory value has changed. In the last sub-period, the algorithm selects eight inputs (autoregressive terms of the INDP, M1, PCE and PI variables). The second lag of M1 is always selected as input from the model. The different set of inputs in each sub-period reveals that inflation is difficult to predict and models with a constant or a limited set of independent variables will have no value in the long-run.

In the case of unemployment, the GA-SVR selects more macroeconomic variables and respective lags than in the inflation exercise. This might indicate that forecasting the US unemployment is a more complex and demanding task that requires a larger set of independent variables than the US inflation. The set of potential inputs suggests that the second lag of WAGE is always selected and that the first four autoregressive lags of IND are a popular choice from the algorithm. The set of inputs changes for each sub-period. This indicates that structural breaks dominate unemployment forecasting as the set of explanatory variables is constantly changing.

INDP, M1 and PCE are the only common economic indicators in the four periods under study for both inflation and unemployment. In each out-of-sample, though, the algorithm accepts different autoregressive lags of them as common inputs. For example, the first three autoregressive terms of INDP, the third of M1 and the fourth of PCE are common predictors of inflation and unemployment during 1997-2000. In the period of 2001-2004 the algorithm selects the third and fourth lag of INDP, the second lag of M1 and the fourth lag of PCE for forecasting both series. Similarly during 2005-2008, the first two autoregressive terms of INDP, the third of M1 and the first of PCE qualify as potential predictors for both CPI and UNEMP. Finally, in 2009-2012 the first lag of INP and the second of M1 and PCE are kept in the inputs' pool for each exercise. The exchange rates are found to be irrelevant for all the out-of-samples. The HOUSE variable is pooled during 1997- 2000 and 2001-2004, but discarded for the periods 2005-2008 and 2009-2012 (during and after the US housing bubble burst). It is interesting to note that autoregressive terms of the potential inputs with order of six or higher have no value for the model. More specifically for the periods 2005-2008 and 2009-2012 the majority of the selected inputs are first and second autoregressive lags of the respective macroeconomic variables.

From a technical point of view, the selection process of GA-SVR does not suffer from over-fitting since in both exercises and all out-of-sample periods the parameter γ is relatively small (see table 7-3 note). Small values of γ are in general welcome because they result in smoother marginal decisions. The restrictiveness of the SVR 'tube' though depends on all three parameters and therefore it is difficult to assess if the genetic SVR procedure is more adaptive in the CPI or UNEMP forecasting exercise. In general, the algorithm requires more time (iterations[15]) to converge in UNEMP optimal chromosomes than CPI ones.

7.5.2 Statistical Performance

Similar to previous chapters, the forecasts are evaluated by means of Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE) and Theil-U statistics. The mathematical formulas of these statistics are presented in Appendix B.4. For all four statistical measures retained, the lower the output the better the forecasting accuracy of the model concerned.

The in-sample statistical performances of the models for the CPI and UNEMP during all relevant periods are presented in table 7.4 that follows. The results indicated that GA-SVR presents the best in-sample statistical performance for both series under study for all the statistical measures. The second best model is GP. It outperforms both NNs and the traditional strategies, but it is always inferior to the GA-SVR. Although the models perform differently during each period in both forecasting tasks, the ranking of the models remains the same throughout 1974-2008. The worst performances are observed in the 1982-2004 and 1986-2008. Table 7-5 summarizes the statistical performances of the models in the relevant out-of-sample periods for CPI and UNEMP. From the results of Table 7-5, it is obvious that GA-SVR retains its forecasting superiority for the statistical measures applied in all four out-of-sample sub-periods. The statistical ranking of the models remains consistent with the in-sample results. Once more, the GP outperforms the MLP and RNN, while traditional models like RW, ARMA and MACD present the worst forecasts in term of statistical accuracy. The worst statistical results are attained in the

[15] $Iterations = Population * Generations$

2005-2008 and 2009-2012 sub-periods. It seems the US subprime crisis increases the difficulty in this forecasting exercise. Nonetheless, the performance of the GA-SVR seems robust in both periods of economic instability.

	IN-SAMPLE PERIODS	MODELS						
CPI	**01/1974 – 12/1996**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0153	0.0151	0.0087	0.0058	0.0056	0.0051	**0.0047**
	MAPE	102.23%	101.86%	98.54%	62.67%	63.14%	59.79%	**53.44%**
	RMSE	0.0095	0.0091	0.0084	0.0069	0.0068	0.0061	**0.0055**
	Theil-U	0.8561	0.8456	0.6758	0.5881	0.5721	0.5377	**0.5112**
UNEMP	**01/1974 – 12/1996**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0171	0.0168	0.0093	0.0062	0.0059	0.0055	**0.0052**
	MAPE	101.21%	98.67%	87.94%	62.89%	61.34%	57.51%	**56.47%**
	RMSE	0.0175	0.0169	0.0144	0.0124	0.0099	0.0092	**0.0087**
	Theil-U	1.2595	1.2568	0.9884	0.8197	0.8155	0.7823	**0.7514**
CPI	**01/1978 – 12/2000**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0155	0.0154	0.0084	0.0055	0.0054	0.0052	**0.0046**
	MAPE	105.98%	102.15%	98.85%	63.03%	63.19%	58.99%	**53.17%**
	RMSE	0.0121	0.0102	0.0081	0.0068	0.0066	0.0063	**0.0056**
	Theil-U	0.8573	0.8511	0.6692	0.5775	0.5659	0.5412	**0.5067**
UNEMP	**01/1978 – 12/2000**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0188	0.0187	0.0089	0.0063	0.0058	0.0054	**0.0053**
	MAPE	98.15%	97.88%	86.53%	63.27%	62.14%	58.71%	**55.84%**
	RMSE	0.0166	0.0158	0.0139	0.0116	0.0098	0.0094	**0.0089**
	Theil-U	1.1884	1.1825	0.9992	0.8341	0.8216	0.8013	**0.7673**
CPI	**01/1982 – 12/2004**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0239	0.0233	0.0094	0.0074	0.0072	0.0069	**0.0064**
	MAPE	132.09%	131.84%	103.25%	69.88%	67.26%	64.21%	**61.42%**
	RMSE	0.0132	0.0129	0.0091	0.0076	0.0077	0.0072	**0.0069**
	Theil-U	0.9764	0.9715	0.8469	0.7198	0.7145	0.6755	**0.6211**
UNEMP	**01/1982 – 12/2004**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0202	0.0196	0.0098	0.0081	0.0079	0.0075	**0.0068**
	MAPE	124.11%	123.27%	90.37%	73.89%	71.26%	68.55%	**63.37%**
	RMSE	0.0215	0.0189	0.0157	0.0101	0.0099	0.0096	**0.0093**
	Theil-U	1.3965	1.3947	1.2558	0.9377	0.9358	0.9122	**0.8847**
CPI	**01/1986– 12/2008**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0191	0.0188	0.0092	0.0071	0.0069	0.0064	**0.0061**
	MAPE	118.64%	113.58%	99.56%	64.55%	63.17%	62.44%	**59.83%**
	RMSE	0.0129	0.0098	0.0085	0.0072	0.0072	0.0069	**0.0065**
	Theil-U	0.9322	0.9126	0.7941	0.6853	0.6751	0.6239	**0.5845**
UNEMP	**01/1986 – 12/2008**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0112	0.0106	0.0088	0.0075	0.0073	0.0068	**0.0064**
	MAPE	102.87%	100.68%	84.57%	68.12%	67.89%	64.58%	**60.29%**
	RMSE	0.0175	0.0168	0.0135	0.0097	0.0096	0.0093	**0.0091**
	Theil-U	1.2801	1.2745	0.9957	0.9254	0.9136	0.8947	**0.8667**

Table 7-4: Summary of In-Sample Statistical Performances

	OUT-OF-SAMPLE PERIODS	MODELS						
CPI	**01/1997 – 12/2000**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0165	0.0162	0.0091	0.0059	0.0059	0.0052	**0.0049**
	MAPE	104.25%	103.58%	100.54%	66.15%	66.86%	62.47%	**57.34%**
	RMSE	0.0098	0.0094	0.0086	0.0071	0.007	0.0065	**0.0058**
	Theil-U	0.8755	0.8632	0.6955	0.6013	0.5971	0.5521	**0.5317**
UNEMP	**01/1997 – 12/2000**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0182	0.0178	0.0098	0.0065	0.0063	0.0059	**0.0055**
	MAPE	103.88%	100.12%	91.74%	65.38%	64.59%	61.13%	**59.11%**
	RMSE	0.0178	0.0174	0.015	0.0134	0.0107	0.0094	**0.009**
	Theil-U	1.2708	1.2647	1.0294	0.8465	0.8334	0.8037	**0.7867**
CPI	**01/2001 – 12/2004**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0161	0.0158	0.0086	0.0061	0.0057	0.0055	**0.0051**
	MAPE	105.87%	105.19%	99.65%	65.11%	64.83%	61.35%	**55.62%**
	RMSE	0.0128	0.0116	0.0084	0.007	0.0068	0.0065	**0.0059**
	Theil-U	0.8914	0.8845	0.7259	0.6018	0.5845	0.5633	**0.5297**
UNEMP	**01/2001 – 12/2004**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0264	0.0213	0.0092	0.0067	0.0061	0.0057	**0.0055**
	MAPE	102.67%	99.66%	89.45%	66.76%	64.88%	60.24%	**56.84%**
	RMSE	0.0167	0.0161	0.0142	0.0135	0.0102	0.0097	**0.0092**
	Theil-U	1.2298	1.2254	1.105	0.8656	0.8417	0.8229	**0.7837**
CPI	**01/2005 – 12/2008**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0325	0.0311	0.0112	0.0078	0.0075	0.0071	**0.0067**
	MAPE	146.15%	144.21%	105.83%	72.57%	70.64%	67.41%	**64.23%**
	RMSE	0.01447	0.0135	0.0096	0.0079	0.0078	0.0075	**0.0072**
	Theil-U	1.0156	1.0051	0.8657	0.7403	0.7367	0.7147	**0.6647**
UNEMP	**01/2005 – 12/2008**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0285	0.0215	0.0103	0.0084	0.0081	0.0078	**0.0073**
	MAPE	128.55%	125.64%	92.54%	75.21%	74.83%	71.75%	**67.28%**
	RMSE	0.0209	0.0197	0.0162	0.0129	0.0117	0.0099	**0.0096**
	Theil-U	1.4338	1.4269	1.2783	0.9531	0.9457	0.9314	**0.9158**
CPI	**01/2009– 12/2012**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0214	0.0208	0.0097	0.0074	0.0071	0.0068	**0.0064**
	MAPE	118.27%	116.17%	102.68%	69.82%	68.93%	66.71%	**62.67%**
	RMSE	0.0116	0.0108	0.0088	0.0075	0.0074	0.0070	**0.0068**
	Theil-U	0.9455	0.9384	0.8211	0.7139	0.6957	0.6483	**0.6144**
UNEMP	**01/2009– 12/2012**	**RW**	**ARMA**	**MACD**	**MLP**	**RNN**	**GP**	**GA-SVR**
	MAE	0.0119	0.0114	0.0092	0.0081	0.0078	0.0071	**0.0067**
	MAPE	108.84%	102.67%	88.98%	72.55%	71.39%	68.27%	**64.17%**
	RMSE	0.0194	0.0172	0.0145	0.0102	0.0099	0.0097	**0.0093**
	Theil-U	1.3274	1.3128	1.1296	0.9485	0.9318	0.9133	**0.8926**

Table 7-5: Summary of Out-of-Sample Statistical Performances

The statistical superiority of the best proposed architecture is further validated by the Modified Diebold-Mariano (MDM) statistic for forecast encompassing, as proposed by Harvey *et al.* (1997). The MDM statistic is an extension of the Diebold-Mariano (1995) statistic (DM) and its formula is the following:

$$MDM = T^{-1/2}\left[T + 1 - 2k + T^{-1}k\left(k-1\right)\right]^{1/2} DM \tag{7.4}$$

where T the number of the out-of-sample observations and k the number of the step-ahead forecasts.

The use of MDM is common practice in forecasting because it is found to be robust in assessing the significance of observed differences between the performances of two forecasts (Hassani *et al.* (2009) and Barhoumi *et al.* (2012)). MDM also overcomes the problem of over-sized DMs in moderate samples. The statistic is measured in each out-of-sample period and the MSE and the MAE are used as loss functions. The MDM test follows the Student's *t*-distribution with *f-1* degrees of freedom, where *f* is the number of forecasts. Table 7-6 below presents the values of the statistics, comparing the GA-SVR with its benchmarks.

PERIODS	VARIABLES	STATISTICS	RW	ARMA	MACD	MLP	RNN	GP
01/1997 – 12/2000	**CPI**	MDM_1	-7.22	-7.19	-6.65	-4.54	-3.92	**-3.15**
		MDM_2	-9.81	-9.45	-8.77	-7.19	-6.98	**-5.19**
	UNEMP	MDM_1	-5.21	-5.09	-4.91	-4.13	-4.08	**-3.02**
		MDM_2	-7.71	-7.68	-7.43	-5.51	-4.98	**-4.51**
01/2001 – 12/2004	**CPI**	MDM_1	-7.07	-6.96	-6.53	-4.24	-3.97	**-3.22**
		MDM_2	-9.34	-8.97	-8.58	-7.81	-7.12	**-6.79**
	UNEMP	MDM_1	-5.23	-5.03	-4.84	-4.19	-4.10	**-3.26**
		MDM_2	-7.90	-7.82	-7.48	-5.40	-4.97	**-4.87**
01/2005 – 12/2008	**CPI**	MDM_1	-8.14	-8.05	-7.54	-7.19	-6.88	**-6.34**
		MDM_2	-9.84	-9.80	-9.30	-8.95	-8.80	**-8.62**
	UNEMP	MDM_1	-9.25	-9.16	-8.73	-8.15	-7.51	**-7.07**
		MDM_2	-10.37	-10.27	-9.81	-9.54	-9.17	**-8.75**
01/2009 – 12/2012	**CPI**	MDM_1	-6.46	-6.27	-5.92	-5.71	-5.48	**-4.77**
		MDM_2	-7.95	-7.88	-7.71	-7.44	-7.32	**-7.04**
	UNEMP	MDM_1	-7.82	-7.66	-7.08	-6.77	-6.33	**-6.09**
		MDM_2	-8.75	-8.54	-8.28	-7.83	-7.39	**-7.25**

Note: MDM_1 and MDM_2 are the statistics computed for the MSE and MAE loss function respectively.

Table 7-6: Modified Diebold-Mariano statistics for MSE and MAE loss functions

The MDM null hypothesis of forecast encompassing is rejected for all comparisons and for both loss functions at the 1% confidence interval. The statistical superiority of the GA-SVR forecasts is also confirmed as the realizations of the MDM statistic are always negative[16]. GP is found to have the closest forecasts with the GA-SVR model and remains the second best model in statistical terms. From the MDM values it is safe to claim that there is no conclusive evidence of encompassing between the GA-SVR forecasts of inflation and unemployment and their benchmarks. Finally, the in-sample and out-of-sample results indicate that the models implementing genetic approaches, GP and GA-SVR, project in general more accurate forecasts in comparison with popular NN techniques (MLP, RNN) or traditional linear models (RW, ARMA, MACD).

7.6 Conclusions

The motivation of this chapter is to introduce a hybrid Genetic Algorithm – Support Vector Regression (GA-SVR) model in economic forecasting and macroeconomic variable selection. The proposed algorithm is applied to the task of forecasting the US inflation and unemployment. The GA-SVR genetically optimizes the SVR parameters and adapts to the optimal feature subset from a feature space of potential inputs. The feature space includes a wide pool of economic indicators that might affect the two series under study. The forecasting performance of the GA-SVR is benchmarked with a Random Walk model (RW), an Autoregressive Moving Average model (ARMA), a Moving Average Convergence/Divergence model (MACD), a Multi-Layer Perceptron (MLP), a Recurrent Neural Network (RNN) and a Genetic Programming (GP) algorithm. More specifically, the statistical performance of all models is investigated in four rolling samples during the period of 1974-2012.

In terms of the results, the GA-SVR outperforms all benchmark models for both forecasting exercises. The model is able to genetically adapt to a small number of relevant variables and project superior forecasts at the same time. This performance is consistent also in periods of economic turmoil, which proves that the genetic SVR selection of the predictors is both computationally and statistically efficient. With this variable selection process, GA-SVR attempts to provide evidence on what inputs can be important predictors

[16] The MDM test is applied to couples of forecasts (GA-SVR vs. another forecasting model). A negative MDM value indicates that the first forecast (GA-SVR) is more accurate than the second forecast. The lower the negative value, the more accurate are the GA-SVR forecasts.

of US inflation and unemployment in the specific periods under study. The autoregressive lags of the past quarter are found to be of great importance, while information going back more than a semester seems irrelevant. The in-sample and out-of-sample results show that the models implementing genetic approaches, GP and GA-SVR, project the most accurate forecasts and outperform their benchmarks. This superiority is further validated by the MDM test. In general, the two forecasting exercises of this chapter attempt to shed more light on the difficult quest of nonlinear mapping of macroeconomic variables over different sample periods.

Chapter 8

Rolling Genetic Support Vector Regressions: An Inflation and Unemployment Forecasting Application in EMU.

8.1 Introduction

Predicting inflation and unemployment changes is an issue of paramount importance for economists, bankers and government officials. Many monetary and policy decisions are made by appraising such forecasts. As a result the empirical literature on forecasting macroeconomic variables is voluminous (see amongst others Ang *et al.* (2007), Stock and Watson (2009) and Cogley *et al.* (2010). The challenge, though, is that in periods of economic instability, traditional statistical models do not project accurate results (Ager *et al.*, 2009). In such periods of recessions and structural breaks, suggested linear models based on a fixed set of predictors are not efficient. Therefore, the following idea can be generally postulated: Realistic inflation and unemployment forecasts in a constantly changing world should depend on a number of different macroeconomic variables, rather than on fixed underlying relationships.

The economies of the European Monetary Union (EMU) members are perfect examples to evaluate the validity of the above statement. In 2009 the sovereign debt crisis broke out in Greece and then spread in all Europe. This contagion originated from the unstable integration of peripheral countries in the common currency and the inability of core countries to lead to decisive changes in the EMU's monetary and fiscal policy (Lapavitsas et *al.* (2010)). Austerity measures, political instability, negative Euro speculation provided regular economic shocks in countries, such as Greece, Ireland, Italy, Portugal and Spain. The effects of this contagion are evident throughout all Europe today and heavily endanger the EMU's future. Therefore, traditional core countries, such as Belgium, France and Germany, also cannot 'feel safe' through this turmoil.

In this chapter a hybrid Rolling Genetic – Support Vector Regression (RG-SVR) model is introduced in economic forecasting and macroeconomic variable selection. The proposed algorithm is applied to a monthly rolling forecasting task of inflation and unemployment in the abovementioned eight EMU countries. The RG-SVR genetically optimizes the SVR parameters and adapts to the monthly optimal feature subset from a feature space of potential inputs. The feature space includes a wide pool of macroeconomic indicators that might affect the two series under study of every country. The forecasting performance of the RG-SVR is benchmarked with a 'fixed' Random Walk model (f-RW), an Atkeson and Ohanian Random Walk (AO-RW) and a Smooth Transition Autoregressive Model (STAR). The study engages with two rolling forecasting exercises over the period of August 1999 to April 2013. The first exercise focuses on forecasting the inflation of these countries, while the second one attempts to predict their unemployment. The statistical performance of RG-SVR is benchmarked with a f-RW, an AO-RW and a STAR. The results prove that RG-SVR statistically outperforms all benchmark models. It also presents evidence on what macroeconomic variables can be relevant predictors of the monthly inflation and unemployment and how these vary in each EMU country during the specific period under study.

The novelty of the model lies in its ability to capture the monthly asymmetries and nonlinearities in the given sample of predictors, select the optimal feature subsets and provide robust rolling SVR forecasts for the specific country and series under study. As potential inputs, the proposed algorithm uses a pool of one hundred sixty eight potential predictors. From an economic perspective, this increases the model's flexibility and allows it to explore a large universe of potential relationships between those predictors of each country's inflation and unemployment. The selection of the proposed model's inputs and parameters is based on a GA algorithm, while the pool of potential inputs is only limited by the monthly data availability. From an econometric perspective the rolling forward estimation makes the results of the forecasting exercise more realistic and robust. From a technical point of view, the proposed model is superior to non-adaptive algorithms presented in the literature. Similarly to the GA-SVR proposed and implemented in previous chapters, RG-SVR does not require analytic parameter calculation as Cherkassky and Ma (2004) propose, but also avoids time consuming optimization approaches (cross validation or grid search) that are used in similar applications (Lu *et al.* (2009) and Kim and Sohn (2010)). An additional attribute of RG-SVR in comparison to GA-SVR is that

SVR optimization is achieved with the minimum number of support vectors, while its single optimization procedure restrains data snooping bias effects.

The rest of the chapter is organized as follows. Section 8.2 describes the dataset used for this study, while a brief description of the benchmark models is given in section 8-4. Section 8-5 describes the hybrid RG-SVR model. Finally, the empirical results and conclusions are presented in Section 8-6 and 8-7 respectively.

8.2 Data Description

This chapter implements two rolling forecasting exercises with monthly data over the period of August 1999 to April 2013. The first exercise attempts to forecast the percentage change of the inflation of eight European countries, namely Belgium, France, Germany, Greece, Ireland, Italy, Portugal and Spain. The Consumer Price Index (CPI) of each country is used as a proxy of its inflation. The second exercise focuses on predicting the percentage change of the unemployment rate (UNEMP) of the above countries.

Following similar studies (Stock and Watson (2003), Wright (2009) and Groen *et.al* (2012)), I select fourteen predictors that can explain the economic premises of inflation and unemployment or are found to be useful in forecasting them. Four predictors are individual macroeconomic indicators of each country. Since the RG-SVR model is applied to a Eurozone case study, the rest ten predictors are country non-specific indicators that qualify as explanatory variables of the euro area economic activity and structure. The final pool of the potential inputs includes the first twelve autoregressive terms of these predictors. Thus, the feature space consists of hundred sixty eight series of monthly percentage changes. The sources of the data are Bloomberg (BLOOM) and the Statistical Data Warehouse of the European Central Bank (ECB). The series are seasonally adjusted, where applicable. Table 8-1 below summarizes the list of variables used in this application.

No	MNEMONIC	DESCRIPTION	SOURCE
1	CPI	Consumer Price Index (SA)	BLOOM
2	UNEMP	Eurostat Unemployment Rate (SA)	BLOOM
3	INDP	Eurostat Industrial Production: Total Industry excluding Construction Nace 2 Rev. (SA)	BLOOM
4	ESI	European Commission Economic Sentiment Indicator (SA)	BLOOM
5	LOAN	EU MFI Balance Sheet Outstanding Amounts: Government Loans to Euro area residents (SA)	BLOOM
6	TRBAL	Eurostat External Trade Balance (SA)	BLOOM
7	EUM1	ECB Money Supply M1 (SA)	BLOOM
8	USD	EUR/USD Exchange Rate (NSA)	BLOOM
9	JPY	EUR/JPY Exchange Rate (NSA)	BLOOM
10	GBP	EUR/GBP Exchange Rate (NSA)	BLOOM
11	FTSE	FTSE 100 Index (NSA)	BLOOM
12	STOXX50	Eurostoxx 50 Index (NSA)	BLOOM
13	GDAX	Deutsche Borse AG German Stock Index (NSA)	BLOOM
14	OIL	Brent Crude Oil 1-month Forward (fob) per barrel (SA)	ECB
15	SP1	Spread between swaps 6-month Euribor and benchmark bonds of 2-year maturity (SA)	ECB
16	SP2	Spread between swaps 6-month Euribor and benchmark bonds of 10-year maturity (SA)	ECB

Note: CPI and UNEMP are the two observed variables. INDP, ESI, LOAN and TRADE are individual indicators of each country. The rest are country non-specific Eurozone indicators. The pool of predictors consists of the first twelve autoregressive terms of variables 3-16 (168 series in total). BLOOM refers to the Bloomberg database, while ECB stands for the Statistical Data Warehouse of the European Central Bank. All series are in monthly percentage changes. SA and NSA means that the series is seasonally adjusted and not seasonally adjusted respectively.

Table 8-1: List of all the variables

The proposed methodology evaluates depending on the country the underlying domestic and external economic forces that could rule the inflation and unemployment changes in Eurozone. For example, INDP, LOAN and TRBAL are commonly selected as relevant individual indicators in similar studies (see Schirm (2003), Stock and Watson (2004) and Rondorf (2012)). Including each country's ESI into the pool of potential inputs adds extra validity to this effort, since it is considered a leading macroeconomic indicator for every EMU country (see Banerjee et *al.* (2005), Diron (2008) and Giannone et *al.* (2012)). Based on Eurostat's definition, ESI is a composite indicator that comprises of four confidence indicators with different weights, namely the Industrial confidence indicator (weight 40%), Consumer confidence indicator (weight 20%), Construction confidence indicator (weight 20%) and Retail trade confidence indicator (weight 20%). Those indicators are derived from business and consumer surveys, which provide a realistic consensus of the business activity, consumers' purchasing power and price trend. Other researchers believe that the EMU economy can be appraised as a whole and based on that premise they form their analysis (Marcellino (2004) and Ruth (2008)). For that reason, country non-specific EMU indicators, such as EUM1, main ECB exchange rates and stock indices, OIL, SP1 and SP2 are also used in each country's analysis.

8.3 Benchmark Forecasting Models

The forecasting efficiency of the RG-SVR model is benchmarked with three traditional models, namely a 'fixed ρ' Random Walk (f-RW), an Atkeson and Ohanian Random Walk (AO-RW) and a Smooth Transition Autoregressive Model (STAR). These benchmark models aim to forecast the one month ahead inflation and unemployment value in percentage changes.

8.3.1 'Fixed ρ' Random Walk (f-RW)

The simple RW is a non-stationary process, where the current value of a variable is calculated from the past value plus an error term. The error term follows the standard normal distribution. Instead of using a simple RW, this application follows Faust and Wright (2012) that use a 'Fixed ρ' forecast as their baseline inflation benchmark. Thus, both target series are fitted to an AR (1) process with a fixed slope coefficient ρ. The specification of the model is the following:

$$\hat{Y}_t = \rho Y_{t-1} + e_t,\ e_t \sim N(0,1) \tag{8.1}$$

Where $\hat{Y}_t$ is the forecasted value for period *t*, Y_{t-1} is the actual value of period *t-1* and ρ=0.46[17].

8.3.2 Atkeson and Ohanian Random Walk (AO-RW)

Atkenson and Ohanian (2001) note that inflation indicators cannot show the short term changes of inflation reliably. Therefore, they suggest that a RW forecasting the current value of a variable based on its previous four lags is preferable to a simple RW. Following again Faust and Wright (2012), the AO-RW is adopted as a benchmark forecasting model and specified as below:

$$\hat{Y}_t = \frac{1}{4}(Y_{t-1} + Y_{t-2} + Y_{t-3} + Y_{t-4}) + \varepsilon_t, \ \ \varepsilon_t \sim N(0,1) \quad (8.2)$$

Where:

- $\hat{Y}_t$ is the forecasted value at time t
- Y_{t-1}, Y_{t-2}, Y_{t-3} and Y_{t-4} are the four previous actual values
- ε_t is the error term

8.3.3 Smooth Transition Autoregressive Model (STAR)

The STAR combines two AR models with a function that defines the degree of non-linearity (smooth transition function). The general two-regime STAR specification is the following:

$$\hat{Y}_t = \Phi_1' X_t (1 - F(z_t, \zeta, \lambda)) + \Phi_2' X_t F(z_t, \zeta, \lambda) + u_t \quad (8.3)$$

[17] Based on Faust and Wright (2012) the value of ρ is the slope coefficient that is derived from fitting an AR (1) to the 1985Q1 vintage GDP deflator inflation from 1947Q2 to 1959Q4.

Where:

- $\hat{Y}_t$ the forecasted value at time t
- $\Phi_i = (\tilde{\varphi}_{i,0}, \tilde{\varphi}_{i,1}, ...\tilde{\varphi}_{i,p}), i = 1,2$ and $\tilde{\varphi}_{i,0}, \tilde{\varphi}_{i,1}, ...\tilde{\varphi}_{i,p}$ the regression coefficients of the two AR models
- $X_t = (1, \tilde{\chi}_t')'$ with $\tilde{\chi}_t' = (Y_{t-1}, ..., Y_{t-p})$
- $0 \le F(z_t, \zeta, \lambda) \le 1$ the smooth transition function
- $z_t = Y_{t-d}, d > 0$ the lagged endogenous transition variable
- ζ the parameter that defines the smoothness of the transition between the two regimes
- λ the threshold parameter
- u_t the error term

The main characteristic of a STAR is that $\hat{Y}_t$ is calculated at any given t as a weighted average of two AR models. The weights of the two AR models are defined based on the value of $F(z_t, \zeta, \lambda)$. The regime-switching ability of STARs derives from the fact that at each t a regime is selected based on the values of z_t and $F(z_t, \zeta, \lambda)$. In this chapter, both series are best modeled as Logistic STAR (LSTAR) processes for all eight countries.[18] The LSTAR approach allows the association of the two regimes with large and small values of z_t relatively to λ. Such a regime-switching is useful to identify expansions and recessions in the business cycle (Lin and Terasvitra (1994)).

8.4 Rolling Genetic – Support Vector Regression (RG-SVR)

This sections includes the description and specification of the hybrid Rolling Genetic – Support Vector Regression (RG-SVR) model for rolling optimal SVR parameter and monthly macroeconomic variable selection. This model genetically searches over a feature space (the pool of macroeconomic predictors as in Table 8-1) and then provides a single optimized SVR rolling forecast for each series under study. The required theoretical background of SVR, GAs and genetic feature selection and the extension of this model in

[18] I also experimented with a Multiple Regime STAR (MRSTAR) of more than two regimes, as described in detail by Dijk and Franses (1999). LSTAR though presented better statistical performance than MRSTAR in all cases. This plus the lower model complexity of LSTAR allows me to disqualify MRSTAR from our benchmark models' selection.

comparison to the GA-SVR is given in detail chapter 3. Extending the GA-SVR model of chapter 7, in this application the RG-SVR is able to capture the monthly asymmetries and nonlinearities in the given sample of predictors, but most importantly select the optimal monthly feature subsets. The GA in this case evolves chromosomes, similar to figure 6-2 in chapter 6. The chromosome again consists of feature genes and parameter genes.

In order to better distinguish the extension of RG-SVR to GA-SVR, the forecasting process needs to be explained. The RG-SVR model performs a rolling window forecasting exercise as follows. The window size is always equal to hundred twenty five observations (months). The algorithm requires the window size to be further divided in a training and test subset in order to validate the goodness of fit of each chromosome. The first eighty nine observations are the training subset. The rest thirty six form the test subset. The population of chromosomes is initialized in the training sub-period. The optimal selection of chromosomes is achieved, when their forecasts minimize the MSE in the test-sub period. Then, the optimized parameters and selected predictors of the best solution are used to train the SVR and produce the final optimized forecast for the next observation. After this is completed, the window rolls forward by one observation and the procedure is repeated. In that way, the RG-SVR model presents forty monthly rolling forecasts. For each of these forecasts, the algorithm stores its optimized C, γ and v parameters and set of optimal predictors.[19]Obviously, the GA-SVR technique is not able to do that and the only way to approximate RG-SVR performance is to drastically decrease the length of the rolling periods that are evaluated (see the three periods of chapter 7). These would incur many repetitions and increase substantially the computational demands of the task.

Nonetheless, the RG-SVR rolling procedure as explained before can also be computationally heavy. Its accuracy depends on the trade-off between a high-complexity model (over – fitting) and a large-margin (incorrect setting of the ‘tube’). The number of support vectors can vary from few to every single observation (complete over-fitting). Algorithms attempting to use efficiently extensive datasets and simultaneous take into account large sets of variables suffer from computational complexity. This complexity burden makes them practically infeasible and their results cannot be used in realistic terms. RG-SVR is able to overcome this issue by giving optimal SVR forecasts with the

[19] The monthly data start on August 1999 and end on April 2013. In order to derive the first forecast (January 2010), RG-SVR uses the first 89 months (August 1999 - December 2006) as a training subset and the rest 36 months (January 2007-December 2009) as a test subset. The second forecast (February 2010) is similarly given by rolling forward the previous samples by one month. Thus, the second training subset is from September 1999 till January 2007, while the second test subset extends from February 2007 till January 2010. The exercise ends when all the RG-SVR forecasts from January 2007 until April 2013 are gathered (40 months).

minimum number of support vectors, which further contributes to the algorithm’s novelty. Indicative is the fact that RG-SVR is implemented in a modern mainstream computer within a couple of hours for this specific dataset.

In genetic algorithm modeling the fitness functions need to be increasing functions. Therefore, the algorithm is minimizing the MSE by maximizing the following function:

$$\text{Fitness} = 1/(1+MSE) \tag{8.4}$$

The size of the initial population is set to 600 chromosomes while the maximum number of generations is set to 5000. The algorithm in general terminates when the number of generations is 4000 on average. This process is also associated with the convergence of the evaluated population (see chapter 3). Convergence is needed in order to keep populations that can lead to more efficient ones as the process goes on. The summary of the GA’s characteristics is presented in the following table, while the detailed flowchart is given in figure 3-6 of chapter 3.

Population Size	600
Maximum Generations	5000
Selection Type	Roulette Wheel Selection
Elitism	Best member of every population is maintained in the next generation.
Crossover Probability	0.80
Mutation Probability	0.20
Fitness Function	1/(1+MSE)
Window size	125
Support Vectors	Minimized

Table 8-2: GA Characteristics and Parameters

8.5 Empirical Results

This section summarizes the empirical results of this application. The macroeconomic contribution of this chapter is based on the fact that proposed algorithm is able to genetically adapt in the most relevant variables for forecasting the inflation and unemployment of eight EMU countries. The first subsection describes the predictor selection for each country for both exercises, while the second one evaluates statistically the derived CPI and UNEMP forecasts.

8.5.1 Selection of predictors

The RG-SVR algorithm examines the cases of three core countries (Belgium, France and Germany) and five peripheral ones (Greece, Ireland, Italy, Portugal and Spain), mapping their relevant indicators for forty months (January 2010 – April 2013). In every table[20] presenting the selected predictors, seven specific months are highlighted. These months could be considered as structural breaks in the Eurozone economy during this volatile period. These derive from EU central financial and political decisions, events and news' reports, which lead to positive or negative speculation in the Euro area in general. More details regarding the highlighted months are given in appendix F.1.

8.5.1.1 Inflation Exercise

The following three tables refer to the three core countries, namely Belgium, France and Germany. Table 8-3 presents the selected predictors of CPI for the case of Belgium. The results show that INDP, ESI, STOXX50, GDAX and OIL are selected almost in all months as potential inputs, while FTSE is always discarded. LOAN, TRBAL, EUM1, USD, JPY, GBP are all not found important before April 2011. SP1 and SP2 are pooled only after January 2012. The selected macroeconomic variables of CPI for the French case follow in Table 8-4. From this table is suggested that only OIL is always selected for all the months. SP1 and SP2 are discarded, except of one month for SP1. EMU1, USD and FTSE are found irrelevant before February 2012, while STOXX50 and GDAX after February 2012. ESI is always kept in the pool after April 2011. The German monthly pool of predictors is given in Table 8-5. The German EUM1, USD, GDAX and OIL are included in the pool during all months, while LOAN, JPY, GBP and FTSE are not. INDP is not selected only during five months, whereas STOXX50 is included only for three months. ESI and TRBAL are relevant indicators after September 2011, while SP1 and SP2 after September 2010.

[20] In every table the numbers represent the orders of the autoregressive terms. For example, the number 1 in the column of IND means that RG-SVR selects as input the first autoregressive term of the Industrial Production.

BELGIUM														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	2, 3	2, 4	-	-	-	-	-	-	-	1, 3	1, 4	3, 5	-	-
Feb-10	1, 3	1, 2	-	-	-	-	-	-	-	3, 4	4, 5	1, 3	-	-
Mar-10	1, 3	1, 3, 4	-	-	-	-	-	-	-	1	1, 3	3	-	-
Apr-10	3	2, 3, 5	-	-	-	-	-	-	-	4	3, 5	1, 2, 4	-	-
May-10	1, 2, 5, 6	2, 3	-	-	-	-	-	-	-	2, 4	1, 2, 6	1, 2, 4	-	-
Jun-10	1,2, 4, 5	1, 4	-	-	-	-	-	-	-	5	3	4, 5	-	-
Jul-10	2, 4	6	-	-	-	-	-	-	-	2, 3, 5	1	5	-	-
Aug-10	-	1	-	-	-	-	-	-	-	1, 4	3, 4, 5	1, 2	-	-
Sep-10	-	1	-	-	-	-	-	-	-	1, 2	4, 6	2, 3, 5	-	-
Oct-10	2, 4, 6	2, 4	-	-	-	-	-	-	-	1	2, 4	6	-	-
Nov-10	2, 4, 6	4	-	-	-	-	-	-	-	1, 2, 4	1, 2, 3	3, 5	-	-
Dec-10	4	5	-	-	-	-	-	-	-	1	2, 3, 5	1, 2	-	-
Jan-11	1	5	-	-	-	-	-	-	-	5, 6	1, 2	4	-	-
Feb-11	1, 5, 6	1, 2	-	-	-	-	-	-	-	2, 4	2, 3, 6	1, 4	-	-
Mar-11	1, 5	3	-	-	-	-	-	-	-	2, 3, 6	1	5	-	-
Apr-11	2, 3, 4, 5, 6	4, 5	-	2, 5	2, 3	6	2, 5	1, 2, 4	-	5	3, 4	2	-	-
May-11	1, 4	1, 3	-	3, 5	1, 2	4	1, 2	4, 5	-	1	1, 4	6	-	-
Jun-11	6	4	-	4	5	1	2, 3	3, 5	-	5	6	3	-	-
Jul-11	6	5	-	1	2, 3	1	2	4	-	5, 6	2, 3, 6	3	-	-
Aug-11	1	2, 3	-	3	1, 2	1, 3, 4	1	5	-	1, 5	1, 2	5	-	-
Sep-11	2, 3, 5	4	2,3,5	3, 4, 5	5	-	-	-	-	5	6	2	-	-
Oct-11	-	2, 5	4	1	3, 5	-	-	-	-	1, 4	3, 5	4	-	-
Nov-11	-	4	1	2, 3, 5	1, 4	-	-	-	-	1, 2	3, 4	2, 3, 6	-	-
Dec-11	3, 6	1, 2	1, 5, 6	5, 6	5	-	-	-	-	1, 3, 4	1, 3	1, 4	-	-
Jan-12	3, 6	1, 5	3,	4	-	-	-	-	-	1, 2, 4	3	2, 4	-	-
Feb-12	1, 4, 5, 6	3, 5, 6	3, 4	2, 3	-	1	1, 3	1, 5	-	5	3	1, 3, 4	2	5
Mar-12	1, 2, 4, 5	1	1, 2, 4	1, 5	1	3, 4, 5	4, 5	1, 3	-	3, 4, 5	1	1, 2	4, 5	5
Apr-12	1, 2, 4	1	1, 3	2	2, 4	-	1, 3	3, 4, 5	-	1, 2	2, 3, 5	-	1, 3	5
May-12	2, 3, 6	1	3	2	2, 3, 5	-	2, 4	1, 3, 5, 6	-	2	1, 4	-	5, 6	3, 4, 5
Jun-12	1, 4	1	1, 3	2, 5	2	-	1	1,2,4	-	3, 4, 5	2	-	1, 5	4
Jul-12	1, 4, 5, 6	1	3	2, 5	1, 5	5, 6	1,2,4	-	-	2, 4	2, 3	-	2, 3	2, 4
Aug-12	1, 2	3, 4	2, 4, 5	1, 2, 4	-	-	-	-	-	3	3, 5	3	3, 4, 5	4, 5
Sep-12	-	2, 4	5	2, 3, 5	-	-	-	-	-	3	3, 4, 5	1, 2	1, 5	4, 5
Oct-12	-	2	3	5, 6	-	-	-	-	-	1, 4	3, 4	2, 4	1, 4	3, 5
Nov-12	-	3	4, 5	4, 5	-	-	-	-	-	5	3, 6	3, 5	2, 4	6
Dec-12	5	5, 6	5	1, 4	-	-	-	-	-	5	1	5, 6	4	5
Jan-13	1, 2, 6	1, 2	1	1, 2, 3	-	-	-	-	-	1, 3, 4	2, 3, 5	1, 2, 3	3, 5	3, 4, 5
Feb-13	5, 6	3, 5	5, 6	2, 4	-	-	-	-	-	3, 4	2	1, 2, 3	2	6
Mar-13	1, 3, 5	1, 4	1, 3, 4	1, 2	-	-	-	-	-	5	2, 5	2, 4	2, 4	1, 5
Apr-13	2, 6	4	2	1, 2	-	-	-	-	-	1, 2	2, 4	4, 5	1, 2	4, 5

Table 8-3: The selected predictors for the Belgian inflation

FRANCE														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 4	5	2, 3	1	-	-	-	-	-	2	2, 4	1, 2	-	-
Feb-10	1, 4	4	2, 4	3, 4, 5	-	-	-	-	-	2, 3	4	3, 4, 5	-	-
Mar-10	3, 4	5	2	3, 6	-	-	-	-	-	3, 6	4, 5, 6	3	-	-
Apr-10	3, 4	5	2	2, 3	-	-	-	-	-	6	4,5	4	-	-
May-10	3, 4	2	1, 2	-	-	-	-	-	-	3, 4, 5	-	4	-	-
Jun-10	1, 5	2, 3	3	-	-	-	-	-	-	3	-	2, 3	-	-
Jul-10	3, 4, 6	2	4, 6	-	-	-	-	-	-	3	-	2	-	-
Aug-10	2, 4	4, 5, 6	3	-	-	-	-	-	-	1, 2, 3	-	2, 4	-	-
Sep-10	2	-	2, 4, 6	-	-	-	-	-	-	3	-	1, 3, 4	-	-
Oct-10	2	-	5, 6	1, 5	-	-	-	-	-	1	-	2	-	-
Nov-10	1	-	6	2, 3	-	-	-	-	-	2, 5	-	3, 4	-	-
Dec-10	4, 5	-	3, 6	1, 2	-	-	-	-	-	2, 3	-	1, 3, 6	-	-
Jan-11	1, 3, 6	-	3	4, 6	-	-	-	-	-	1, 2	-	2	-	-
Feb-11	3, 4, 6	-	3	3, 6	-	-	-	-	-	1, 4, 5	-	2	-	-
Mar-11	1, 2	-	4, 6	6	-	-	-	-	-	2	-	3, 4, 5	-	-
Apr-11	-	-	3, 6	-	-	-	-	-	-	2	-	6	-	-
May-11	-	2, 3, 6	2	-	-	-	5	1, 2	-	1, 3	3	5	-	-
Jun-11	-	5, 6	2, 5	-	-	-	2	2, 3	-	3	3, 4, 5	6	-	-
Jul-11	-	2, 3, 4, 5, 6	3, 6	-	-	-	2, 5	1, 5, 6	-	5, 6	4	2, 5, 6	-	-
Aug-11	-	2, 3, 4	5	-	-	-	2, 3	4	-	1, 3, 5	4	4, 6	-	-
Sep-11	-	3, 4	5	-	-	-	2, 4	4	-	2	4	2	-	-
Oct-11	1, 6	2	1, 4	-	-	-	1, 4, 5	4	-	2	4	3, 4	-	-
Nov-11	3, 4	2, 3	2, 4	-	-	-	2	2, 3	-	2	2, 4	2, 5	3, 4, 5	-
Dec-11	2, 5, 6	4	5	-	-	-	2, 3	2, 6	-	4, 5	4, 6	2, 5, 6	-	-
Jan-12	4, 5	4, 5	6	-	-	-	1, 4, 5, 6	5, 6	-	6	4	2	-	-
Feb-12	1, 4, 5	6	-	-	3	2, 4	1	2, 5, 6	-	-	-	2, 4	-	-
Mar-12	3	2, 6	-	4	4, 5, 6	4, 6	5	4	2	-	-	1	-	-
Apr-12	4	2, 5	-	4, 5	1, 2	4	1, 3	4	2	-	-	1	-	-
May-12	1, 3	1, 2, 5	-	3	3	5	5	4	1	-	-	1, 4, 5	-	-
Jun-12	4	1, 4	-	4	2, 3	4	2	2, 3	1, 2	-	-	1	-	-
Jul-12	-	5, 6	-	1, 4	3	4	3, 5	-	5	-	-	1	-	-
Aug-12	-	1, 3, 5	3	3, 4	3	1	1, 6	-	5	-	-	2	-	-
Sep-12	-	4, 5	3	1, 3, 4	3, 4	2	1, 2	-	5, 6	-	-	2, 5	-	-
Oct-12	-	1, 5	1	3, 5	4	1, 2	2	-	2, 6	-	-	2, 6	-	-
Nov-12	-	1, 5	3	5	4, 5	1, 2	2, 4	-	2, 3	-	-	1, 2	-	-
Dec-12	-	5	3, 5	3, 4, 5	3	2	2, 4	-	2, 3	-	-	2, 4, 5	-	-
Jan-13	-	5	3, 4	1, 2	1, 2, 5, 6	2	1, 2	-	2	-	-	3	-	-
Feb-13	-	1, 2	3	1	4, 5, 6	6	2	-	6	-	-	3	-	-
Mar-13	-	1, 2	2,3	1	4, 5	6	2	3	4, 5	-	-	3, 6	-	-
Apr-13	-	3	4	1	4	5, 6	2, 3	2, 4, 5, 6,	3, 5	-	-	2, 3	-	-

Table 8-4: The selected predictors for the French inflation

GERMANY														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	2	-	-	-	1	2	-	-	-	-	1	1	-	-
Feb-10	2	-	-	-	2, 4	1, 2	-	-	-	-	3, 4	4	-	-
Mar-10	2	-	-	-	3, 4, 5	2	-	-	-	-	2, 3, 6	4	-	-
Apr-10	2, 3	-	-	-	4, 5	2, 5	-	-	-	-	4, 6	4	-	-
May-10	3	-	-	-	2	3, 5	-	-	-	-	3, 5	4	-	-
Jun-10	3	-	-	-	1	1, 4	-	-	-	-	3, 4	2, 4	-	-
Jul-10	1	-	-	-	1	2	-	-	-	-	3, 6	2, 5	-	-
Aug-10	-	-	-	-	1	4, 5	-	-	-	-	4, 6	4	-	-
Sep-10	-	-	-	-	2	4, 5	-	-	-	-	3, 4, 5	4	-	-
Oct-10	-	-	-	-	2	1, 2, 5	-	-	-	-	4, 5	4	-	-
Nov-10	-	-	-	-	2, 3	5, 6	-	-	-	-	2, 3	4	3	-
Dec-10	-	-	-	-	3	2, 4	-	-	-	-	1, 2	3, 5	3	-
Jan-11	1, 3	-	-	-	2, 3	1, 2, 5	-	-	-	-	1, 2, 5	5	2	-
Feb-11	3	-	-	-	3	3, 5	-	-	-	-	2	1, 4	2, 5	-
Mar-11	3	-	-	-	1	1, 4	-	-	-	-	2	5	3	-
Apr-11	5	-	-	-	6	1, 6	-	-	-	-	2, 6	5	3, 5	1
May-11	5, 6	-	-	-	4, 6	6	-	-	-	-	2, 3	5	2	1
Jun-11	4, 5	-	-	-	2, 4	6	-	-	-	-	1, 3, 4	5	2	1
Jul-11	5	-	-	-	4, 6	6	-	-	-	-	3	4	2, 1	1
Aug-11	5	-	-	-	3, 5	6	-	-	-	-	3, 5	2, 4	1	2, 5
Sep-11	5	-	-	-	3	1	-	-	-	-	3	1, 5	1, 2	1
Oct-11	5	2, 3	-	-	1, 2, 5	1, 2	-	-	-	2	3	1, 4	3	1
Nov-11	1, 4	3	-	-	3	2	-	-	-	-	1, 3	4	3	2, 5
Dec-11	4	3, 4	-	-	3	2, 4	-	-	-	-	3	4	3	1
Jan-12	4	3, 5	-	-	2	2, 5	-	-	-	-	3	4, 5	3	2
Feb-12	4, 5	1, 2	-	2, 3	2	4, 5	-	-	-	-	3	5, 6	3	2
Mar-12	1, 2, 4	2	-	3, 4	2	3, 5	-	-	-	-	1	1	3	2
Apr-12	3, 4	2	-	1, 2, 5	2	5, 6	-	-	-	-	1	2	3	1
May-12	2, 3, 4	1, 3	-	4	2	5	-	-	-	-	2, 4	2	2, 4	1
Jun-12	4	1, 2	-	5, 6	1, 2	2, 5	-	-	-	-	1	2, 3	3	2
Jul-12	4, 5	6	-	1, 5	2, 4	1, 3	-	-	-	2, 4	3, 6	3	3	1
Aug-12	2	4, 5	-	5	3	3, 5	-	-	-	-	6	3, 4	1, 3	3
Sep-12	3	5	-	5, 6	3	3, 6	-	-	-	-	6	4, 6	3	3
Oct-12	1	5	-	1, 5	3, 5	5, 6	-	-	-	-	5, 6	3, 5	1, 2, 5	5, 6
Nov-12	1	5, 6	-	1, 4	5	3, 4, 6	-	-	-	-	3, 5	6	1	6
Dec-12	1, 2	3	-	2, 6	1, 6	3, 5	-	-	-	-	4, 6	6	3	2, 5
Jan-13	2	2	-	3	3, 4	3	-	-	-	2, 5	4	6	3, 4	3, 5
Feb-13	6	1, 2	-	1, 5	4	1, 4	-	-	-	-	1, 3, 6	6	3, 5	2, 5
Mar-13	5	2	-	5	4, 6	1	-	-	-	-	1, 2, 5	1	3, 6	2, 4
Apr-13	5, 6	1, 4	-	6	6	1, 3	-	-	-	-	3, 5, 6	1	5	5, 6

Table 8-5: The selected predictors for the German inflation

The results of the previous three tables indicate that OIL is a common relevant predictor for the core countries during all months under study. ESI is always kept in the pool of potential inputs after October 2011, while JPY, GBP and FTSE always discarded before April 2011. All monthly forecasts are derived by less than thirty inputs from the hundred sixty eight in total, which are autoregressive terms with order up to six. Finally, the average number of terms selected for a monthly forecast is seventeen.

The next five tables present the same information for the five peripheral countries, namely Greece, Ireland, Italy, Portugal and Spain. In Table 8-6 the results for the Greek case are summarized. TRBAL, USD, JPY, GBP and OIL are not useful to predict the Greek CPI. On the other hand, autoregressive terms of EUM1, SP1 and SP2 are always used for this task. ESI is selected only before June 2010 and after August 2011.The rest of the predictors are included in the pool of potential inputs only for limited number of months. Table 8-7 describes the Irish inflation predictors, selected by the RG-SVR. This pool of predictors indicates that only SP2 is found irrelevant for all months. All the other variables are found important during different months. For example, INDP is selected after January 2011, except from the period of September 2011 to February 2012. ESI is found insignificant mainly July 2011, while LOAN from November 2010 to March 2012. FTSE and SP1 are included only in the last months of the exercise. Finally, JPY, GBP, FTSE and GDAX are all not found relevant macroeconomic indicators of Irish inflation before July 2011. Next, the Italian case is analyzed. Table 8-8 shows that GBP is found important in all the forecast period, while FTSE is not. SP2 is kept in the Italian pool of predictors only after April 2012. The rest of the indicators are selected in various patterns. ESI, TRBAL, EMU1 and GDAX all disqualify as potential inputs during May 2011 to September 2011. Similarly, INDP, EMU1, JPY and GDAX are not selected during February 2012 till May 2012. The Portuguese relevant macroeconomic variables are presented in table 8-9. From the above it is obvious that TRBAL and FTSE are common variables throughout the forty months. On the other hand, INDP, LOAN, USD, JPY, GBP and OIL are not kept in the pool of potential inputs. SP1 is not selected only from September 2010 to April 2010. ESI, EMU1, STOXX50, GDAX and SP2 are found irrelevant during almost the whole 2012. Finally, the Spanish inflation predictors are summarized in the table 8-10. In this case RG-SVR discards many indicators during the forecast period (LOAN, TRBAL, USD, JPY, GBP, FTSE, OIL, SP1 and SP2), but always keeps as potential inputs autoregressive terms of ESI and EMU1. INDP, STOXX50 and GDAX are also macroeconomic variables used throughout most of the forty months, except some consecutive months.

GREECE														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	-	1, 3	-	-	1, 3	-	-	-	-	-	1, 4	-	1, 2, 3, 4	3
Feb-10	-	2, 4	-	-	3, 4	-	-	-	-	-	1, 2, 3, 4	-	2, 3	3
Mar-10	-	4	-	-	4	-	-	-	-	-	3	-	2, 3, 4	1, 3
Apr-10	-	4	-	-	4	-	-	-	-	-	1, 3	-	3, 4	3
May-10	-	1,4	-	-	1	-	-	-	-	-	3, 4	-	4, 5	1, 2
Jun-10	-	1	-	-	2	-	-	-	-	-	1	-	1, 2	2
Jul-10	-	-	-	-	1, 2	-	-	-	-	-	1	-	1, 3	2, 3, 4
Aug-10	-	-	-	-	2	-	-	-	-	-	1	-	1, 2	3, 4
Sep-10	-	-	-	-	1, 3	-	-	-	-	-	1	-	1, 2	2, 4
Oct-10	-	-	-	-	2, 1	-	-	-	-	-	1	-	1, 2, 3	4
Nov-10	-	-	-	-	1, 4	-	-	-	-	-	1	-	1, 4	4
Dec-10	-	-	-	-	3	-	-	-	-	-	1, 4	-	4	1
Jan-11	-	-	-	-	3, 4	-	-	-	-	-	1, 4	-	3, 4	1, 2, 3
Feb-11	-	-	-	-	2, 4	-	-	-	-	-	3	-	4	1
Mar-11	-	-	-	-	3	-	-	-	-	-	3, 4	-	4	1
Apr-11	-	-	-	-	3	-	-	-	-	-	4	-	4	1
May-11	1, 2	-	3, 4	-	3	-	-	-	-	-	4	-	1	1, 3
Jun-11	2	-	2, 4	-	3	-	-	-	-	-	1, 2	-	1	1
Jul-11	2	-	3	-	3	-	-	-	-	-	2, 4	-	1, 2, 3	1
Aug-11	2, 3	1	4	-	1, 3	-	-	-	-	-	2, 4	-	2	1
Sep-11	3, 4	1, 3	1, 3	-	1	-	-	-	-	-	1, 4	-	2	1, 2, 3, 4
Oct-11	2,3	1	3	-	1	-	-	-	-	-	1, 3	-	1, 3	2, 4
Nov-11	3	1	3	-	3	-	-	-	-	-	3	-	1, 3	2, 3, 4
Dec-11	3	1	-	-	2	-	-	-		1	2, 3	-	3, 4	4
Jan-12	-	3, 4	-	-	2, 4	-	-	-	3, 4	1	3	-	3, 4	4
Feb-12	-	1	-	-	1, 2	-	-	-	4	1,2	3, 4	-	4	1
Mar-12	-	1	-	-	3, 4	-	-	-	4	3, 4	1, 2	-	4	1, 2
Apr-12	-	1	-	-	1, 4	-	-	-	2	2	4	-	1, 2	1
May-12	-	1	-	-	3, 4	-	-	-	-	-	3	-	1, 2, 3	4
Jun-12	-	1, 3	-	-	1, 2, 4	-	-	-	-	-	3	-	2, 3, 4	1, 3
Jul-12	-	1, 3	-	-	3, 4	-	-	-	-	-	3, 4	-	1	2
Aug-12	-	2	-	-	1, 2, 4	-	-	-	-	-	1	-	2, 4	2
Sep-12	-	2	-	-	1, 3	-	-	-	-	-	1, 3	-	4	2, 3, 4
Oct-12	-	1, 2, 3	-	-	3, 4	-	-	-	-	-	1	-	4	2, 3
Nov-12	-	1, 3	-	-	1, 2	-	-	-	-	-	1	-	2, 3, 4	3
Dec-12	-	1, 2, 3, 4	-	-	1, 2, 3, 4	-	-	-	-	-	1, 2	-	1, 4	1, 2
Jan-13	-	3, 4	-	-	4	-	-	-	4	1	2	-	1, 3, 4	1, 3
Feb-13	4	2, 3,4	-	-	3, 4	-	-	-	2, 4	1, 3	1, 3, 4	-	3, 4	1
Mar-13	3, 4	3	4	-	1	-	-	-	3	2, 3	4	-	1, 2	1, 2
Apr-13	4	4	4	-	1, 2	-	-	-	3,4	3	4	-	1, 2, 3, 4	1, 2, 3

Table 8-6: The selected predictors for the Greek inflation

IRELAND														
CPI	INDP	ESI	LOAN	TRBAL	EUM1	USD	JPY	GBP	FTSE	STOXX50	GDAX	OIL	SP1	SP2
Jan-10	3	1, 4	5	2	4	2, 5	-	-	-	5	-	1, 2	-	-
Feb-10	-	5	5	1, 2	4, 5	1, 6	-	-	-	2	-	2	-	-
Mar-10	-	2, 5	2, 5	-	1, 4	2, 3	-	-	-	2, 5, 6	-	3, 4	-	-
Apr-10	-	-	1, 3	-	1, 6	2	-	-	-	2, 3, 4	-	2, 4	-	-
May-10	-	-	3, 4	-	-	2	-	-	-	2, 4	-	1, 2	-	-
Jun-10	-	-	5	-	-	1, 3	-	-	-	1, 2, 4	-	2	-	-
Jul-10	-	-	1, 2, 3, 5	-	-	1, 2	-	-	-	1, 2	-	4, 5	-	-
Aug-10	-	-	2, 4, 6	-	-	2	-	-	-	5, 6	-	2, 4	-	-
Sep-10	-	-	1, 2	-	-	3, 4, 5	-	-	-	2, 3, 4	-	1, 2	-	-
Oct-10	-	1, 4	4	-	-	2, 4	-	-	-	1	-	4	-	-
Nov-10	-	4, 6	-	-	-		-	-	-	5, 6	-	1, 4	-	-
Dec-10	-	6	-	3	-	2, 4	-	-	-	1, 3	-	1, 3	-	-
Jan-11	-	6	-	1, 3	-	4	-	-	-	5	-	5, 6	-	-
Feb-11	4, 5, 6	4	-	1	-	2, 4	-	-	-	2, 4, 5	-	2, 3	-	-
Mar-11	3, 4	4, 6	-	1	-	5	-	-	-	3, 5	-	2, 4, 5	-	-
Apr-11	3, 4	1, 3, 4	-	3	-	2, 3, 5	-	-	-	1, 6	-	2	-	-
May-11	1, 3	4, 5	-	2	-	1, 4	-	-	-	1, 2	-	1, 3	-	-
Jun-11	1, 2	1, 4	-	2, 4	-	1, 2	-	-	-	2	-	5	-	-
Jul-11	3	1, 5	-	1, 2	-	2, 4	-	-	-	2, 4	-	4, 5, 6	-	-
Aug-11	1, 2, 4	-	-	3	-	2, 3, 6	-	-	-	2	2, 4	1, 2, 5	-	-
Sep-11	-	-	-	1, 2	-	5	2	-		1, 3	2, 3,6	5	-	-
Oct-11	-	-	-	1	3, 6	1	2, 5	-		3	2	1, 4	-	-
Nov-11	-	-	-	1, 2, 4	1, 3, 6	1, 2	1, 2	-	-	2	3, 5	1, 2	-	-
Dec-11	-	-	-	3, 4	3	-	2	-	-	2, 3	2	1, 3, 4	-	-
Jan-12	-	-	-	1, 2, 4	2, 4	-	3, 4, 5	-	-	-	1, 3	1, 2, 6	-	-
Feb-12	-	-	-	1, 3	5	-	2, 4	-	-	-	3, 4, 6	5	-	-
Mar-12	2, 3, 5	-	-	3, 4	1, 2	-	1, 2	-	-	-	1, 3	3, 4, 5	-	-
Apr-12	1, 4, 5	-	1, 2	1, 2	2	-	2	-	-	-	1, 2, 4	2, 3	-	-
May-12	2, 4	-	2	1, 2, 3, 4	3, 4, 5	-	3, 4, 5	1, 3, 4	-	-	2	2	-	-
Jun-12	5	-	3, 5	5, 6	2, 3	-	2, 3	2, 5	-	-	2	2	-	-
Jul-12	2, 3, 5	-	2, 4	-	4, 5	-	2	1, 2, 5	-	-	2, 4	1, 3	-	-
Aug-12	1, 2	-	1, 4	-	3, 5	-	2	1, 6	-	-	3	3	-	-
Sep-12	2	-	5	-	5, 6	-	1, 3	6	-	-	1, 4 , 5	3	2, 5	-
Oct-12	3, 4, 5	-	3, 4	-	5	-	4, 6	2, 4	-	-	3, 6	1, 4	5	-
Nov-12	3, 4	-	5	-	2, 5	-	1, 3	5	-	-	2, 5, 6	5	1, 4	-
Dec-12	1, 2	-	1, 2	-	1, 3	-	3, 4	2, 3, 5	2, 4	2, 3	1, 4, 5, 6	5	4, 5, 6	-
Jan-13	1, 2, 3, 4	-	5	-	3	-	1, 2, 4, 6	1	1, 2	2, 4	1, 2, 4	1, 3, 4	1, 2	-
Feb-13	2, 3	-	5	-	1, 4	1	3, 5, 6	2, 3	3	2, 4	2, 3, 5	3, 4	2, 5	-
Mar-13	2	-	1, 2	-	2	1, 3	1, 4	3, 5	1, 4	1, 2	2, 5	5	2	-
Apr-13	2	-	2	-	1	3, 4	2, 4, 6	1, 4, 5, 6	5	2	5, 6	1, 2	2,4	-

Table 8-7: The selected predictors for the Irish inflation

ITALY														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 3, 5	2	-	4	1	1, 3, 5	3	2	-	1, 5	1, 2, 4	1, 2	2, 5	-
Feb-10	2	1, 3	-	2, 5	1	1, 3	1, 3	2	-	1	3, 5	2	1, 5	-
Mar-10	2, 4	3	-	3, 5	1, 2, 3	**1, 4**	1	1, 2, 3	-	2	5, 6	2, 4	2, 4	-
Apr-10	3, 5	4	-	1, 4	2,3	3, 5	1	2	-	2	1	3, 4	2	-
May-10	5	1, 4, 5	-	4, 5	5, 6	4	3	3, 5	-	2, 3	1	1, 2	2	-
Jun-10	1, 4	1, 3	-	2, 3	3	-	2	1, 4	-	1, 2	1	2	2, 3	-
Jul-10	1, 2	5, 6	-	3	1, 5	-	2, 4	1, 5	-	1	1	3, 5	1, 2, 4	-
Aug-10	2, 4	2, 3	-	3, 5	3, 5	-	1, 2, 4	2	-	1	1, 2	3, 4	2	-
Sep-10	2, 3, 6	2, 3	4, 5	6	3	-	3, 4	4, 5	-	3	1	1, 2	1, 4, 5	-
Oct-10	2	2, 4	1, 5	5, 6	3, 6	-	1, 2, 4	2	-	3, 4	1	4	1, 4	-
Nov-10	1, 3, 4, 5	1, 2	2, 3, 4	6	3	1, 3	1, 3	2, 5	-	4, 5	1	1, 4	2	-
Dec-10	2, 4	2	1, 4	1, 2	1, 3	3, 4	4	1, 4	-	5, 6	3	1, 3	2, 5	-
Jan-11	2, 4	5	2, 5	2	2	3, 4	4	1, 3	-	5	3, 5	1, 6	4, 5	-
Feb-11	4	4, 6	2, 5	3, 5	1, 3	5	3, 5	4, 6	-	5	3	1, 3	2, 4	-
Mar-11	2, 4	1, 2, 5	1, 2, 5	-	1, 2	4, 5	2, 4	1, 3	-	5	3	1, 4, 5	5, 6	-
Apr-11	5	-	3, 5	-	-	1, 2	4	3, 4	-	1, 2	3	2	1, 3, 5	-
May-11	2, 3, 5	-	1, 3	-	-	1, 2, 3	2	1, 2, 4, 6	-	2, 3	-	1, 3	2, 4	-
Jun-11	1, 4	-	3	-	-	1, 3, 4	3, 4	3, 5, 6	-	2, 5	-	5	-	-
Jul-11	2	-	5	-	-	3, 4, 6	-	1, 4	-	2, 4, 6	-	4, 6	-	-
Aug-11	1, 3	-	2, 4	-	-	1, 2	-	2, 6	-	1, 4	-	1, 5	-	-
Sep-11	5	-	3, 5	-	-	3, 4	-	5	-	1	-	5	-	-
Oct-11	5	-	4	5, 6	-	**4**	-	2	-	3	-	1, 4	-	-
Nov-11	1	-	1	6	-	4	-	2, 5, 6	-	3	-	1, 2, 3	-	-
Dec-11	1, 2	5	1, 3	6	-	2	-	2	-	3	-	1, 4	-	-
Jan-12	-	4, 5	2, 4	2	-	2	-	2, 5	-	4	-	2, 6	-	-
Feb-12	-	1, 3, 5	1, 3, 4	2	-	1, 2, 3	-	1, 4	-	4	-	1	1, 6	-
Mar-12	-	5	1, 2	2, 4	-	2	-	1, 2, 3	-	1, 2	-	1	1, 2	-
Apr-12	-	1, 4	3, 5, 6	2, 5	-	4, 5	-	5, 6	-	2, 4	-	1, 4	2	2,5
May-12	-	2, 3	1, 2	2	-	1, 2	-	1, 3, 4	-	4	-	2	2, 4	1
Jun-12	-	3	3	2	-	1, 3	-	1	-	1, 6	4, 5	2, 4	3, 5	1
Jul-12	-	3	1, 2, 5	1, 4	-	1, 3, 4	4	5, 6	-	6	5, 6	1, 3	3	2
Aug-12	-	1, 4	1, 2, 4	2, 3	-	3, 4	5, 6	2, 3	-	6	6	2	1, 4	2
Sep-12	-	5, 6	4, 5	3	-	3, 4	6	5	-	6	6	3	3, 5	4
Oct-12	-	1, 3	1	3, 5	2, 3, 4, 6	1, 3	4, 6	2, 4, 5	-	6	3, 6	5	1, 3, 4	4, 5
Nov-12	3, 4	3	2, 5	1, 2	1, 3	3, 4	6	3, 5, 6	-	5, 6	3, 5	1, 3	1, 3, 4	1, 4
Dec-12	1, 3	3	1, 2, 4	2	5, 6	2, 4, 5	1, 2	1, 2, 6	-	5, 6	5	3, 5	4	3, 4
Jan-13	3	2, 4	2, 4, 5	3, 5	3, 4	4	2	1, 2	-	5. 6	5	4	4	1
Feb-13	3	1, 5	5, 6	5, 6	3	1	3, 4	2	-	1, 2	5	2, 6	1, 4, 6	1
Mar-13	1, 2, 4	5	4, 5	6	2, 3	2, 4	1, 2	2, 4	-	2, 3	1	5	2,	2
Apr-13	3	1, 6	2, 3	1,2	1, 4	4	1, 2, 3, 4	2, 3	-	2	1	3	1, 4	4

Table 8-8: The selected predictors for the Italian inflation

PORTUGAL														
CPI	INDP	ESI	LOAN	TRBAL	EUM1	USD	JPY	GBP	FTSE	STOXX50	GDAX	OIL	SP1	SP2
Jan-10	-	2	-	1	2	-	-	-	2, 4	1	2	-	2	2, 3
Feb-10	-	2, 4	-	1	-	-	-	-	1, 3	1	2, 4	-	2,3	1, 2
Mar-10	-	3	-	1, 2	-	-	-	-	2	1	2	-	3	1, 3
Apr-10	-	3	-	2, 4	-	-	-	-	1, 4	1	2, 3	-	1, 4	1, 5
May-10	-	2, 4	-	1	-	-	-	-	1, 2	3	2	-	1	1
Jun-10	-	4	-	1	-	-	-	-	2, 4	4	4	-	1	1
Jul-10	-	4	-	2, 3	-	-	-	-	2	3	4	-	1	1
Aug-10	-	4	-	2	-	-	-	-	1, 2	3	4	-	1	1, 4
Sep-10	-	1, 2	-	1	-	-	-	-	3	-	-	-	-	1, 3
Oct-10	-	2	-	2, 4	-	-	-	-	1	-	-	-	-	1, 3
Nov-10	-	2	-	3	3, 4	-	-	-	4	-	-	-	-	1, 3
Dec-10	-	1, 3	-	3	3	-	-	-	1	-	-	-	-	1, 4
Jan-11	-	3	-	1, 3	2, 4	-	-	-	1, 4	-	-	-	-	1, 2
Feb-11	-	-	-	3	2, 4	-	-	-	2, 3	-	-	-	-	1
Mar-11	-	-	-	3	2	-	-	-	3	-	-	-	-	1
Apr-11	-	-	-	2, 4	1, 3	-	-	-	3	-	-	-	-	3
May-11	-	-	-	1, 4	-	-	-	-	1	-	-	-	4	3, 4
Jun-11	-	-	-	4	-	-	-	-	2	-	-	-	4	3
Jul-11	-	-	-	1, 3	-	-	-	-	3, 4	-	-	-	4	-
Aug-11	-	-	-	4	-	-	-	-	4	-	-	-	4	-
Sep-11	-	-	-	4	-	-	-	-	4	-	-	-	4	-
Oct-11	-	-	-	3, 4	-	-	-	-	1, 2	-	-	-	3	-
Nov-11	-	-	-	4	-	-	-	-	3, 4	-	-	-	3	-
Dec-11	-	-	-	1, 3	-	-	-	-	1, 2	-	-	-	3, 4	-
Jan-12	-	-	-	2	-	-	-	-	1, 4	-	-	-	1, 2	-
Feb-12	-	-	-	1, 2	-	-	-	-	2, 3	-	-	-	1	-
Mar-12	-	3, 4	-	2	-	-	-	-	1	2, 3	2, 4	-	1	-
Apr-12	-	1, 2	-	1	1	-	-	-	1	2, 4	4	-	1	-
May-12	-	2, 3	-	2	2, 4	-	-	-	1	1	3, 4	-	1	-
Jun-12	-	3	-	1, 2	2, 3	-	-	-	1	1	4	-	1	-
Jul-12	-	3	-	3	1, 2	-	-	-	1	-	4	-	2, 3	-
Aug-12	-	1	-	1	3	-	-	-	1	-	1, 3	-	3	-
Sep-12	-	1	-	2, 4	3	-	-	-	1	-	1, 4	-	3	-
Oct-12	-	1	-	2, 3	3	-	-	-	3, 2	-	1, 2	-	3	1, 3
Nov-12	-	1	-	1, 3	4	-	-	-	2	-	1	-	3	2
Dec-12	-	1, 2, 4	-	2	4	-	-	-	2, 5	-	1	-	2, 4	2
Jan-13	-	2, 3	-	3	1, 2	-	-	-	4	-	1, 3	-	3	2
Feb-13	-	4	-	4	2, 4	-	-	-	4	-	3	-	3	3, 4
Mar-13	-	1, 2	-	3	1, 2, 3, 4	-	-	-	1, 3	-	3	-	1, 3	1, 2
Apr-13	-	2	-	1, 2	1, 2	-	-	-	3	-	1	-	4	2

Table 8-9: The selected predictors for the Portuguese inflation

SPAIN														
CPI	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 2	2, 3	-	-	1, 3	-	-	-	-	2	3	-	-	-
Feb-10	2	2	-	-	3	-	-	-	-	2	3	-	-	-
Mar-10	2, 4	3, 5	-	-	4, 6	-	-	-	-	1, 2, 3	3, 4	-	-	-
Apr-10	1	1, 5	-	-	5, 6	-	-	-	-	1	4	-	-	-
May-10	1	6	-	-	2	-	-	-	-	1, 4	1, 6	-	-	-
Jun-10	3	6	-	-	2	-	-	-	-	1, 5, 6	4	-	-	-
Jul-10	3, 5	2, 3, 6	-	-	1, 3	-	-	-	-	-	3	-	-	-
Aug-10	4	6	-	-	1	-	-	-	-	-	4, 5	-	-	-
Sep-10	2, 6	3	-	-	1, 2	-	-	-	-	-	1	-	-	-
Oct-10	1	4	-	-	1	-	-	-	-	-	3	-	-	-
Nov-10	-	1, 3	-	-	5	-	-	-	-	-	2, 3	-	-	-
Dec-10	-	1, 2, 3	-	-	5, 6	-	-	-	-	-	3	-	-	-
Jan-11	-	2, 3	-	-	1	-	-	-	-	2, 4	2, 6	-	-	-
Feb-11	-	3	-	-	2	-	-	-	-	2	3	-	-	-
Mar-11	-	3	-	-	5	-	-	-	-	1, 2	4	-	-	-
Apr-11	-	1	-	-	1	-	-	-	-	3	1, 2, 3	-	-	-
May-11	-	1, 2	-	-	1	-	-	-	-	1, 2, 3	2	-	-	-
Jun-11	-	1	-	-	1, 2	-	-	-	-	3	2, 4, 6	-	-	-
Jul-11	-	1, 3, 5	-	-	1, 3	-	-	-	-	3, 5	2	-	-	-
Aug-11	-	2	-	-	1	-	-	-	-	3	-	-	-	-
Sep-11	-	2, 4	-	-	2	-	-	-	-	3	-	-	-	-
Oct-11	4, 5, 6	1, 2, 4	-	-	2, 4, 5	-	-	-	-	4, 5, 6	-	-	-	-
Nov-11	4, 5	1	-	-	1	-	-	-	-	4	-	-	-	-
Dec-11	1, 2, 4	1, 2, 4	-	-	2	-	-	-	-	3, 5	-	-	-	-
Jan-12	4	1	-	-	2, 6	-	-	-	-	4	-	-	-	-
Feb-12	1	3	-	-	2	-	-	-	-	4, 6	-	-	-	-
Mar-12	2	3, 5, 6	-	-	2, 3	-	-	-	-	1, 4	-	-	-	-
Apr-12	2, 3	3	-	-	3	-	-	-	-	2	-	-	-	-
May-12	2	3, 6	-	-	2	-	-	-	-	4, 5	-	-	-	-
Jun-12	1, 3, 4	3	-	-	4, 5	-	-	-	-	4	-	-	-	-
Jul-12	1	4	-	-	4, 6	-	-	-	-	1, 2	-	-	-	-
Aug-12	1, 2, 4	4, 6	-	-	1, 2	-	-	-	-	2, 4	-	-	-	-
Sep-12	1	5	-	-	3, 6	-	-	-	-	1	1	-	-	-
Oct-12	1, 2, 4	5, 6	-	-	6	-	-	-	-	2, 3	4, 5, 6	-	-	-
Nov-12	2	5	-	-	4, 6	-	-	-	-	2	6, 4, 5	-	-	-
Dec-12	2, 3, 4	1, 4, 5	-	-	6	-	-	-	-	2, 4	2, 4, 5	-	-	-
Jan-13	2	5	-	-	4, 5	-	-	-	-	2	1, 3, 6	-	-	-
Feb-13	3, 4, 5	5	-	-	4	-	-	-	-	3	3	-	-	-
Mar-13	3	1, 3	-	-	4	-	-	-	-	2, 4	6	-	-	-
Apr-13	1, 2, 4	1	-	-	4	-	-	-	-	4	6	-	-	-

Table 8-10: The selected predictors for the Spanish inflation

Taking under consideration the results from the previous five tables, FTSE is found to be a common relevant indicator for all periphery countries, except Portugal, for the majority of the months. Prior to August 2011, JPY and GBP are always discarded from the pool of potential inputs with the Italian case to be the only exception. GDAX and EMU1 are common predictors for all these five countries before September 2010 and after September 2012 respectively. The same is confirmed for ESI after March 2012, but not for Ireland. The monthly forecasts of the periphery countries are also derived by less than thirty inputs from the hundred sixty eight in total. Those inputs are autoregressive terms with order up to six. The exception is the Greek CPI, which is forecasted by autoregressive terms with order of four or lower. Finally, the average number of terms selected for a monthly forecast is twelve. Summarizing the predictor selection evidence from this inflation exercise leads to the following conclusions. ESI is a common inflation indicator for all countries under study after March 2012, with Ireland being the only exception. On the other hand, JPY and GBP are discarded prior to April 2011, except from the Italian case.

8.5.1.2 Unemployment Exercise

The next three tables, as previously, refer to the three core countries and their unemployment predictor selection. Initially the Belgium case is presented in Table 8-11. It is found that ESI, GDAX and OIL qualify as potential predictors of Belgian unemployment in the majority of the months under study. The opposite happens in terms of GBP and STOXX50. ESI, TRBAL, USD, JPY and FTSE are constantly included in the predictors' pool after September 2011. SP1 and SP2 are both relevant predictors within April 2011 and February 2012, but both are discarded before that time. Table 8-12 below describes France's pool of potential inputs. In this case LOAN and OIL are always included in this pool. The same applies for ESI, EUM1 and FTSE in the majority of the months, but not for USD, JPY, SP1 and SP2. GBP is a relevant input only after September 2011. Finally, autoregressive terms of INDP, ESI, LOAN, GBP, STOXX50 and OIL are repeatedly considered in the pool after July 2012. Next follow the German predictors (table 8-12). The results indicate that EUM1, STOXX50, OIL and LOAN, USD, JPY, GBP, FTSE are found relevant and not relevant indicators in the whole sample respectively. INDP and TRBAL are selected after October 2011, while SP1 and SP2 are not included in the selection prior to February 2012.

BELGIUM														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	5, 6	2, 3, 6	3, 4, 6	-	5, 6	1, 5	-	2, 3, 6	-	-	2	3, 5	-	-
Feb-10	1, 2	1, 4	3	-	5, 6	1, 5	-	1, 4	-	-	2, 4	-	-	-
Mar-10	-	1, 4	3	-	1, 2	5	-	5	-	-	1, 2	2, 5	-	-
Apr-10	-	1, 4	5	-	2, 3,4	-	-	5, 6	-	-	5, 6	-	-	-
May-10	-	1, 4	2	-	2, 3,4	-	-	2, 3, 4, 5, 6	-	-	2	-	-	-
Jun-10	-	5, 6	4	-	1, 4, 5	-	-	-	-	-	2, 4	1, 4, 5, 6	-	-
Jul-10	-	1, 2, 3, 4	2, 3, 6	-	2	1, 2	-	-	-	-	5	1, 4, 5	-	-
Aug-10	-	5	1, 4	-	2, 3	2	-	-	-	-	3, 4, 6	2, 4	-	-
Sep-10	-	2	2, 4	-	1, 4, 5, 6	3, 5	-	-	-	-	-	2, 4	-	-
Oct-10	-	1, 2	1, 3, 4	-	1	-	-	-	-	-	-	-	-	-
Nov-10	1, 2	3, 5	1, 2	-	3, 4, 5	-	-	-	-	-	1, 2	1, 4, 5	-	-
Dec-10	5, 6	3, 5	3	-	1, 3, 3	-	-	-	-	-	1, 3, 3	-	-	-
Jan-11	2, 3, 5	5, 6	4	-	5	-	-	-	-	-	1, 4, 5, 6	2, 3, 6	-	-
Feb-11	2	5, 6	4	-	1, 2	-	-	-	-	-	2, 5, 6	-	-	-
Mar-11	4	-	4	-	3, 5	-	-	-	-	-	3, 5	-	-	-
Apr-11	1, 6	-	-	1, 4, 5	1, 6	-	-	-	-	1, 4	3	-	2	1, 3, 3
May-11	1, 2, 4	-	-	3	2	-	-	-	-	1, 4, 5	3, 4, 6	3, 5	2, 5	1, 3
Jun-11	4	-	-	2, 3,4	2	-	-	-	-	4	1, 4	3, 4, 5	2, 4	3, 4, 5
Jul-11	4	-	-	3	2, 4	-	-	-	-	4	4	4	5	3
Aug-11	4	-	-	1, 4	2, 4	-	-	-	-	1, 4	-	1, 3, 4	2, 5	3
Sep-11	4	-	-	4, 5, 6	1, 2	2, 3, 4, 5, 6	1, 3, 4	-	2	-	-	5, 6	5	3
Oct-11	5, 6	1, 4, 5	-	3, 4	3, 4, 5	1, 3	3, 5	-	2, 3	-	-	3	3, 5	2, 4
Nov-11	-	3	-	5	-	5, 6	2, 5	-	3, 4, 6	-	3, 4, 5	1, 3, 4	3, 6	3, 4, 6
Dec-11	-	4	-	3, 4, 6	-	1, 2	4, 5	-	2, 3,4	-	-	3	3, 5	2, 4
Jan-12	-	3, 4, 6	-	1	-	5, 6	2,6	-	2, 3	-	-	1, 2	3, 4, 5	5, 6
Feb-12	-	1, 4, 5, 6	-	1, 4, 5, 6	-	1, 5	2, 3, 6	-	2	-	2, 3, 4, 5, 6	3	-	-
Mar-12	-	3, 5	-	1, 2	4, 5	5, 6	1	-	5, 6	-	2, 5	1, 2	-	-
Apr-12	-	1	-	1, 5	5	3	1, 4, 5	-	1	-	3, 5	2, 4	-	-
May-12	-	3	-	5	-	1, 5	4	-	2, 5	-	5	1, 4, 5	-	-
Jun-12	-	5, 6	-	1	-	1, 4, 5	4	-	2, 3, 6	-	3, 5	1, 2	-	-
Jul-12	2, 3, 5	2	3	5, 6	-	1, 5, 6	4	-	1, 4, 5, 6	-	5	1, 2	3	5, 6
Aug-12	1, 3	3, 5, 6	3, 4, 5	1	2, 3,4	2, 5	5, 6	-	4	-	5, 6	1, 4, 5	1, 4, 5, 6	1
Sep-12	3, 4	1, 3, 6	1, 6	3	1, 2	2, 3	2, 4	-	1, 2, 3	-	-	2	-	3
Oct-12	3, 4, 5, 6	2, 5	5	1, 3, 4	1, 2	1, 4, 5, 6	1	-	4	-	-	3, 4, 6	-	1, 2, 4
Nov-12	1, 2, 4	4	3	1, 4, 5	1, 2	3, 4	1	-	1, 2	-	-	2, 3,4	-	3
Dec-12	5, 6	4	1, 2, 3	1, 4, 5	2, 3,4	1, 4	3, 4, 5	-	4	-	1, 4, 5	3	3, 5	1, 2
Jan-13	2, 4	3, 4, 6	3	3	5	5	1	-	1	-	5	3	5	1, 3
Feb-13	1, 2, 3	2	4	1, 2	5	2, 4, 5	1, 3, 6	-	2, 3,4	-	5, 6	3, 4	3	1, 3
Mar-13	3, 5	3	1, 2	1, 6	2, 5	1, 5	1, 5	-	3	-	5	1	1	5
Apr-13	5, 6	1, 2	2	1, 2	1	2	2, 3,4	-	2, 5	-	1, 4, 5	1, 2	2, 3	2, 5

Table 8-11: The selected predictors for the Belgian unemployment

FRANCE														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	2, 3	1,3	5, 6	4	4, 6	-	-	-	3, 5	1, 2	2	4, 5	-	-
Feb-10	1, 4, 5	1, 4	3	4	3,4	-	-	-	4	2	1, 2	5	-	-
Mar-10	4, 5	1, 2	1	-	1, 3	-	-	-	4	2	2, 3	5	-	-
Apr-10	3, 5	3	1	-	3	-	-	-	2, 5	1	2, 4	3	-	-
May-10	-	2, 3, 6	2	-	1, 2, 5	-	-	-	3, 5	-	-	4, 6	-	-
Jun-10	-	4, 6	1, 4, 5	-	1, 2	-	-	-	1, 4	-	-	4	-	-
Jul-10	-	3, 4	2, 4, 5	-	5, 6	-	-	-	4, 5	-	-	2, 3	-	-
Aug-10	-	-	4, 5	-	2, 4, 5	-	-	-	2, 4	-	-	4	-	-
Sep-10	-	-	1	-	1	-	-	-	1, 4, 5	-	-	1, 2, 5	-	-
Oct-10	2, 5, 6	-	1, 2	2, 3	1, 2	-	-	-	1, 2	-	-	1	-	-
Nov-10	1, 5, 6	-	1, 4	3	3	-	-	-	2	-	-	3,4	-	-
Dec-10	5, 6	-	1,3	3,4	1, 4, 5	-	-	-	2	-	-	1	-	-
Jan-11	2, 3	-	2, 3	3	3	-	-	-	2	-	-	1, 2	-	-
Feb-11	5, 6	-	3	3	1, 4	-	-	-	2, 4	-	-	1	-	-
Mar-11	5	-	3	-	2, 3	-	-	-	2, 5	-	-	4, 5	-	-
Apr-11	5, 6	-	3	-	3	-	-	-	3, 5	-	-	3, 4	-	-
May-11	1, 2	-	1	-	3, 5	-	-	-	1, 4	-	-	4	-	-
Jun-11	2	-	1, 6	-	6	-	-	-	2, 4, 5	-	-	3	-	-
Jul-11	3, 4	-	2, 5	-	5, 6	-	-	-	4, 5	-	-	5	-	-
Aug-11	1, 6	-	4, 5	-	6	-	-	-	3, 4, 5	-	-	2, 5, 6	-	-
Sep-11	-	-	3	-	6	-	-	-	1, 2	-	-	1	-	-
Oct-11	-	3, 5, 6	1, 2, 5	-	2, 3	-	-	3	2	-	-	1	-	-
Nov-11	-	4, 6	2, 5	-	3	-	-	2, 3, 6	3, 5	-	-	1	-	-
Dec-11	-	1, 2	2, 5	-	1, 2	-	-	4, 6	-	2	4, 5	2, 3	-	3, 4
Jan-12	-	1, 3, 4	2, 4	-	2, 5, 6	-	-	3, 5	-	2	5	1	-	-
Feb-12	-	4, 6	6	-	-	-	-	3, 7	-	6	2, 3	1	-	-
Mar-12	-	2, 5, 6	6	-	-	-	-	3, 6	-	5, 6	5	1	-	-
Apr-12	-	3, 4	3, 6	-	-	-	-	4, 6	-	2, 4, 5	3, 5	1	-	-
May-12	-	1, 2, 5	5, 6	-	-	-	-	3, 4, 5	-	4	1, 3	2, 3, 6	-	-
Jun-12	-	2	3, 4	-	-	-	-	4, 5	-	1, 4, 5	3	1	-	-
Jul-12	2, 5, 6	2	2, 5, 6	-	-	-	-	2, 3	-	1	-	1	-	-
Aug-12	2, 3	6	2	-	-	-	-	1, 2	-	3	-	3	-	-
Sep-12	4, 5	6	1, 5	-	-	-	-	1, 2, 5	1, 4	3	-	2, 3	-	-
Oct-12	1	5, 6	4, 5	-	4, 6	-	-	2	4	1, 2, 5	-	4, 6	-	-
Nov-12	5, 6	5	5, 6	-	3	-	-	2	4, 5	3	-	1, 2, 5	-	-
Dec-12	1	5, 6	6	-	1, 2	-	-	2, 6	1, 4, 5	5, 6	-	3, 4	-	-
Jan-13	2	2, 5, 6	6	-	4, 6	-	-	2, 3	3, 4	3	-	2, 5, 6	-	-
Feb-13	2	1	2, 3, 6	-	1, 5	-	-	1, 3, 4	1	1	-	4	-	-
Mar-13	2	1	2	-	5	-	-	3	1	1, 2	-	1, 4, 5	-	-
Apr-13	4, 6	2	2	-	5	-	-	3, 5	1, 4	2	-	4	-	-

Table 8-12: The selected predictors for the French unemployment

GERMANY															
UNEMP	INDP	ESI	LOAN	TRBAL	EUM1	USD	JPY	GBP	FTSE	STOXX50	GDAX	OIL	SP1	SP2
Jan-10	2, 4	5, 6	-	-	1, 2, 5	-	-	-	-	5, 6	3	1, 2, 5	-	-
Feb-10	3	2, 4	-	-	2, 4	-	-	-	-	5, 6	3	3, 6	-	-
Mar-10	4	1, 2	-	-	2	-	-	-	-	1, 2	3	2, 4	-	-
Apr-10	-	2, 3	-	-	1, 3, 6	-	-	-	-	2, 3,4	1, 2	1, 4	-	-
May-10	-		-	-	3,4	-	-	-	-	2, 3, 4	5	1	-	-
Jun-10	-		-	-	1, 2	-	-	-	-	1, 4, 5	5	2, 3	-	-
Jul-10	-	-	-	-	1	-	-	-	-	2	3, 5	3, 4, 5	-	-
Aug-10	-	-	-	-	1	-	-	-	-	2, 3	5	3	-	-
Sep-10	-	-	-	-	5	-	-	-	-	1, 4, 5, 6	5, 6	3, 5	-	-
Oct-10	-	-	-	-	1, 3, 4,5	-	-	-	-	1	1	2, 4	-	-
Nov-10	-	-	-	-	4, 5	-	-	-	-	3, 4, 5	1, 2	1	-	-
Dec-10	-	-	-	-	5	-	-	-	-	1, 3, 5	2, 4	1	-	-
Jan-11	-	-	-	-	2, 4	-	-	-	-	5	-	1	-	-
Feb-11	-	-	-	-	5	-	-	-	-	1, 2	-	1, 4	-	-
Mar-11	-	-	-	-	3, 4, 5	-	-	-	-	3, 5	-	1	-	-
Apr-11	-	-	-	-	1, 2, 5	-	-	-	-	1, 6	-	5	-	-
May-11	-	-	-	-	3, 4	-	-	-	-	2	-	1	-	-
Jun-11	-	-	-	-	4	-	-	-	-	2	-	1, 2	-	-
Jul-11	-	2, 3	-	-	4	-	-	-	-	2, 4	-	1	-	-
Aug-11	-	2, 3	-	-	5	-	-	-	-	2, 4	-	1, 3, 6	-	-
Sep-11	-	2, 4	-	-	4, 5	-	-	-	-	1, 2	-	1	-	-
Oct-11	-	2, 3	-		1	-	-	-	-	3, 4, 5	-	2	-	-
Nov-11	1, 3	1, 2	-	2, 4	1, 2	-	-	-	-	5, 6	-	1, 2	-	-
Dec-11	4	2, 3	-	1, 3, 6	2, 4	-	-	-	-	6	-	2, 4	-	-
Jan-12	4	3	-	5	3	-	-	-	-	6	-	4	-	-
Feb-12	3, 5	3	-	5	3	-	-	-	-	1, 2	-	4	-	-
Mar-12	2, 4	2, 4	-	1, 2	1, 2, 5	-	-	-	-	1, 2	-	1, 4	-	-
Apr-12	4	2	-	2	1, 2	-	-	-	-	2	4	4, 5	3, 5	4
May-12	4	2	-	3	2	-	-	-	-	2	4	3	4, 6	4, 5
Jun-12	4	3	-	3	2	-	-	-	-	2	3, 4	1, 4	2, 4	5, 6
Jul-12	4	3	-	3	1, 2	-	-	-	-	2, 3	3	1, 2, 5	6	1, 2
Aug-12	4	2, 4	-	6	4, 5	-	-	-	-	3, 4, 5	1, 5	3, 6	6	2
Sep-12	4	1	-	2, 6	4, 5	-	-	-	-	3 ,4	4	-	6	3
Oct-12	5, 6	-	-	3, 4, 6	5	-	-	-	-	1	5	-	6	2, 4
Nov-12	6	-	-	4, 5	3, 4, 5	-	-	-	-	1, 2, 5	4, 5	-	3, 4, 5	2
Dec-12	4, 6	-	-	5	5, 6	-	-	-	-	1	3, 4	1, 2	6	2, 3
Jan-13	6	-	-	5	3, 5	-	-	-	-	1, 2	4	5	6	3
Feb-13	1, 2	-	-	5	1, 4	-	-	-	-	2	3, 4	4	6	2, 4
Mar-13	2	-	-	2, 4	2	-	-	-	-	2	4	5	2, 4	4
Apr-13	3, 4	-	-	6	1	-	-	-	-	1, 2	5	1	6	6

Table 8-13: The selected predictors for the German unemployment

The previous three tables indicate that OIL is a common unemployment predictor for the core countries during the period under study. ESI is always kept in the pool of potential inputs from September 2011 till July 2012. The same applies for INDP and EUM1 after July 2012 and up to October 2011. GBP is also constantly selected, except in the period between May 2010 and September 2011. On the other hand, JPY is discarded prior to September 2011, whereas SP1 and SP2 are not kept in the pool prior to April 2011. Similarly to the inflation exercise, all monthly forecasts are obtained by using less than thirty inputs from the hundred sixty eight in total. From the inputs autoregressive terms with order higher than six are always rejected. The average number of terms used for each monthly forecast of the core countries is fifteen.

The rest five tables present the cases of the periphery countries, starting with the results for the Greek UNEMP. Table 8-14 shows that the autoregressive terms of ESI, LOAN, EUM1 and GDAX always qualify as potential inputs, while TRBAL, USD, JPY, GBP, FTSE and STOXX50 ones do not. INDP, OIL and SP2 are also consistently included except during some short periods (i.e. after July 2012 for OIL). Table 8-15 summarizes the Irish UNEMP predictors. The Irish LOAN, TRBAL, FTSE and OIL are kept in the pool for all forty months, but EUM1, USD, JPY, STOXX50 and GDAX are not. ESI is not selected within September 2010 and September 2011. Finally, SP1 and SP2 are discarded prior to April 2011, while INDP after September 2011. The Italian case is described in table 8-16. These results show that LOAN and FTSE are found always relevant indicators of Italian UNEMP. On the other hand, USD, JPY and GBP do not. EMU1, STOXX50 and SP1 are included into the pool after April 2011. Few autoregressive terms of INDP and ESI are obtained, while the algorithm uses OIL and SP2 prior to April 2011. The next table focuses on Portugal. In this case the proposed algorithm always uses autoregressive lags of LOAN, EMU1, FTSE and OIL to forecast UNEMP. INDP's and SP1's term are constantly pooled prior to April 2011, while ESI, USD, JPY, STOXX50 and GDAX only after July 2012. SP2 is also not selected as potential input after May 2010. Finally, the Spanish relevant macroeconomic variables are presented in table 8-18. This pool of predictors suggests that ESI and EMU1 are always found to be relevant indicators. However, LOAN, TRBAL, USD, JPY, GBP, FTSE, OIL, SP1 and SP2 are totally excluded from this pool. The remaining variables, INDP, STOXX50 and GDAX, are not included in the potential inputs except in specific short periods of consecutive months (i.e. September 2010-September 2011 for IND).

GREECE														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1	2	4	-	1, 3	-	-	-	-	-	3, 4	1, 3	1, 3	
Feb-10	2	2	4	-	3, 4	-	-	-	-	-	3	2	2	-
Mar-10	1, 2	2	1, 4	-	4	-	-	-	-	-	2, 4	1, 3	2	-
Apr-10	2,3	2, 3	4	-	4	-	-	-	-	-	1, 4	3, 4	1, 2	-
May-10	3	3	2	-	1	-	1, 3	-	-	-	2	1, 3, 4	1, 4	-
Jun-10	3	3	2, 3	-	1	-	-	-	-	-	2, 3	1, 3, 4	4	-
Jul-10	3	3	3	-	1	-	-	-	-	-	3, 4	3	4	-
Aug-10	-	3	3	-	1	-	-	1, 2, 3	-	-	1, 3	1, 3	1, 3	2, 3
Sep-10	-	1	1	-	1	-	-	-	-	-	1, 2, 3	2	2	1
Oct-10	-	1, 2	3	-	1, 2	-	-	-	-	-	3, 4	3	2	2
Nov-10	-	2	3	-	1, 2	-	-	-	-	-	1, 3, 4	2, 3	2	3
Dec-10	-	2, 3	3	-	2	-	-	-	-	-	1, 3, 4	3, 4	2	1, 3
Jan-11	1, 3	3	3,4	-	1	-	-	-	-	-	1, 2, 3, 4	1, 3	1, 2, 4	2
Feb-11	3	1, 2, 3	3	-	1	-	-	-	-	-	1, 3	2	4	3
Mar-11	3	2, 3	3	-	1	-	-	-	-	-	2	2	4	1, 3, 4
Apr-11	1, 3	1, 3	1, 3	-	1	-	-	-	-	-	2	2	1	2, 3
May-11	2	3, 4	2	-	1, 3	-	-	-	-	-	2	1, 2	1,4	3, 4
Jun-11	2	4	3	-	1	-	-	-	-	-	3, 5	1, 4	4	1
Jul-11	2	1, 2	1, 2, 4	-	1	-	-	-	-	-	1, 4	4	4	1, 2
Aug-11	2	1, 4	4	-	1, 3	-	-	-	-	-	1	4	1, 2	2
Sep-11	2	4	2	-	3	-	-	-	-	-	1	1, 3	1, 3	2
Oct-11	2	4	2, 3	-	3	-	-	-	-	-	1, 2, 3	2	2	1
Nov-11	2, 3	1, 2, 3	2	-	3	-	-	-	-	-	1, 2	2, 4	2	1
Dec-11	3	3	2	-	3	-	-	-	-	-	2	1, 3	1, 2, 3, 4	1, 2
Jan-12	3	3	1, 3	-	3	-	-	-	-	-	2	2	1, 2	2,3
Feb-12	1	3	2	-	3	-	-	-	-	-	2, 4	3	3, 4	3
Mar-12	1, 2	1, 3, 4	2	-	2, 4	-	-	-	-	-	3	1	1	3, 4
Apr-12	2	4	3	-	4	-	-	-	-	-	1, 3	3	1	3
May-12	1, 2, 3	4	1	-	2, 4	-	-	-	-	4	2	3	2	3,4
Jun-12	3	1, 2	1, 2	-	2, 4	-	-	-	-	-	1	3	1, 3	3
Jul-12	3	2	2	-	1, 4	-	-	-	-	-	1	-	2	1, 3
Aug-12	3	2, 3	2, 3	-	4	-	-	-	-	-	1, 2, 3	-	1, 3	2
Sep-12	3	1, 3, 4	4	-	1, 3	-	-	-	-	-	1, 2, 4	-	2	4
Oct-12	3	4	3	-	1, 4	-	-	-	-	-	3	-	2	2
Nov-12	3	3	3	-	1	-	-	-	-	-	3	-	1	1, 3
Dec-12	3	3	2, 3	-	1	-	-	2	-	-	1, 2, 3, 4	-	3	2
Jan-13	1, 2,3	2, 3	1	-	1	-	-	-	-	-	1, 2	-	2, 3	1
Feb-13	2, 3	1	3	-	1, 4	-	-	-	-	2, 4	3, 4	-	1	1, 2
Mar-13	1, 2, 3	1, 2	2, 3	-	4	-	-	-	-	-	2, 3	-	1	2, 4
Apr-13	1, 2	1	1	-	1, 2	-	-	-	-	-	1, 2, 3	-	1	4

Table 8-14: The selected predictors for the Greek unemployment

IRELAND														
UNEMPL	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 5	2, 3	6	1, 2, 4	-	-	-	3, 6	2, 4	-	-	3, 5	-	-
Feb-10	3, 5, 6	4, 5	3, 5	1, 3	-	-	-	4, 5	2, 5	-	-	1, 3	-	-
Mar-10	1	3, 6	1, 2	3, 4	-	-	-	4	4, 5	-	-	5, 6	-	-
Apr-10	1	1, 3, 6	4	3	-	-	-	1, 2, 4	3, 5	-	-	1, 2	-	-
May-10	1	1, 3	1, 4	3	-	-	-	5, 6	6	-	-	3, 5	-	-
Jun-10	-	3	4, 5	3	-	-	-	3	1	-	-	1, 3	-	-
Jul-10	-	2	5	1, 4	-	-	-	1, 3, 4	1, 2	-	-	3, 5	-	-
Aug-10	1, 4	2, 3	1, 2	3, 4	-	-	-	3	2	-	-	1, 4	-	-
Sep-10	6	-	5	1, 2, 4	-	-	-	1, 4	2, 5	-	-	2, 3, 6	-	-
Oct-10	1	-	2	3, 4	-	-	-	3	3, 5	-	-	5	-	-
Nov-10	2, 3	-	6	4	-	-	-	1, 2	1, 2	-	-	3, 4, 5	-	-
Dec-10	4	-	4, 5	4	-	-	-	2, 4	3, 5	-	-	1, 2, 5	-	-
Jan-11	3, 5	-	1, 5	1	-	-	-	1, 3, 5	1, 3	-	-	5	-	-
Feb-11	1, 4	-	2, 3, 6	1, 4	-	-	2, 4	1, 2	3	-	-	4, 5	-	-
Mar-11	3	-	1, 4	3, 4	-	-	-	1, 2	5	-	-	1	-	-
Apr-11	4, 5	-	2, 4	1, 3	-	-	-	1, 5	5, 6	-	-	1, 2	-	-
May-11	1, 3	-	1, 3, 4	2, 1	-	-	-	2	5, 6	-	-	2	-	-
Jun-11	2, 3, 5	-	1, 2	1, 4	-	-	-	3, 4	3, 4, 6	-	-	2, 3	5, 6	2, 4
Jul-11	2, 3	-	3, 5	3	-	-	-	2, 3,4	6	-	-	3, 5	3	2, 4
Aug-11	1, 4	-	1, 3	1, 2, 5	-	-	-	3	1	-	-	5, 6	1, 5	1, 2
Sep-11	-	-	3	3, 4	-	-	-	3	1, 2	-	-	3	2, 3	2, 3
Oct-11	-	-	5	4	-	-	-	3, 5	2	-	-	1, 5	6	1, 4, 5, 6
Nov-11	-	-	2	4	-	-	-	1, 2	2, 4	-	-	1, 4, 5	6	2, 3,4
Dec-11	-	1, 2	6	5	-	5	-	1, 2	3, 5	-	-	5, 6	1, 2, 5, 6	1, 4, 5
Jan-12	-	3	3, 5	4, 5	-	-	-	-	5, 6	-	-	1, 4	1,2, 4, 5	2
Feb-12	-	4, 5	1, 2	1, 2	-	-	-	-	5	-	-	5, 6	1, 5	5, 6
Mar-12	-	1, 5	3	2	-	-	-	-	2, 5	-	-	3	5, 6	1, 2
Apr-12	-	3, 5, 6	1, 2, 4	2	-	-	-	-	1, 3	-	-	6	-	2, 3,4
May-12	-	2, 4	1, 2, 4	1, 2	-	-	-	-	3, 5	-	-	6	2, 4, 6	-
Jun-12	-	1, 2	4, 5	3, 4	-	-	-	-	2, 5	-	-	4	2, 3, 6	-
Jul-12	-	1, 4	1	1, 4	-	-	-	-	3, 5	-	-	4, 6	4	-
Aug-12	-	4	1	5	-	-	-	-	1, 4	-	-	2,	5	-
Sep-12	-	3, 5, 6	1, 3	2	-	-	-	1, 4	2	-	-	1, 4	1, 4, 5	-
Oct-12	-	1, 2	2	3, 4	-	-	-	4, 6	3, 4, 6	-	-	5	1, 5	-
Nov-12	-	1, 3	2, 4	4, 5	-	-	-	1, 2, 5, 6	3, 5	-	-	2, 4	3, 5	-
Dec-12	-	5, 6	1, 3	5	-	-	-	2, 5	2	-	-	2,5	6	-
Jan-13	-	1, 2	2	2, 4	-	-	-	2	1, 2	-	-	1	2, 3	-
Feb-13	-	3, 5, 6	3	5	-	-	-	2, 5	2	-	-	1	4	-
Mar-13	-	1, 4, 5	1	1, 4, 6	-	-	-	1	2, 5	-	-	1	5, 6	-
Apr-13	-	2	1, 6	1, 2, 4, 5, 6	-	-	-	1	1, 4	-	-	1	6	-

Table 8-15: The selected predictors for the Irish unemployment

ITALY														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	-	3, 4	2, 4	-	1, 2	-	-	-	3, 5	-	2	2	4	1, 2
Feb-10	-	4, 5	1, 2	-	3	-	-	-	1, 3	-	2	2, 4	4	2
Mar-10	-	4	1, 3, 4	-	1, 6	-	-	-	5, 6	-	2	1, 2	4	2
Apr-10	-	4	1, 4	-	3	-	-	-	1, 2	-	2	2	4	2
May-10	-	1, 4	6	-	2, 5, 6	-	-	-	3, 5	-	2	3, 4, 6	1	2, 5
Jun-10	-	4	1	-	1, 6	-	-	-	1, 3	-	2	2, 4	-	1
Jul-10	-	4	1	-	6	-	-	-	2	-	2, 3	1, 2	-	1
Aug-10	-	-	2, 4	-	4, 6	-	-	-	1, 2	-	3	2	-	4, 5
Sep-10	-	-	1	-	-	-	-	-	3	-	1	3, 4, 5	-	6
Oct-10	-	-	2, 4	-	-	-	-	-	5	-	1	2, 4	-	6
Nov-10	-	-	4	-	-	-	-	-	3, 4, 5	-	1	2	-	6
Dec-10	-	-	5	-	-	-	-	-	1, 2, 5	-	1, 4	2	-	1, 3
Jan-11	-	-	5	-	-	-	-	-	5	-	4	1, 5	-	2
Feb-11	-	-	1, 2	-	-	-	-	-	3, 5	-	4	4, 6	-	2
Mar-11		-	3	-	-	-	-	-	5	-	-	1, 3	-	1, 5
Apr-11	2	-	6	-	-	-	-	-	6	1, 4	-	3, 4	-	5
May-11	2, 3	-	3, 6	-	2, 3	-	-	-	2, 6	3	-	1, 2, 5, 6	3	1
Jun-11	3	-	3	-	2, 4	-	-	-	1, 2	1, , 5	-	6	3	1
Jul-11	3	-	3	-	2	-	-	-	1	3, 4	-	1, 4	3	-
Aug-11	4	-	2, 3	-	2	-	-	-	1	4	-	2, 6	1, 5	-
Sep-11	5, 6	-	4	-	1, 2	-	-	-	1, 4	4	-	1, 2	2	-
Oct-11	-	-	2, 5	-	3	-	-	-	3	1	2, 4	1, 5	2	-
Nov-11	-	-	4	-	1, 3, 4	-	-	-	3	1, 5	2, 4	6	2	-
Dec-11	-	-	1, 2	-	2, 3, 5	-	-	-	3	1, 2	2, 5	1, 2	1, 4	-
Jan-12	-	-	1, 5	-	2, 3	-	-	-	3	2, 4	2, 6	1, 4	4	-
Feb-12	-	-	3, 5, 6	-	1, 4	-	-	-	3	2	1, 2	2, 5	4	-
Mar-12	-	-	1	-	6	-	-	-	3	1, 2	1, 2, 3	1, 3, 5	5	-
Apr-12	-	-	1	-	2, 4	-	-	-	3	3, 5	4	4	5	-
May-12	-	-	5	-	2	-	-	-	3, 4	1, 6	4	4	5	-
Jun-12	-	-	2, 3	-	3	-	-	-	3, 5	5, 6	4	5, 6	1, 4	3, 6
Jul-12	-	-	4	-	5, 6	-	-	-	3	1, 2	5, 6	-	3	5
Aug-12	1, 2	-	2, 5	-	5	-	-	-	3	1, 4	1, 3	-	2, 5	5
Sep-12	2	-	4	-	1, 4	-	-	-	3	2, 5	3, 4	-	3	3, 5
Oct-12	2, 4	3, 5	2	-	2, 4	-	-	-	1, 4	1, 2, 5	4	-	5	2, 4
Nov-12	4	5	3	-	3	-	-	-	4	6	4	-	5	1, 6
Dec-12	4	6	1, 2	-	4, 6	-	-	-	1, 5	3, 6	4	-	1	5
Jan-13	5	6	3, 5	-	3	-	-	-	5	1, 4	4	2	1, 5	5
Feb-13	5	1, 2	1, 4	-	2, 4, 6	-	-	-	1, 2	5	1, 2	2, 3	3	5
Mar-13	1, 2	2	4	-	5, 6	-	-	-	1, 5	3, 4, 5	2	3	2	1, 2
Apr-13	1, 2	1, 4	4	-	6	-	-	-	6	5, 6	2	1, 2, 3	2	2

Table 8-16: The selected predictors for the Italian unemployment

PORTUGAL														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 3	1, 2	2	-	4	-	-	2, 3, 4	2, 3	-	-	2	1, 3	2, 3
Feb-10	1, 3	2, 4	2	-	1, 3	-	-	3	1, 2	-	-	2, 3	1, 3	2
Mar-10	3	2	2, 3	-	2	-	-	3, 4	1, 3	-	-	3, 4	1, 2	1, 4
Apr-10	3, 4	2, 3	2	-	1, 4	-	-	3	1,4	-	-	1, 2	2	1, 2, 3
May-10	3	-	3, 4	-	1, 2	-	-	-	1	-	-	3	4	1, 2, 3, 4
Jun-10	3	-	3	1, 4	2, 4	-	-	-	1	-	-	1	1	
Jul-10	3	-	3, 4	4	2	-	-	-	1, 4	-	-	2, 4	1, 2	-
Aug-10	3, 4	-	4	4	1, 2	-	-	-	1	-	-	1	1, 3	-
Sep-10	3	-	1	3	4	-	-	-	2, 4	-	-	3	4	-
Oct-10	3, 4	-	2, 3	3, 4	3	-	-	-	1, 3	-	-	1, 2	4	-
Nov-10	1, 3	-	3	2, 4	4	-	-	-	1, 4	-	-	1	1, 4	-
Dec-10	1, 3	-	2, 3	1, 2	3	-	-	-	1, 3	-	-	1	2, 4	-
Jan-11	4	-	3	2	3	-	-	-	3	-	-	4	1	-
Feb-11	1, 4	-	4	-	3, 4	-	-	-	1, 4	-	-	3, 4	1, 3	-
Mar-11	4	-	1, 3	-	1, 2	-	-	1, 2, 3, 4	1, 3	-	-	3	1, 4	-
Apr-11	2, 4	-	1	-	3	-	-	3, 4	4	-	-	2	-	-
May-11	2, 4	-	3	-	1	-	-	1, 4	1, 4	-	-	3, 4	-	-
Jun-11	3, 4	-	4	-	2	-	-	1, 4	1, 2	-	-	3	-	-
Jul-11	-	-	1, 2	-	3	-	-	2, 4	3	-	-	1, 2	-	-
Aug-11	-	-	1, 4	-	2, 4	-	-	1, 2	1	-	-	3	-	-
Sep-11	-	-	3	-	4	-	-	1, 2	2, 4	-	-	4	-	-
Oct-11	-	-	1	-	1, 2	-	-	3, 4	1, 3, 4	-	-	1, 4	-	-
Nov-11	-	-	4	-	1, 4	-	-	2, 4	1, 4	-	-	1	-	-
Dec-11	-	-	2, 3	-	3, 4	-	-	2, 3, 4	1	-	-	3, 4	-	-
Jan-12	-	-	1, 2	1, 2	1, 2	-	-	1, 2, 4	1, 2	-	-	4	-	-
Feb-12	-	-	2, 4	1	2, 3	-	-	1, 2	1, 2	-	-	4	-	-
Mar-12	-	-	2, 3	3, 4	3	-	-	1	4	-	-	1, 2, 3	-	-
Apr-12	-	-	2, 4	4	3	2, 4	1, 2, 3	1	2	2, 3, 4	1, 2, 3	1	-	-
May-12	-	-	4	2, 4	1, 3	2, 3	1, 2, 4	1, 3	3, 4	2, 4	1	4	-	-
Jun-12	-	4	3	4	1	2	2, 4	-	3, 4	1, 2	1, 2	1	-	-
Jul-12	-	4	2	1	1	3	2	-	4	1, 2	1, 4	3	-	-
Aug-12	-	4	4	1, 3	1	2, 4	3	-	4	2, 3	1	3	-	-
Sep-12	-	2	3, 4	1, 4	1	4	1	-	1	2	2, 4	4	-	-
Oct-12	-	2, 3	3	1	3, 4	2, 3	1	-	1, 3	2	4	2	-	-
Nov-12	-	3	1	1, 4	2	1, 3	1, 2	-	1, 4	2,4	1, 2, 3	1	-	-
Dec-12	-	4	2	-	1, 5	1, 3	1, 2	-	2, 3	1, 2	4	1	-	-
Jan-13	-	1, 2, 4	2, 3	-	4	1, 2	4	-	1	1	1, 2	1	-	-
Feb-13	-	2, 3	1	-	3, 4	2	1, 2	-	1	1	2	2	-	-
Mar-13	-	1, 3, 4	3	-	1	2	4	-	1	1	3, 4	1	-	-
Apr-13	-	2	1	-	3	3	1, 3, 4	-	1	1, 2, 3, 4	4	1, 2	-	-

Table 8-17: The selected predictors for the Portuguese unemployment

SPAIN														
UNEMP	**INDP**	**ESI**	**LOAN**	**TRBAL**	**EUM1**	**USD**	**JPY**	**GBP**	**FTSE**	**STOXX50**	**GDAX**	**OIL**	**SP1**	**SP2**
Jan-10	1, 2	2, 3	-	-	-	-	-	3, 5	4	3	-	4	-	-
Feb-10	1, 4	2, 5	-	-	-	-	-	3	4	3, 5	-	3, 5	-	-
Mar-10	1, 5	3	-	-	-	-	-	4, 5	4	3	-	4	-	-
Apr-10	-	2, 5	-	-	-	-	-	-	4	3	-	4, 5	-	-
May-10	-	2, 5	-	-	-	-	-	-	4	1, 4	-	4	-	-
Jun-10	-	1	-	-	-	-	-	-	4	1, 4	2	1, 2	-	-
Jul-10	-	4, 6	-	-	-	-	-	-	5	1	1	4	-	-
Aug-10	-	1	-	-	-	-	-	-	5	1, 2	5, 6	4, 6	-	-
Sep-10	-	1, 2	-	-	-	-	-	-	-	-	-	2	-	-
Oct-10	-	6	-	-	-	-	-	-	-	-	-	5	-	-
Nov-10	-	1, 2, 4	-	-	-	-	-	-	-	-	-	2	-	-
Dec-10	-	1	-	-	-	-	-	-	-	-	-	5, 6	-	-
Jan-11	-	3	-	-	-	-	-	2, 5	-	-	-	5	-	-
Feb-11	-	5, 6	-	-	-	-	-	3	-	-	-	1, 5	-	-
Mar-11	-	5, 6	-	-	-	-	-	4, 6	-	-	-	5	-	-
Apr-11	-	5	-	-	-	-	-	5	-	-	-	2	-	-
May-11	5, 6	6	-	-	-	-	-	1	-	-	-	5	-	-
Jun-11	5	6	-	-	-	-	-	2	-	-	-	2	-	-
Jul-11	4, 5	4, 6	-	-	-	-	-	2	-	-	-	1, 3, 4	-	-
Aug-11	1, 5	2, 6	-	-	-	-	-	1	-	-	-	1	-	-
Sep-11	5	6	-	-	-	-	-	2	-	-	-	1	-	-
Oct-11	3, 6	-	2	2	1, 5	-	-	3	-	-	-	1, 2	-	-
Nov-11	4, 6	-	2, 5	2, 6	5	-	-	4	-	-	-	1, 2	-	-
Dec-11	6	-	3	4	5	-	-	5	-	-	-	2	-	-
Jan-12	4, 5	-	3, 6	2, 6	5	-	-	-	-	-	-	1	-	-
Feb-12	1, 2, 3, 5, 6	-	4	2	5	-	-	-	-	-	-	1, 3	-	-
Mar-12	1, 2, 5	-	4, 5	4	2	-	-	-	-	-	-	2	-	-
Apr-12	3	-	4	4, 5	1, 2	-	-	-	-	-	-	5	-	-
May-12	3, 4	-	2, 3	4	3	-	-	-	-	-	-	3, 4, 5	-	-
Jun-12	2	-	3	4	4	-	-	-	-	-	-	2	-	-
Jul-12	2	-	-	1, 2, 4	6	-	-	-	-	-	-	3	-	-
Aug-12	2, 3, 4	1, 2	-	4	3	-	-	-	4	2	3, 4, 5, 6	3, 6	-	-
Sep-12	2	1, 2	-	4	2, 3	-	-	-	4, 6	2	3	3	-	-
Oct-12	2	1, 4	-	1, 2, 3	3	-	-	-	5, 6	2, 3	5, 6	2, 6	-	-
Nov-12	2, 5	1, 3	-	2	3	-	-	-	5, 6	1, 3	6	3	-	-
Dec-12	1	1, 2, 4	-	3	3, 5	-	-	-	1	1, 5	4, 6	1, 5	-	-
Jan-13	2, 5	1, 2, 4	-	1, 3	1	-	-	-	3, 4	1, 6	5, 6	2, 4	-	-
Feb-13	1	1, 2	-	2	3	-	-	-	3	1, 2	6	2	-	-
Mar-13	4, 5, 6	2, 5	-	1	5	-	-	-	2, 4	3, 5	1, 2, 4, 6	1, 3, 6	-	-
Apr-13	4, 6	2, 4	-	1	1	-	-	-	5	4, 4	1	2	-	-

Table 8-18: The selected predictors for the Spanish unemployment

Observing the previous five tables, OIL is found to be a relevant unemployment indicator for all peripheral countries. Consistent to that is also the EUM1, with Ireland being the only exception. On the contrary, USD and JPY are rejected from the pool of potential inputs prior to February 2012. GBP is also discarded from this selection, except in Portugal's case. Finally, autoregressive terms of LOAN are constantly obtained by RG-SVR algorithm, except during the period of September 2011 to July 2012 in the Spanish analysis. The forecasts of the peripheral countries are again derived by less than thirty inputs from the hundred sixty eight in total. Those inputs are autoregressive terms with order of four or lower. Similar to the first exercise the exception is again the Greek CPI, which is forecasted by autoregressive terms with order of up to four. The average number of terms selected for a monthly forecast is thirteen in the periphery countries' cases. The predictor selection of the unemployment exercise concludes that EMU1 and OIL qualify almost in all cases and months as a relevant macroeconomic indicator for Eurozone unemployment. This is different than the inflation case. JPY, though, is never included in the previous eight pools prior to September 2011, which is consistent with the CPI analysis.

In general, both exercises establish an erratic mapping of the predictors in every month per month and country per country analysis. This proves that structural breaks dominate the Eurozone inflation and unemployment, making their forecasting a very challenging task. Consequently, models with a constant or a limited set of independent variables have no value in the long-run. Non-linear time-varying approaches, such as the proposed hybrid model, can prove more efficient and realistic. The RG-SVR provides an output of the changing composition of the relevant macroeconomic indicators for each country, giving a glimpse of its economic and financial micro-structure. This can in a sense extend to an ability of capturing structural breaks. In all cases the selected predictors seem to follow and change patterns associated with the specific highlighted months. Very often predictors are accepted or rejected from the potential pool before, after or within some of these months. This is more clearly observed in core countries than in periphery ones. This would be an expected outcome, since the peripheral EU economy is indeed much more unstable compared to the core one, especially during the forty months under study.

All the forecasts are obtained by taking under consideration always autoregressive lags less than thirty. The tables of the first exercise show that there are many cases where individual variables are pooled with three or more autoregressive terms. This is not so common in the second one, where usually up to two autoregressive lags seem sufficient to describe each variable's contribution to the final monthly forecast. The RG-SVR excludes autoregressive terms with order higher than six. Nonetheless, the previous sixteen tables show that the first four autoregressive terms are usually more evident. This suggests that the practitioner should focus on the past quarter, while information going back more than a semester seems irrelevant. In the periphery cases, the RG-SVR model obtains optimal forecasts by using less five predictors on average in comparison to the core cases. It would be interesting to see if the abovementioned optimal RG-SVR variable selection leads to statistically robust forecasts.

8.5.2 Statistical Performance

The statistical performance of the RG-SVR forecasts follows in comparison to their benchmarks. Similar to previous chapters, the RMSE, MAE, MAPE and Theil-U statistics are computed in order to evaluate statistically these forecasts. This is standard in literature and the mathematical formulas of these statistics are presented in Appendix B.4. For all four statistical measures retained, the lower the output the better the forecasting accuracy of the model concerned. As mentioned in the description of the model, GA-SVR stores also the SVR parameters per month (encoded in the monthly optimal chromosome). These parameters for both exercises are given in Appendix F.2.

8.5.2.1 Inflation Exercise

The following table presents the statistical performance of all models for each country, when forecasting inflation.

CPI	COUNTRIES	STATISTICS	MODELS			
			f-RW	AO-RW	STAR	RG-SVR
CORE	BELGIUM	MAE	0.2445	0.2421	0.2308	**0.2083**
		MAPE	83.76%	80.01%	82.25%	**76.09%**
		RMSE	0.3264	0.3101	0.2822	**0.2484**
		THEIL-U	0.6928	0.5676	0.5615	**0.4610**
	FRANCE	MAE	0.1564	0.1522	0.1504	**0.1352**
		MAPE	71.10%	70.75%	68.48%	**64.70%**
		RMSE	0.1959	0.1907	0.1885	**0.1594**
		THEIL-U	0.7306	0.6970	0.6058	**0.5613**
	GERMANY	MAE	0.1972	0.1802	0.1658	**0.1366**
		MAPE	94.81%	89.24%	82.51%	**78.18%**
		RMSE	0.2543	0.2291	0.2014	**0.1854**
		THEIL-U	0.8039	0.7301	0.7025	**0.6558**
PERIPHERY	GREECE	MAE	0.4508	0.4052	0.3558	**0.3095**
		MAPE	167.91%	162.58%	159.51%	**149.66%**
		RMSE	0.5742	0.5427	0.5158	**0.4865**
		THEIL-U	0.8619	0.8423	0.8047	**0.7810**
	IRELAND	MAE	0.5236	0.4950	0.4751	**0.4544**
		MAPE	171.76%	164.23%	159.47%	**144.34%**
		RMSE	0.6653	0.6357	0.6258	**0.5786**
		THEIL-U	0.8998	0.8696	0.8422	**0.8021**
	ITALY	MAE	0.2988	0.2636	0.2428	**0.2276**
		MAPE	99.87%	95.17%	93.17%	**89.03%**
		RMSE	0.4232	0.4075	0.3741	**0.3267**
		THEIL-U	0.7895	0.7253	0.6851	**0.6639**
	PORTUGAL	MAE	0.4377	0.4031	0.3729	**0.3488**
		MAPE	160.84%	153.81%	151.25%	**147.10%**
		RMSE	0.4663	0.4459	0.4137	**0.3803**
		THEIL-U	0.8023	0.7814	0.7419	**0.7065**
	SPAIN	MAE	0.4186	0.3931	0.3515	**0.3268**
		MAPE	114.48%	133.06%	130.47%	**122.66%**
		RMSE	0.4321	0.4129	0.3911	**0.3418**
		THEIL-U	0.7914	0.7599	0.7155	**0.6728**

Table 8-19: Out-of-Sample statistical performances for the inflation exercise

The RG-SVR presents the best statistical performance in all cases for every statistical measure applied in the inflation analysis. The ability of the algorithm to project superior inflation forecasts suggests that the predictor selection of this exercise is successful. The second best model is STAR, since it outperforms both f-RW and AO-RW. Reviewing the core countries' results, the best forecasts are obtained for French inflation and the worse for the Belgian one. Turning to the periphery cases, the Irish inflation seems the hardest to forecast, where the Italian statistics are the closest to the Belgian ones. The second best performance from the periphery countries is confirmed in the Spanish analysis, since Portugal and Greece have less accurate results. In general, the performance is always statistically better in the core countries than in the periphery ones. Although all models perform differently in every case, their ranking remains the same regardless the country under study. It would be interesting to see if the success of the proposed algorithm in this inflation exercise extends also in the unemployment one.

8.5.2.2 Unemployment Exercise

The table below summarizes the statistical performance of the models regarding the unemployment of all eight countries under study.

UNEMP	COUNTRIES	STATISTICS	MODELS			
			f-RW	AO-RW	STAR	RG-SVR
CORE	BELGIUM	MAE	0.1610	0.1432	0.1214	**0.1104**
		MAPE	53.13%	51.25%	48.11%	**47.04%**
		RMSE	0.1887	0.1728	0.1601	**0.1351**
		THEIL-U	0.5713	0.5352	0.5039	**0.4626**
	FRANCE	MAE	0.2567	0.2206	0.2118	**0.1827**
		MAPE	58.68%	57.75%	54.48%	**51.61%**
		RMSE	0.2215	0.2076	0.1887	**0.1603**
		THEIL-U	0.6178	0.5916	0.5624	**0.5273**
	GERMANY	MAE	0.1470	0.1374	0.1254	**0.1028**
		MAPE	49.33%	46.88%	45.74%	**44.22%**
		RMSE	0.1771	0.1638	0.1484	**0.1259**
		THEIL-U	0.5504	0.5233	0.4958	**0.4624**
PERIPHERY	GREECE	MAE	0.4458	0.4202	0.4098	**0.3570**
		MAPE	105.19%	100.93%	95.51%	**89.64%**
		RMSE	0.4129	0.3854	0.3408	**0.3016**
		THEIL-U	0.8254	0.8017	0.7881	**0.7436**
	IRELAND	MAE	0.4135	0.4005	0.3855	**0.3321**
		MAPE	88.37%	84.78%	81.15%	**76.41%**
		RMSE	0.3554	0.3314	0.3151	**0.2837**
		THEIL-U	0.7758	0.7525	0.7219	**0.6855**
	ITALY	MAE	0.3201	0.2906	0.2748	**0.2453**
		MAPE	69.90%	64.91%	62.55%	**57.85%**
		RMSE	0.2673	0.2313	0.2178	**0.1758**
		THEIL-U	0.6491	0.6246	0.6115	**0.5675**
	PORTUGAL	MAE	0.3681	0.3518	0.3243	**0.2958**
		MAPE	84.48%	80.23%	73.89%	**68.13%**
		RMSE	0.3214	0.3023	0.2871	**0.2744**
		THEIL-U	0.7055	0.6891	0.6627	**0.6218**
	SPAIN	MAE	0.3499	0.3144	0.2814	**0.2539**
		MAPE	74.54%	70.47%	68.28%	**61.53%**
		RMSE	0.3009	0.2883	0.2615	**0.2288**
		THEIL-U	0.6764	0.6407	0.6358	**0.5917**

Table 8-20: Out-of-Sample statistical performances for the unemployment exercise

The above summary suggests that RG-SVR retains its statistical superiority in all cases of the unemployment exercise, as in the inflation one. STAR continues to outperform the other two RW benchmarks. The analysis of the core countries reveals that the German unemployment forecasts are the most accurate statistically. The second best core results are given in the Belgian case. Regarding the periphery countries, the Italian unemployment seems the easiest to forecast, while the opposite applies in the Greek case. The Spanish analysis provides with the second lower statistic values from the rest of the periphery countries. In Portugal more accurate results are observed in comparison with Ireland. In general, core countries present constantly lower values than peripheral ones in all four statistics retained in this study. Finally, the model statistical ranking in the unemployment exercise is consistent with the inflation one.

The statistical evidence from both exercises lead to some interesting conclusions. The proposed RG-SVR statistically outperforms all benchmark models for all countries, regardless if CPI or UNEMP is under study. The STAR and AO-RW models are the second and third best models, leaving f-RW last in the statistical ranking. Hence, non-linear models with time-varying parameters are statistically more efficient from traditional random walk approaches. All the statistics indicate that core EMU inflation is always easier to forecast than the periphery one. Especially in the cases of Greece or Ireland this task is even more challenging. The RG-SVR statistical performance in Italy’s case is the only one that somewhat approaches the core countries’ performances. These results show that the previous selection process is promising. The periphery countries are those more affected by the Eurozone sovereign debt crisis, adopting vast austerity and economic reform measures through the period under study. It could be expected that the algorithm would perform poorly in those cases. The opposite, though, happens. RG-SVR adapts efficiently to the underlying market shocks in the periphery economy by accepting or rejecting several macroeconomic variables. This genetic mapping leads to improved periphery CPI and UNEMP forecasts compared to tradition models such as, f-RW, AO-RW and STAR.

8.6 Conclusions

The motivation of this chapter is to introduce a hybrid Rolling Genetic – Support Vector Regression (RG-SVR) model in economic forecasting and monthly optimal macroeconomic variable selection. The proposed algorithm is applied in a monthly rolling forecasting task of inflation and unemployment in eight EMU countries. The RG-SVR genetically optimizes the SVR parameters and adapts to the optimal feature subset from a feature space of potential inputs. The feature space includes a wide pool of macroeconomic variables that might affect the two series under study of every country. The forecasting performance of the RG-SVR is benchmarked with a 'fixed' Random Walk model (f-RW), an Atkeson and Ohanian Random Walk (AO-RW) and a Smooth Transition Autoregressive Model (STAR). More specifically, the statistical performance of all models is investigated over the period of August 1999 to April 2013.

In terms of the results, the proposed RG-SVR statistically outperforms all benchmark models for all countries in both exercises. The other non-linear model, the STAR, is always second in the statistical ranking. The RW models are less efficient in this application, but AO-RW always beats f-RW. The performance of the model is consistent in core and periphery cases, although core EMU inflation is proved easier to forecast than the periphery one. Hence, the rolling genetic SVR selection of the predictors is both computationally and statistically efficient. Every monthly forecast is obtained by maximum thirty autoregressive term of several predictors, which is a significant decrease from the total one hundred sixty eight available. From those the terms with order higher than six are rejected, while the first four autoregressive terms are usually more evident. Thus, the practitioner should focus on the past quarter, while information going back more than a semester seems irrelevant.

In general, this chapter sheds more light on the difficult quest of non-linear mapping of macroeconomic variables over different EMU countries. The rolling nature of both forecasting exercises establishes erratic patterns in the selected predictors. This proves that structural breaks dominate the Eurozone inflation and unemployment, making their prediction a very challenging task. Consequently, models with a constant or a limited set of independent variables are not efficient in the long-run. On the other hand, non-linear time-varying approaches like the proposed hybrid model can prove more efficient and realistic.

Chapter 9

General Conclusions

Nowadays, the necessity to perform human tasks with minimum cost and higher speed, along with the need to process voluminous data, justifies the expansion of computational intelligent models in various scientific fields, such as Finance. Adding to this the fact that financial forecasting is inherently connected with the high degree of uncertainty ruling the modern world, such adaptive techniques can be efficient alternatives to traditional models. In order to achieve that, computer engineers must put much effort into their proper financial task-specific calibration. Nonetheless, generalizing the performance of these models can be a 'wall' standing between their financial or economic interpretability and their statistical success. The scope of this thesis is to 'breach the wall' by combining the virtues of several computational intelligence models into superior hybrid architectures.

Chapter 4 -6 apply techniques, such as Neural Networks, Support Vector Regressions and Genetic Algorithms in exchange rate forecasting and trading exercises. Within this application framework, more specific contributions are made. Firstly, stochastic and genetic forecast combinations are found to be successful, adding to the existing literature of model selection and combination. Secondly, time-varying leverage strategies are found to cope with the instability deriving from economy shocks and prove their success in periods of market turmoil. Thirdly, architectures enabled with efficient recursive estimation power always outperform traditional models with fixed parameters. Finally, the empirical evidence prove that genetic tuning of the SVR parameters is successful. Therefore, hybrid models deriving from the previous techniques are robust in terms of statistical accuracy and trading efficiency.

The utility of these hybrid architectures is extended in macroeconomic forecasting in chapters 7 and 8. The genetic support vector regression hybrids are providing rolling robust estimations for inflationary and unemployment changes in US and EU, attempting to capture and assess their world-wide constantly changing dynamics. The proposed hybrid models feature several novelties in terms of their econometric and computational modelling, while their ability to adapt in set of relevant predictors of changing composition extends their realistic economic interpretability. Their genetic adaptive nature allows them to capture underlying asymmetries and nonlinearities evident in the given set of predictors, while the optimal feature selection (rolling or not) is extremely promising. The main reason for that is that the models are providing superior forecasts in periods of recessions (global financial crisis, Eurozone sovereign debt crisis) and win forecasting competitions with traditional linear models or architectures with fixed sets of explanatory variables. Hence, their introduction extends the voluminous literature, which suggests that non-linear time-varying approaches are more efficient and realistic in similar studies.

In general, this thesis addresses issues and provides extensions to the knowledge of the field of Finance. Although universal approximations can never been embraced in scientific research, the evidence of previous chapters have strong implications on decision making. Their impact on financial or economic decisions, especially, is greater within the context of structural instabilities, market shocks and non-linearities in the information extrapolated from large datasets. In addition, more light is shed in the demanding issue of achieving statistical and trading efficiency in the foreign exchange markets through computational intelligent models. Traders and hedge fund managers should experiment beyond the boundaries of traditional models. Their trading decisions should be based on forward-looking expectations from models and strategies that are optimized in a hybrid trading and statistical approach. Government, institutional and central banking policies can also be affected in the same context. All these parties do have constant interest in the monitoring of large numbers of variables that could affect the inflation or unemployment, and as a consequence the economy. The architectures proposed could be found particular useful in this monitor process, while their relevant indicator mapping ability could help with the realistic evaluation of implemented or future policies within a specific timeframe or geographical spectrum. Nonetheless, there are still many paths to be taken in the search of efficient calibration of computational intelligent models for financial and economic forecasting tasks.

Appendices

Appendix A (Chapter 3)

A.1 Kalman Filter and Smoothing Process

A generalized linear state space model of the *n*x*1* vector y_t is defined as:

$$y_t = c_t + Z_t a_t + \varepsilon_t, \ \varepsilon_t \sim NID\left(0, \sigma_\varepsilon^2\right) \tag{A.1}$$

$$a_{t+1} = d_t + T_t a_t + n_t, \ n_t \sim NID(0, \sigma_n^2) \tag{A.2}$$

In these equations, α_t is a *m*x1 vector of possible state variables and c_t, Z_t, d_t and T_t are conformable vectors and matrixes. The ε_t and n_t vectors are assumed to be serially independent, with contemporaneous variance structure:

$$\Omega_t = \text{var}_t \begin{bmatrix} \varepsilon_t \\ n_t \end{bmatrix} = \begin{bmatrix} H_t & G_t \\ G_t' & Q_t \end{bmatrix} \tag{A.3}$$

H_t is a *n*x*n* symmetric variance matrix, Q_t is a *m*x*m* symmetric variance matrix and G_t is a *n*x*m* matrix of covariances (Welch and Bishop, 2001).

Considering the conditional distribution of the state vector α_t, given information available at time *t-1*, the Kalman Filter can define the mean and variance matrix of the conditional distribution as:

$$a_{t|t-1} = E_{t-1}(a_t) \tag{A.4}$$

$$P_{t|t-1} = E_{t-1}[(a_t - a_{t|t-1})(a_t - a_{t|t-1})'] \tag{A.5}$$

Thus, the recursive algorithm of the Kalman filter calculates the following three:

1. The one-step ahead mean $\alpha_{t|t-1}$ and one-step ahead variance $P_{t|t-1}$ of the states. Under the Gaussian error assumption, $\alpha_{t|t-1}$ is the minimum mean square error estimator of α_t and $P_{t|t-1}$ is the mean square error (MSE) of $\alpha_{t|t-1}$.

2. The one-step ahead estimate of y_t as:

$$\hat{y}_t = y_{t|t-1} = \mathrm{E}_{t-1}(y_t) = E(y_t \mid a_{t|t-1}) = c_t + Z_t a_{t|t-1} \quad \text{(A.6)}$$

3. The one-step ahead prediction errors and their variances respectively as:

$$\hat{\varepsilon}_t = \varepsilon_{t|t-1} = y_t - \hat{y}_{t|t-1} \quad \text{(A.7)}$$

$$\hat{F}_t = F_{t|t-1} = \mathrm{var}(\varepsilon_{t|t-1}) = Z_t P_{t|t-1} Z_t' + H_t \quad \text{(A.8)}$$

In this case it is set $\hat{y}_0 = 0$ and P_0=1. If P_0 was also set equal to zero, that would mean that there is no noise, so all the estimates would be equal to the initial state. Then, the next step is to embody a smoothing algorithm to this process. The smoothing algorithm, which uses all the information observed, in other words the whole sample T, to form expectations at any period until T, is known as fixed-interval smoothing. In this way it is possible to estimate the smooth estimates of the states and the variances:

$$\hat{\alpha}_t = a_{t|T} = E_T(a_t) \quad \text{(A.9)}$$

$$V_t = \mathrm{var}_T(a_t) \quad \text{(A.10)}$$

Additionally, the smoothed estimates of y_t and their variances can be calculated based on equations A.6, A.7 and A.8 abovementioned, but also the smoothed estimates of the ε_t and n_t vectors and their corresponding smoothed variance matrix:

$$\hat{\varepsilon}_t = \varepsilon_{t|T} = E_T(\varepsilon_t) \quad \text{(A.11)}$$

$$\hat{n}_t = n_{t|T} = E_T(n_t) \quad \text{(A.12)}$$

$$\hat{\Omega}_t = \mathrm{var}_t \begin{bmatrix} \hat{\varepsilon}_t \\ \hat{n}_t \end{bmatrix} = \begin{bmatrix} \hat{H}_t & \hat{G}_t \\ \hat{G}_t' & \hat{Q}_t \end{bmatrix} \quad \text{(A.13)}$$

Appendix B (Chapter 4)

B.1 The ARMA model

Figure B-1 shows the output of the ARMA model selected. The null hypothesis that all the coefficients are not significantly different from zero is rejected at 95% confidence interval.

Dependent Variable: SAMPLE
Method: Least Squares
Date: 06/03/11 Time: 02:59
Sample (adjusted): 14 1781
Included observations: 1768 after adjustments
Convergence achieved after 47 iterations
MA Backcast: 1 13

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.028801	0.014372	2.004036	0.0452
AR(3)	-0.268915	0.089710	-2.997613	0.0028
AR(4)	0.602842	0.030519	19.75272	0.0000
AR(6)	-0.392114	0.033178	-11.81842	0.0000
AR(9)	-0.688370	0.069511	-9.903014	0.0000
AR(13)	0.364073	0.045366	8.025222	0.0000
MA(3)	0.263776	0.098488	2.678264	0.0075
MA(4)	-0.589976	0.033434	-17.64616	0.0000
MA(6)	0.391560	0.035648	10.98413	0.0000
MA(9)	0.622728	0.074974	8.305911	0.0000
MA(13)	-0.316544	0.049824	-6.353206	0.0000

R-squared	0.017546	Mean dependent var	0.028818
Adjusted R-squared	0.011955	S.D. dependent var	0.612764
S.E. of regression	0.609090	Akaike info criterion	1.852501
Sum squared resid	651.8306	Schwarz criterion	1.886581
Log likelihood	-1626.611	Hannan-Quinn criter.	1.865093
F-statistic	3.137972	Durbin-Watson stat	1.991296
Prob(F-statistic)	0.000549		

Inverted AR Roots	.92+.38i	.92-.38i	.80	.47-.81i
	.47+.81i	-.01+1.00i	-.01-1.00i	-.10-.82i
	-.10+.82i	-.76-.58i	-.76+.58i	-.92+.04i
	-.92-.04i			
	Estimated AR process is nonstationary			
Inverted MA Roots	.91-.38i	.91+.38i	.79	.47-.80i
	.47+.80i	-.01-1.00i	-.01+1.00i	-.10-.81i
	-.10+.81i	-.75+.57i	-.75-.57i	-.91+.05i
	-.91-.05i			

Figure B-1: The ARMA model detailed output

B.2 NNs' Training Characteristics

Table B-1 presents the characteristics of the neural networks with the best trading performance in the test sub-period which are used in the NN committees. The choice of these parameters is based on an extensive experimentation in the in-sample sub-period and on the relevant literature (Tenti (1996), Dunis and Chen (2005) and Ghazali *et al.* (2006)). For example for the number of iterations, the experimentation started from 10.000 iterations and stopped at the 200.000 iterations, increasing in each experiment the number of iterations by 5.000.

Parameters	**MLP**	**RNN**	**PSN**
Learning algorithm	Gradient descent	Gradient descent	Gradient descent
Learning rate	0.001	0.001	0.5
Momentum	0.003	0.004	0.5
Iteration steps	100000	60000	40000
Initialisation of weights	N(0,1)	N(0,1)	N(0,1)
Input nodes	9	9	9
Hidden nodes	7	5	4
Output node	1	1	1

Table B-1: The NNs' training characteristics

B.3 Bayesian Information Criteria

AIC measures the relative goodness of fit of a statistical model, as introduced by Akaike (1974). On the other hand, SIC (also known as BIC or SBIC (Schwarz, 1978)) is considered a criterion to select the best model among models with different numbers of parameters. If N is the sample size of the dataset, k the total number of parameters in the equation of interest and s^2 the maximum likelihood estimate of the error variance, then AIC and BIC are calculated as shown below :

$$\begin{Bmatrix} AIC = N\log(s^2) + 2k \\ SIC = N\log(s^2) + k\log(N) \end{Bmatrix} \quad \text{(B.1)}$$

Table B-2 describes the estimation of the Bayesian Information Criteria for the cases of MLP, RNN and PSN forecasts, based on the B.1 set of equations above:

	AIC	SIC	Δ_{AIC}	Δ_{SIC}	w_{AIC}	w_{SIC}
MLP	1.825879871	1.832039254	0.004476988	0.004476604	0.334209988	0.334210009
RNN	1.846203174	1.852362557	0.024800291	0.024799907	0.330831059	0.330831081
PSN	1.821402883	1.827562265	0	0	0.334958953	0.33495891

Table B-2: Calculation of weights for the AIC and SIC Bayesian Averaging model

B.4 The Statistical and Trading Performance Measures

The statistical and trading performance measures are calculated as shown in table B-3 and table B-4 respectively. These measures are used also for the purposes of next chapters.

STATISTICAL PERFOMANCE MEASURES	DESCRIPTION
Mean Absolute Error	$MAE = (\frac{1}{n})\sum_{\tau=t+1}^{t+n}\left\|\hat{Y}_\tau - Y_\tau\right\|$ *with* Y_τ *being the actual value and* $\hat{Y}_\tau$ *the forecasted value*
Mean Absolute Percentage Error	$MAPE = \frac{1}{n}\sum_{\tau=t+1}^{t+n}\left\|\frac{Y_\tau - \hat{Y}_\tau}{Y_\tau}\right\|$
Root Mean Squared Error	$RMSE = \sqrt{\frac{1}{n}\sum_{\tau=t+1}^{t+n}(\hat{Y}_\tau - Y_\tau)^2}$
Theil-U	$Theil-U = \frac{\sqrt{(\frac{1}{n}\sum_{\tau=t+1}^{t+n}(\hat{Y}_\tau - Y_\tau)^2}}{\sqrt{\frac{1}{n}\sum_{\tau=t+1}^{t+n}\hat{Y}_\tau^2} + \sqrt{\frac{1}{n}\sum_{\tau=t+1}^{t+n}Y_\tau^2}}$

Table B-3: Statistical Performance Measures and Calculation

TRADING PERFOMANCE MEASURES	DESCRIPTION
Annualised Return	$R^A = 252 * \frac{1}{N} * (\sum_{t=1}^{N} R_t)$ where R_t the daily return
Cumulative Return	$R^C = \sum_{t=1}^{N} R_t$
Annualised Volatility	$\sigma^A = \sqrt{252} * \sqrt{\frac{1}{N-1} * \sum_{t=1}^{N} (R_t - \overline{R})^2}$
Information Ratio	$SR = \frac{R^A}{\sigma^A}$
Maximum Drawdown	Maximum negative value of $\sum(R_t)$ over the period $MD = \underset{i=1,\cdots,t;t=1,\cdots,N}{Min} \left(\sum_{j=i}^{t} R_j \right)$

Table B-4: The Trading Performance Measures and Calculation

B.5 Diebold-Mariano Statistic for Predictive Accuracy

The Diebold-Mariano (1995) statistic tests the null hypothesis of equal predictive accuracy. If n is the sample size and $e^1{}_i$, $e^2{}_i$ (i=1,2…n) are the forecast errors of the two competing forecasts, then the loss functions are estimated as:

$$L_1^{MSE}(e_i^1) = (e_i^1)^2, L_2^{MSE}(e_i^2) = (e_i^2)^2 \tag{B.2}$$

$$L_1^{MAE}(e_i^1) = \left|e_i^1\right|, \ L_2^{MAE}(e_i^2) = \left|e_i^2\right| \tag{B.3}$$

The Diebold-Mariano statistic is based on the loss differentials:

$$d_i^{MSE} = L_1^{MSE}(e_i^1) - L_2^{MSE}(e_i^2) \tag{B.4}$$

$$d_i^{MAE} = L_1^{MAE}(e_i^1) - L_2^{MAE}(e_i^2) \tag{B.5}$$

The null hypotheses tested based on the s_{MSE} and s_{MAE} are:

- $H_0: \ E(d_i^{MSE}) = 0$ against the alternative $H_1: E(d_i^{MSE}) \neq 0$
- $H_0: \ E(d_i^{MAE}) = 0$ against the alternative $H_1: E(d_i^{MAE}) \neq 0$

The Diebold-Mariano test statistic s is estimated as:

$$S = \frac{\bar{d}_i}{\sqrt{\hat{V}(\bar{d}_i)}} \xrightarrow{d} N(0,1) \qquad \text{(B.6)}$$

where

$$V(\bar{d}_i) = n^{-1}\left[\hat{\gamma}_0 + 2\sum_{k=1}^{n-1}\hat{\gamma}_k\right] \text{ and } \gamma_k = n^{-1}\sum_{i=k+1}^{n}(d_i - \bar{d}_i)(d_{i-k} - \bar{d}_i) \qquad \text{(B.7)}$$

B.6 RiskMetrics Volatility Model

The RiskMetrics Volatility Model is a special case of the general Exponential Weighted Moving Average Model (EWMA). The EWMA suggests that the variance of a financial asset can be calculated using the formula:

$$\sigma_t^2 = \lambda\sigma_{t-1}^2 + (1-\lambda)r_{t-1}^2 \qquad \text{(B.8)}$$

where σ_{t-1}^2 is the EWMA variance at time *t-1*, r_{t-1}^2 the squared returns at time *t-1* and λ a weight between 0 and 1.

The RiskMetrics Volatility Model assumes that the weight λ=0.94. So in the case of this chapter, the daily volatility is estimated with the formula below:

$$RiskMetricsVol = \sqrt{0.94\sigma_{t-1}^2 + 0.06r_{t-1}^2} \qquad \text{(B.9)}$$

Appendix C (Chapter 5)

C.1 NNs' Training Characteristics and Inputs

Table C.1 summarizes the characteristics of the NNs with the best trading performance in the in-sample sub-period, which are used in the applied committees. The choice of these parameters is based on sensitivity tests in all in-sample sub-periods and on the relevant literature (Tenti (1996), Zhang *et al.* (1998), Dunis *et al.* (2011) and Ghazali *et al.* (2006)).

C.2 Genetic Programming Characteristics

Table C-3 presents the parameters selected in this GP application. These parameters are optimized in every exercise. Nonetheless, the final parameters remain the same regardless which out-of-sample is evaluated.

Parameters	MLP			RNN			PSN		
Exercise	F1	F2	F3	F1	F2	F3	F1	F2	F3
Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent
Learning rate	0.001	0.002	0.008	0.002	0.003	0.005	0.003	0.003	0.007
Momentum	0.003	0.004	0.009	0.004	0.004	0.007	0.005	0.005	0.009
Iteration steps	60000	80000	80000	75000	80000	90000	80000	65000	85000
Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)
Input nodes	8	9	7	9	9	7	8	8	7
Hidden nodes	6	7	6	5	6	6	4	6	6
Output node	1	1	1	1	1	1	1	1	1

Table C-1: The NNs training characteristics

MLP	**Lags***			**RNN**	**Lags**			**PSN**	**Lags**		
Explanatory Variables	**F1**	**F2**	**F3**	**Explanatory Variables**	**F1**	**F2**	**F3**	**Explanatory Variables**	**F1**	**F2**	**F3**
EUR/USD Exch. Rate	**1**	**1**	**1**	EUR/USD Exch. Rate	**1**	**1**	**2**	EUR/USD Exch. Rate	**1**	**3**	**1**
EUR/USD Exch. Rate	**3**	**4**	**2**	EUR/USD Exch. Rate	**2**	**3**	**3**	EUR/USD Exch. Rate	**4**	**4**	**2**
EUR/USD Exch. Rate	**5**	**5**	**5**	EUR/USD Exch. Rate	**3**	**5**	**6**	EUR/USD Exch. Rate	**7**	**5**	**5**
EUR/USD Exch. Rate	**9**	**6**	**8**	EUR/USD Exch. Rate	**6**	**7**	**8**	EUR/USD Exch. Rate	**8**	**7**	**6**
EUR/USD Exch. Rate	**10**	**7**	**9**	EUR/USD Exch. Rate	**9**	**11**	**11**	EUR/USD Exch. Rate	**9**	**9**	**8**
EUR/USD Exch. Rate	**11**	**8**	**12**	EUR/USD Exch. Rate	**10**	**12**	**-**	EUR/USD Exch. Rate	**-**	**10**	**11**
EUR/GBP Exch. Rate	**2**	**1**	**1**	EUR/GBP Exch. Rate	**1**	**1**	**2**	EUR/GBP Exch. Rate	**3**	**2**	**2**
EUR/GBP Exch. Rate	**4**	**3**	**-**	EUR/GBP Exch. Rate	**4**	**4**	**-**	EUR/JPY Exch. Rate	**4**	**1**	**-**
EUR/JPY Exch. Rate	**-**	**2**	**-**	EUR/JPY Exch. Rate	**1**	**3**	**2**	EUR/JPY Exch. Rate	**4**	**-**	**-**

**In this case the term 'Lag 1' means that today's closing price is used to forecast tomorrow's one. F1, F2 and F3 columns present the lags selected for every NN in each forecasting exercise.*

Table C-2: Explanatory variables for each NN

GENETIC PROGRAMMING PARAMETERS	
Population Size	250
Termination Criterion	90000
Max. tree depth	8
Function Set	+, -, *, /, ^, ^2, ^3, ^1/2, ^1/3, Exp, If, sin, cos, tan
Fitness evaluation function	Mean Squared Error
Tournament Size	**8**
Crossover trials	1
Mutation Probability	0.75

Table C-3: GP parameters' setting

Appendix D (Chapter 6)

D.1 Non-linear Models

This appendix section includes a brief description of the non-linear forecasting models that are included in the pool of potential inputs of the proposed GA-SVR algorithm of chapter 6.

D.1.1 Nearest Neighbours Algorithm (*k*-NN)

Nearest Neighbours is a nonlinear and non-parametric forecasting method. Its intuition is that pieces of time series in the past present patterns, resembling patterns of the future. This algorithm locates such patterns as 'nearest neighbours' using the Euclidean distance and then they are used to predict the future. It only uses local information to forecast and makes no attempt to fit a model to the whole time series at once.

The user defines parameters such as the number of neighbours K, the length of the nearest neighbour's pattern m and the weighting of final prices in a neighbour α. When α is greater than 1, a greater emphasis is given to similarity between the more recent observations. Guégan and Huck (2004) suggest that a good choice of the parameters K and m can be efficiently approximated based on the size of the information set. In their study the parameter m is chosen from the interval:

$$m = [R(ln(T)),\ R(ln(T)+2)] \tag{D.1}$$

where R is the rounding function, approximating the immediate lower figure and T the size of the dataset.

Guégan and Huck (2004) also approximate K by multiplying m with 2. For this dataset m lies between 8 and 10 and K lies between 16 and 20. Based on the above guidelines and Dunis and Nathani (2007), who apply Nearest Neighbours in financial series, I experiment in the in-sample dataset and select the set of parameters that provide the highest trading performance in the in-sample period. These sets of parameters for each exchange rate under study are presented in Table D-1 below.

	m	**K**	**a**
EUR/USD	8	17	1.3
EUR/GBP	8	17	1
EUR/JPY	9	19	1.1

Table D-1: Nearest Neighbours Algorithm Parameters

D.1.2 Neural Networks

In this application, the feature space includes the forecasts of MLP, RNN, PSN and HONN. The specifications of the first three are given in detail in chapter 3. HONN is a primitive architecture to the PSN and its specification can be found in Dunis *et al.* (2010 and 2011) and Sermpinis *et al.* (2012a).

Concerning the inputs of the NN models, in the absence of any formal theory behind their selection, the trading sensitivity analysis is used as explained in chapters 4 and 5. The different set of inputs of the four NNs is presented in table D-2 below for the three series under study.

	MLP	RNN	HONN	PSN
EUR/USD	EUR/USD (1)*	EUR/USD (3)	EUR/USD (2)	EUR/USD (1)
	EUR/USD (2)	EUR/USD (5)	EUR/USD (6)	EUR/USD (5)
	EUR/USD (5)	EUR/USD (6)	EUR/USD (7)	EUR/USD (6)
	EUR/USD (6)	EUR/USD (8)	EUR/USD (9)	EUR/USD (8)
	EUR/USD (8)	EUR/USD (10)	EUR/USD (10)	EUR/USD (11)
	EUR/USD (10)	EUR/USD (11)	EUR/USD (12)	EUR/USD (12)
	EUR/USD (11)	EUR/USD (12)	EUR/GBP (3)	EUR/GBP (1)
	EUR/GBP (1)	EUR/GBP (5)	EUR/GBP (5)	EUR/GBP (3)
	EUR/GBP (7)	EUR/GBP (7)	EUR/JPY (4)	EUR/GBP (4)
	EUR/JPY (2)	EUR/JPY (1)	EUR/JPY (7)	EUR/JPY (4)
EUR/GBP	EUR/USD (2)	EUR/USD (1)	EUR/USD (4)	EUR/USD (3)
	EUR/USD (3)	EUR/USD (2)	EUR/USD (5)	EUR/USD (4)
	EUR/USD (5)	EUR/USD (5)	EUR/USD (7)	EUR/USD (6)
	EUR/USD (7)	EUR/USD (9)	EUR/USD (8)	EUR/USD (7)
	EUR/USD (8)	EUR/USD (10)	EUR/USD (11)	EUR/USD (10)
	EUR/USD (10)	EUR/USD (12)	EUR/USD (12)	EUR/USD (11)
	EUR/GBP (1)	EUR/GBP (5)	EUR/GBP (1)	EUR/USD (15)
	EUR/GBP (5)	EUR/GBP (6)	EUR/GBP (3)	EUR/GBP (3)
	EUR/JPY (4)	EUR/GBP (8)	EUR/JPY (2)	EUR/GBP (5)
	EUR/JPY (5)	EUR/JPY (6)	EUR/JPY (4)	EUR/JPY (4)
EUR/JPY	EUR/USD (1)	EUR/USD (2)	EUR/USD (1)	EUR/USD (3)
	EUR/USD (2)	EUR/USD (5)	EUR/USD (2)	EUR/USD (6)
	EUR/USD (5)	EUR/USD (6)	EUR/USD (4)	EUR/USD (7)
	EUR/USD (8)	EUR/USD (7)	EUR/USD (7)	EUR/USD (9)
	EUR/USD (9)	EUR/USD (10)	EUR/USD (8)	EUR/USD (10)
	EUR/USD (12)	EUR/USD (11)	EUR/USD (9)	EUR/USD (12)
	EUR/GBP (3)	EUR/GBP (2)	EUR/GBP (2)	EUR/GBP (1)
	EUR/GBP (4)	EUR/GBP (3)	EUR/GBP (4)	EUR/GBP (4)
	EUR/JPY (2)	EUR/GBP (7)	EUR/GBP (5)	EUR/JPY (6)
	EUR/JPY (2)	EUR/JPY (5)	EUR/JPY (1)	EUR/JPY (7)

**EUR/USD (1) means that as input is used the EUR/USD exchange rate lagged by one day. Thus, today's closing price is used to forecast the tomorrow's one.*

Table D-2: Neural Network Inputs

The following table summarizes the design and training characteristics of all the above NN architectures.

	PARAMETERS	MLP	RNN	HONN	PSN
EUR/USD	Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent
	Learning rate	0.004	0.002	0.4	0.3
	Momentum	0.005	0.003	0.5	0.4
	Iteration steps	40000	30000	20000	20000
	Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)
	Input nodes	10	8	10	7
	Hidden nodes	8	7	5	12
	Output node	1	1	1	1
EUR/GBP	Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent
	Learning rate	0.002	0.003	0.5	0.4
	Momentum	0.004	0.005	0.5	0.5
	Iteration steps	35000	30000	30000	30000
	Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)
	Input nodes	8	8	9	8
	Hidden nodes	9	7	5	9
	Output node	1	1	1	1
EUR/JPY	Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent
	Learning rate	0.003	0.003	0.5	0.3
	Momentum	0.005	0.005	0.5	0.4
	Iteration steps	45000	35000	30000	20000
	Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)
	Input nodes	10	9	8	9
	Hidden nodes	13	11	6	10
	Output node	1	1	1	1

Table D-3: Neural Network Design and Training Characteristics

The fitness function used in the training of these NNs is the one presented in chapter 5. The reason for that is that in this way the individual NN forecasts are derived under the same context of fitness of the GA-SVR.

Appendix E (Chapter 7)

E.1 Technical Characteristics of NN's and GP

This appendix section includes the technical characteristics of the computational models used as benchmarks in this application. The parameter setting of the GP follows in table E-1. In table E-2 I present the design and training characteristics of the NNs for each period. The selection of the NN's inputs is based on a sensitivity analysis on the in-sample period. Similarly to previous chapters, the in-sample period is divided into two sub-periods, the training and the test sub-periods. The test sub-period is consisted by the last four years of the in-sample. I experiment with the characteristics and inputs of the NNs in the training sub-period and only architectures that provided the best statistical performance in the test sub-period are retained. No part of the out-of-sample period is involved in the NN parameterization in any forecasting exercise. This approach is common in NN modelling and avoids problems such as the over-fitting and the data-snooping (Lisboa and Vellido (2000) and Zhang (2009)).

GENETIC PROGRAMMING PARAMETERS			
Population Size	200	**Fitness evaluation function**	MSE
Termination Criterion	75000	**Tournament Size**	20
Max. tree depth	12	**Crossover trials**	1
Function Set	+, -, *, /, ^, ^2, ^3, ^1/2, ^1/3, Exp, If, sin, cos, tan	**Mutation Probability**	0.8

Table E-1: GP parameters setting

	PARAMETERS	**01/1974 – 12/2000**		**01/1978 – 12/2004**		**01/1982-12/2008**		**01/1986/12/2012**	
		MLP	**RNN**	**MLP**	**RNN**	**MLP**	**RNN**	**MLP**	**RNN**
CPI	Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent
	Learning rate	0.003	0.002	0.005	0.002	0.004	0.003	0.002	0.002
	Momentum	0.004	0.003	0.006	0.003	0.005	0.005	0.004	0.003
	Iteration steps	50000	45000	50000	40000	35000	25000	60000	40000
	Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)
	Input nodes	9	7	8	7	7	7	9	8
	Hidden nodes	6	5	6	6	4	3	5	6
	Output node	1	1	1	1	1	1	1	1
UNEMP	Learning algorithm	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent	Gradient descent
	Learning rate	0.002	0.003	0.002	0.002	0.004	0.002	0.003	0.002
	Momentum	0.005	0.005	0.004	0.003	0.006	0.005	0.005	0.004
	Iteration steps	35000	30000	35000	30000	35000	30000	35000	30000
	Initialisation of weights	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)	N(0,1)
	Input nodes	7	6	8	6	9	6	8	7
	Hidden nodes	6	4	5	5	7	3	4	4
	Output node	1	1	1	1	1	1	1	1

Table E-2: Neural Network Design and Training Characteristics for all periods under study

Appendix F (Chapter 8)

F.1 Highlighted Months and Related Information

Table F-1 gives a summary of the related EMU policy decisions, political events, news and reports for seven months. These months are highlighted in all the tables, presenting the selection of the relevant predictors.

F.2 Optimized Parameters

Tables F-2 to F-9 summarize the monthly optimized parameters, as selected by RG-SVR for every forecasting exercise, per country and month.

MONTHS	INFORMATION
May 2010	• Huge Greek protests against unprecedented austerity cuts needed for an EU and IMF loans worth as much as €120bn (1st May) • EU ministers agree €500bn fund to save euro from disaster (10th May) • Spain's credit rating downgraded by Ratings agency Fitch, saying austerity measures will affect growth (28th May)
September 2010	• Speculation that Greece's exit from Eurozone is eminent (5th September) • Ireland's economic recovery stalls as figures reveal national output dropped by 1.2% in the second quarter of 2010 (23rd September) • Demonstrations planned in Brussels and dozens of European cities against austerity measures (29th September) • Spain loses top credit rating (30th September)
April 2011	• Portugal's Prime Minister makes last resort plea for a rescue package could total €80bn (7th April)
September 2011	• Ireland gets £1.2bn IMF payout (3rd September) • Italy approves €54bn austerity package (14th September) • Europe's debt crisis prompts central banks to provide dollar liquidity (15th September)
February 2012	• Greece approves extra austerity cuts to secure Eurozone bailout and avoid debt default (13rd February) • Eurozone economy shrinks for first time since 2009 (15th February) • Dow passes 13,000 before quickly dropping back, as Greek bailout package and strong corporate earnings boost US stocks (21st February)
July 2012	• Cyprus becomes fifth Eurozone country to ask for outside financial help after it is caught in backwash of Greek crisis (1st July) • Ireland returns to the debt markets with €500m sale of treasury bills (5th July) • Spanish Prime Minister announces €65bn in austerity measures for Spain (11th July) • Spain in crisis talks with Germany over €300bn bailout (23rd July) • Troika heightens fears of Greek exit from Euro (25th July)
February 2013	• France could join list of Eurozone 'casualties' in a fresh crisis (1st February) • Cyprus faces bailout row over fears of 'haircuts' for investors and savers (3rd February) • European Union leaders agree €34.4bn cut over next seven years after all-night discussions (8th February) • Eurozone recession to continue, European commission backtracks on previous forecasts (22nd February) • US stock markets drop as Italy election reignites fears of Europe debt crisis (25th February) • Spain falls further into recession as GDP plunges by 0.8% (28th February)

Note: The source of the above information is the on-line interactive application of The Guardian: Eurozone Crisis, a timeline of key events (www.theguardian.com).

Table F-1: Highlighted Months and Related Information

BELGIUM	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	779.76	0.01	0.80	390.58	0.52	0.65
Feb-10	307.07	8.47	0.86	889.47	0.22	0.54
Mar-10	423.96	0.03	0.41	1000.47	0.53	0.80
Apr-10	872.43	3.41	0.32	69.85	0.34	0.51
May-10	623.26	0.01	0.63	738.33	0.23	0.79
Jun-10	245.69	0.30	0.80	849.46	0.32	0.23
Jul-10	864.90	9.46	0.96	81.53	0.44	0.44
Aug-10	866.83	14.46	0.72	281.19	0.59	0.39
Sep-10	557.26	9.06	0.91	971.92	0.38	0.61
Oct-10	953.08	14.55	0.14	955.78	0.70	0.25
Nov-10	797.27	4.27	0.77	129.67	0.62	0.05
Dec-10	575.47	9.91	0.76	594.47	0.30	0.38
Jan-11	949.26	5.45	0.72	181.96	1.80	0.17
Feb-11	770.23	3.51	0.45	837.13	1.40	0.45
Mar-11	113.22	0.83	0.34	104.89	0.57	0.25
Apr-11	507.38	13.54	0.32	164.04	9.64	0.32
May-11	818.80	12.75	0.42	417.36	6.70	0.45
Jun-11	685.97	10.77	0.59	46.37	0.33	0.31
Jul-11	739.34	13.88	0.03	620.31	13.78	0.27
Aug-11	368.88	7.72	0.67	761.54	14.44	0.65
Sep-11	664.10	14.43	0.10	612.75	0.49	0.81
Oct-11	1007.44	14.54	0.07	36.05	5.34	0.34
Nov-11	429.72	8.09	0.91	830.64	8.70	0.40
Dec-11	501.86	3.18	0.14	180.91	8.60	0.74
Jan-12	590.82	5.35	0.58	917.19	8.09	0.02
Feb-12	309.54	8.61	0.10	830.25	15.03	0.51
Mar-12	188.92	7.56	0.61	421.79	10.70	0.10
Apr-12	837.63	6.79	0.68	868.29	14.19	0.29
May-12	0.53	7.63	0.27	788.23	13.92	0.06
Jun-12	216.09	4.41	0.41	123.54	3.81	0.94
Jul-12	644.96	2.00	0.07	909.31	0.72	0.74
Aug-12	390.86	11.34	0.92	352.45	2.39	0.58
Sep-12	86.62	4.36	0.30	601.62	15.28	0.93
Oct-12	0.55	2.56	0.22	561.80	9.75	0.95
Nov-12	183.11	2.39	0.74	691.61	12.58	0.45
Dec-12	363.66	15.84	0.08	676.07	3.48	0.46
Jan-13	824.17	0.32	0.34	232.82	1.67	0.18
Feb-13	807.50	3.38	0.50	828.24	5.35	0.87
Mar-13	969.81	7.58	0.12	469.51	7.65	0.98
Apr-13	179.92	0.56	0.66	161.13	8.90	0.29

Table F-2: Optimized SVR parameters for Belgium

FRANCE	CPI			UNEMP		
	C	*γ*	***v***	***C***	*γ*	***v***
Jan-10	4.50	263.85	0.27	794.06	0.24	0.88
Feb-10	0.05	552.48	0.66	514.38	0.13	0.06
Mar-10	5.10	836.05	0.55	192.33	0.17	0.38
Apr-10	12.14	563.57	0.04	1010.71	14.39	0.97
May-10	10.37	916.63	0.99	227.31	0.04	0.11
Jun-10	8.25	582.28	0.49	383.14	0.05	0.91
Jul-10	2.96	796.07	0.56	621.30	0.14	0.62
Aug-10	0.03	160.00	0.81	92.49	0.12	0.74
Sep-10	15.61	336.05	0.07	488.77	0.09	0.60
Oct-10	0.28	57.78	0.69	91.11	0.10	0.56
Nov-10	1.46	813.21	0.49	405.98	0.07	0.05
Dec-10	0.27	899.92	0.68	153.57	0.17	0.08
Jan-11	0.35	723.84	0.34	985.53	0.17	0.94
Feb-11	1.24	931.64	0.19	1000.78	0.19	0.58
Mar-11	0.22	98.52	0.85	742.04	0.27	0.27
Apr-11	14.81	358.17	0.89	6.35	0.01	0.25
May-11	0.25	69.17	0.81	3.68	0.02	0.57
Jun-11	0.16	275.51	0.93	440.52	0.25	0.86
Jul-11	0.64	688.28	0.23	153.65	0.13	0.92
Aug-11	0.36	121.26	0.55	214.52	0.27	0.97
Sep-11	0.26	415.22	0.15	420.23	0.16	0.87
Oct-11	0.16	247.99	0.25	478.71	0.15	0.67
Nov-11	0.14	130.50	0.77	582.79	0.13	0.64
Dec-11	2.45	487.60	0.89	195.15	0.10	0.73
Jan-12	13.50	539.67	0.58	2.50	0.04	0.43
Feb-12	11.30	102.62	0.05	201.02	9.16	0.51
Mar-12	5.18	409.29	0.75	20.95	0.51	0.93
Apr-12	10.46	771.30	0.77	544.99	0.57	0.60
May-12	2.63	400.92	0.26	1012.69	15.64	0.16
Jun-12	7.73	131.14	0.19	780.22	11.50	0.55
Jul-12	6.89	84.43	0.63	702.37	6.94	0.75
Aug-12	5.30	215.19	0.30	184.52	0.90	0.35
Sep-12	7.81	339.25	0.31	286.25	11.15	0.81
Oct-12	15.83	38.16	0.08	672.15	2.53	0.90
Nov-12	11.01	520.26	0.57	78.65	1.71	0.09
Dec-12	0.29	984.67	0.92	383.44	8.21	0.18
Jan-13	0.39	157.85	0.63	747.46	1.88	0.09
Feb-13	0.31	429.44	0.03	107.52	2.48	0.97
Mar-13	0.35	532.97	0.71	952.93	3.00	0.45
Apr-13	0.87	517.95	0.82	813.18	2.49	0.04

Table F-3: Optimized SVR parameters for France

GERMANY	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	757.03	14.73	0.20	397.31	0.50	0.21
Feb-10	793.43	7.13	0.77	493.34	0.32	0.19
Mar-10	96.33	12.82	0.92	657.77	1.87	0.93
Apr-10	936.76	2.71	0.90	513.34	1.01	0.87
May-10	182.74	15.38	0.60	690.10	1.56	0.68
Jun-10	400.34	2.35	0.72	569.17	1.55	0.47
Jul-10	465.09	8.33	0.15	1003.05	2.41	0.15
Aug-10	994.49	6.85	0.46	314.56	8.18	0.94
Sep-10	69.02	9.59	0.64	798.20	0.98	0.56
Oct-10	923.67	7.37	0.43	37.01	3.84	0.09
Nov-10	279.02	14.18	0.20	723.22	8.06	0.80
Dec-10	309.83	10.99	0.09	137.43	6.67	0.13
Jan-11	585.79	0.34	0.87	404.39	6.73	0.02
Feb-11	55.71	0.15	0.01	414.04	4.46	0.92
Mar-11	241.24	0.32	0.74	96.65	4.35	0.91
Apr-11	590.57	0.09	0.95	921.75	11.29	0.49
May-11	442.78	12.42	0.22	842.79	7.66	0.88
Jun-11	792.67	6.22	0.34	707.39	7.70	0.21
Jul-11	114.70	0.00	0.23	974.66	5.68	0.91
Aug-11	270.62	0.08	0.94	157.32	10.67	0.13
Sep-11	734.75	13.96	0.93	849.16	2.52	0.76
Oct-11	398.06	0.32	0.49	287.86	10.26	0.57
Nov-11	1011.84	0.13	0.64	673.25	0.58	0.56
Dec-11	886.43	12.43	0.65	97.55	7.55	0.74
Jan-12	850.50	11.09	0.09	919.37	0.57	0.52
Feb-12	163.23	11.05	0.15	70.27	8.38	0.34
Mar-12	1003.09	14.88	0.90	585.15	1.07	0.15
Apr-12	215.39	1.94	0.52	524.49	12.43	0.41
May-12	851.42	6.53	0.27	440.99	6.42	0.57
Jun-12	204.63	12.09	0.05	652.30	0.25	0.67
Jul-12	466.95	7.38	0.69	185.05	7.65	0.64
Aug-12	220.31	7.80	0.27	69.24	9.59	0.45
Sep-12	43.59	6.50	0.94	427.42	9.03	0.99
Oct-12	732.46	0.25	0.80	953.86	9.56	0.63
Nov-12	299.66	14.71	0.59	720.43	10.88	0.90
Dec-12	313.74	0.34	0.52	31.76	8.62	0.25
Jan-13	413.53	1.97	0.23	449.61	7.59	0.92
Feb-13	643.27	4.41	0.61	763.50	6.75	0.39
Mar-13	103.40	1.20	0.07	12.65	5.01	0.13
Apr-13	300.68	0.41	0.97	5.41	2.15	0.82

Table F-4: Optimized SVR parameters for Germany

GREECE	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	156.66	5.01	0.35	803.04	6.04	0.31
Feb-10	179.10	11.16	0.07	436.62	0.47	0.04
Mar-10	85.01	1.04	0.15	443.55	6.63	0.78
Apr-10	98.34	12.02	0.27	996.35	8.34	0.22
May-10	109.38	16.01	0.86	321.83	6.49	0.51
Jun-10	198.15	9.23	0.52	435.08	9.37	0.38
Jul-10	880.52	3.86	0.42	541.89	13.03	0.41
Aug-10	318.95	13.99	0.65	217.01	8.84	0.74
Sep-10	827.25	4.15	0.18	171.27	0.49	0.71
Oct-10	605.18	9.83	0.07	828.29	8.99	0.95
Nov-10	403.35	6.01	0.40	459.04	20.05	0.20
Dec-10	155.99	6.62	0.07	58.69	15.06	0.03
Jan-11	255.18	10.54	0.58	525.58	5.07	0.02
Feb-11	528.03	3.68	0.36	215.75	1.05	0.36
Mar-11	686.51	9.17	0.60	892.95	0.76	0.83
Apr-11	264.60	13.09	0.73	209.78	8.57	0.53
May-11	971.18	1.08	0.08	461.77	0.06	0.11
Jun-11	167.84	12.04	0.60	550.36	5.59	0.18
Jul-11	175.97	9.01	0.09	480.28	0.06	0.16
Aug-11	320.85	12.92	0.83	542.78	3.60	0.82
Sep-11	609.85	1.78	0.13	930.40	17.08	0.20
Oct-11	117.82	13.40	0.39	386.07	10.06	0.56
Nov-11	369.28	9.89	0.43	659.03	8.17	0.09
Dec-11	589.70	9.49	0.43	871.79	4.97	0.37
Jan-12	875.25	8.69	0.65	801.76	2.07	0.65
Feb-12	777.68	9.57	0.34	525.18	8.09	0.94
Mar-12	12.61	1.98	0.16	608.23	7.01	0.61
Apr-12	952.96	13.12	0.95	706.87	7.15	0.28
May-12	329.39	12.30	0.10	228.15	11.14	0.79
Jun-12	665.21	10.16	0.37	874.67	9.63	0.15
Jul-12	715.65	5.32	0.19	256.39	11.13	0.97
Aug-12	142.96	8.43	0.15	128.97	24.51	0.48
Sep-12	722.84	0.75	0.85	847.67	9.21	0.77
Oct-12	100.39	5.87	0.54	381.49	11.03	0.31
Nov-12	138.23	9.90	0.45	714.79	15.78	0.64
Dec-12	385.71	14.94	0.98	659.71	7.98	0.87
Jan-13	955.00	1.02	0.57	731.86	4.08	0.83
Feb-13	194.06	12.49	0.83	234.44	14.14	0.42
Mar-13	249.93	5.43	0.86	853.04	6.18	0.77
Apr-13	534.15	3.73	0.76	544.09	14.16	0.24

Table F-5: Optimized SVR parameters for Greece

IRELAND	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	162.70	0.14	0.70	744.65	3.58	0.79
Feb-10	234.31	0.07	0.43	900.94	4.28	0.84
Mar-10	648.37	0.28	0.53	499.86	8.07	0.25
Apr-10	625.21	0.07	0.48	473.20	1.88	0.65
May-10	596.93	0.06	0.44	547.30	15.14	0.26
Jun-10	255.50	0.07	0.86	991.76	1.55	0.30
Jul-10	955.89	0.09	0.92	439.58	2.44	0.24
Aug-10	513.59	0.14	0.01	626.04	5.81	0.39
Sep-10	376.94	0.06	0.34	743.98	4.12	0.41
Oct-10	850.17	0.13	0.20	566.87	3.03	0.15
Nov-10	133.72	0.25	0.85	620.65	4.97	0.74
Dec-10	987.09	0.16	0.09	817.56	6.22	0.32
Jan-11	381.87	0.13	0.70	798.26	5.13	0.99
Feb-11	749.22	0.13	0.94	928.93	4.66	0.53
Mar-11	76.92	0.26	0.89	529.13	9.10	0.40
Apr-11	443.39	0.32	0.89	74.37	1.07	0.68
May-11	324.90	0.15	0.01	502.73	10.67	0.79
Jun-11	69.31	0.15	0.53	800.59	10.79	0.34
Jul-11	62.66	0.23	0.42	858.52	5.06	0.96
Aug-11	784.43	0.14	0.92	554.94	3.32	0.43
Sep-11	263.96	0.10	0.20	855.55	0.05	0.37
Oct-11	745.55	0.07	0.29	375.45	1.08	0.44
Nov-11	751.66	0.03	0.85	90.66	5.16	0.60
Dec-11	537.78	0.15	0.03	873.49	0.07	0.10
Jan-12	494.96	0.15	0.84	745.52	0.06	0.70
Feb-12	687.53	0.09	0.90	377.68	0.03	0.25
Mar-12	638.68	0.14	0.47	830.30	0.11	0.90
Apr-12	889.14	0.13	0.11	373.44	0.07	0.09
May-12	467.79	0.13	0.77	981.59	6.10	0.95
Jun-12	774.98	0.13	0.20	980.45	8.75	0.68
Jul-12	578.16	0.13	0.36	663.22	6.34	0.38
Aug-12	84.82	0.28	0.34	622.58	9.26	0.04
Sep-12	657.47	0.15	0.61	545.00	11.71	0.16
Oct-12	322.28	0.12	0.77	467.37	15.79	0.79
Nov-12	337.59	0.12	0.01	172.40	9.55	0.50
Dec-12	118.09	0.10	0.34	1016.05	12.33	0.31
Jan-13	950.70	0.13	0.52	226.29	3.97	0.91
Feb-13	569.21	0.26	0.16	627.47	10.44	0.36
Mar-13	296.46	0.05	0.86	54.66	7.89	0.46
Apr-13	13.40	0.13	0.76	546.73	14.36	0.95

Table F-6: Optimized SVR parameters for Ireland

ITALY	CPI			UNEMP		
	C	*γ*	*ν*	*C*	*γ*	*ν*
Jan-10	842.21	12.50	0.62	579.48	0.08	0.98
Feb-10	399.82	7.78	0.33	846.46	13.63	0.21
Mar-10	635.64	5.61	0.66	100.62	8.93	0.45
Apr-10	167.21	10.61	0.75	445.01	14.17	0.59
May-10	239.50	10.34	0.44	520.52	0.19	0.99
Jun-10	341.66	7.96	0.40	151.18	5.56	0.42
Jul-10	163.41	8.97	0.50	589.69	1.74	0.05
Aug-10	345.02	5.48	0.66	66.10	0.42	0.62
Sep-10	924.00	1.84	0.75	985.74	13.16	0.62
Oct-10	948.88	15.46	0.53	466.34	7.80	0.81
Nov-10	568.30	4.96	0.52	872.09	0.51	0.84
Dec-10	707.46	0.51	0.13	250.65	7.48	0.13
Jan-11	923.14	7.52	0.35	952.98	0.14	0.28
Feb-11	341.32	8.14	0.02	333.40	0.17	0.18
Mar-11	858.11	0.12	0.97	598.61	0.50	0.41
Apr-11	606.55	11.40	0.56	726.35	0.25	0.43
May-11	788.36	0.11	0.84	283.88	0.16	0.86
Jun-11	695.69	14.52	0.77	865.10	0.18	0.17
Jul-11	596.43	4.83	0.19	834.61	0.35	0.23
Aug-11	837.30	11.65	0.37	708.28	0.06	0.85
Sep-11	241.01	8.91	0.20	921.19	0.13	0.62
Oct-11	602.63	3.90	0.37	880.42	0.21	1.00
Nov-11	735.72	5.08	0.22	636.05	0.17	0.05
Dec-11	54.96	0.15	0.42	701.73	0.14	0.08
Jan-12	416.03	0.42	0.03	586.34	0.15	0.90
Feb-12	941.29	0.11	0.68	448.80	0.38	0.51
Mar-12	55.83	0.28	0.70	154.45	0.08	0.42
Apr-12	645.25	0.09	0.29	100.89	0.13	0.05
May-12	456.12	0.26	0.57	95.65	8.94	0.29
Jun-12	976.26	0.27	0.55	381.27	0.25	0.34
Jul-12	630.70	0.07	0.30	133.93	0.16	0.94
Aug-12	397.30	0.04	0.95	633.81	0.21	0.03
Sep-12	60.50	0.13	0.66	991.02	0.29	0.02
Oct-12	507.84	0.27	0.59	698.25	0.30	0.21
Nov-12	679.07	0.18	0.34	757.17	0.21	0.33
Dec-12	870.48	0.03	0.26	548.83	0.27	0.94
Jan-13	344.59	0.11	0.17	110.33	0.07	0.54
Feb-13	824.27	0.12	0.64	201.57	3.42	0.74
Mar-13	767.11	14.31	0.17	553.79	7.44	0.15
Apr-13	512.56	0.24	0.92	58.37	0.17	0.41

Table F-7: Optimized SVR parameters for Italy

PORTUGAL	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	692.40	8.56	0.35	712.64	0.18	0.22
Feb-10	115.90	4.40	0.62	380.33	10.07	0.07
Mar-10	727.53	13.18	0.07	39.93	0.00	0.56
Apr-10	227.33	3.57	0.15	597.17	0.09	0.24
May-10	244.70	12.00	0.12	893.72	0.15	0.21
Jun-10	795.69	1.80	0.62	992.96	0.05	0.53
Jul-10	749.80	9.42	0.26	493.54	0.17	0.70
Aug-10	909.46	11.23	0.13	733.11	0.24	0.88
Sep-10	496.39	15.59	0.87	909.26	14.41	0.07
Oct-10	71.52	10.01	0.40	539.63	0.25	0.29
Nov-10	496.19	0.26	0.56	993.17	0.15	0.84
Dec-10	284.47	15.96	0.16	23.05	0.26	0.95
Jan-11	87.59	14.63	0.66	44.48	0.21	0.49
Feb-11	755.50	13.60	0.40	900.44	0.16	0.24
Mar-11	816.00	9.71	0.64	856.34	0.11	0.93
Apr-11	981.18	1.62	0.74	865.71	0.18	0.63
May-11	647.13	9.44	0.83	856.96	0.21	0.79
Jun-11	652.82	1.68	0.02	170.62	0.19	0.87
Jul-11	266.64	0.13	0.46	264.40	0.18	0.76
Aug-11	914.72	2.52	0.21	898.38	0.15	0.81
Sep-11	581.80	13.82	0.91	876.80	0.26	0.38
Oct-11	738.02	2.65	0.01	279.03	0.21	0.15
Nov-11	360.38	0.27	0.65	735.47	0.08	0.63
Dec-11	203.30	4.43	0.70	641.58	0.15	0.71
Jan-12	3.16	2.64	0.24	854.50	0.11	0.32
Feb-12	327.01	15.87	0.70	7.30	0.06	0.80
Mar-12	912.23	14.83	0.91	133.13	0.13	0.89
Apr-12	537.21	10.08	0.39	399.11	0.18	0.46
May-12	50.59	10.59	0.69	474.12	0.16	0.08
Jun-12	311.92	11.19	0.71	216.01	0.21	0.68
Jul-12	153.68	4.22	0.81	365.97	0.13	0.33
Aug-12	9.46	4.87	0.19	917.25	0.25	0.53
Sep-12	332.05	14.83	0.51	619.59	0.22	0.23
Oct-12	421.55	12.57	0.67	324.12	0.27	0.02
Nov-12	263.67	13.65	0.35	814.90	0.20	0.78
Dec-12	444.28	0.21	0.58	391.17	0.17	0.41
Jan-13	404.50	1.06	0.84	700.79	0.19	0.05
Feb-13	568.78	0.76	0.78	53.73	0.18	0.32
Mar-13	108.28	11.33	0.29	667.96	0.06	0.01
Apr-13	458.77	4.01	0.73	1000.30	0.30	0.42

Table F-8: Optimized SVR parameters for Portugal

SPAIN	CPI			UNEMP		
	C	***γ***	***v***	***C***	***γ***	***v***
Jan-10	276.35	6.80	0.17	463.48	0.49	0.64
Feb-10	29.00	0.09	0.71	777.71	1.46	0.28
Mar-10	919.36	3.84	0.97	627.44	0.88	0.52
Apr-10	768.65	6.53	0.86	727.94	0.49	0.78
May-10	898.11	12.84	0.33	467.27	0.39	0.01
Jun-10	543.76	14.91	0.28	793.96	6.41	0.35
Jul-10	656.04	3.51	0.01	49.24	6.19	0.51
Aug-10	106.33	1.00	0.44	876.70	8.95	0.71
Sep-10	717.35	0.39	0.25	501.07	0.39	0.19
Oct-10	960.08	4.23	0.13	583.59	0.39	0.07
Nov-10	922.19	7.69	0.57	942.23	0.78	0.15
Dec-10	568.78	7.34	0.55	634.74	0.29	0.55
Jan-11	270.50	7.60	0.03	827.66	0.68	0.49
Feb-11	390.15	2.13	0.57	858.39	1.86	0.32
Mar-11	492.03	0.84	0.02	835.86	0.88	0.83
Apr-11	396.36	4.80	0.01	920.81	0.39	0.57
May-11	358.94	12.20	0.15	294.50	2.05	0.11
Jun-11	209.76	5.06	0.56	858.22	1.76	0.01
Jul-11	690.68	0.13	0.37	995.26	3.22	0.70
Aug-11	932.10	0.10	0.18	721.95	1.66	0.72
Sep-11	746.58	5.41	0.14	509.96	3.71	0.88
Oct-11	95.95	1.44	0.55	592.71	3.22	0.51
Nov-11	631.08	14.96	0.43	536.88	7.03	0.07
Dec-11	553.03	0.68	0.56	702.63	10.55	0.27
Jan-12	69.34	15.67	0.35	292.32	6.45	0.95
Feb-12	995.55	2.54	0.10	229.95	10.35	0.56
Mar-12	413.80	4.87	0.42	709.18	9.84	0.85
Apr-12	559.02	12.38	0.10	839.79	1.41	0.81
May-12	435.30	1.70	0.72	63.44	3.36	0.34
Jun-12	273.75	13.55	0.13	469.05	2.83	0.97
Jul-12	1003.93	8.30	0.91	53.81	2.62	0.94
Aug-12	84.70	10.18	0.83	626.84	3.69	0.86
Sep-12	696.32	0.07	0.79	862.92	7.66	0.57
Oct-12	984.95	3.09	0.96	914.73	4.12	0.85
Nov-12	54.73	8.64	0.36	432.98	8.87	0.20
Dec-12	990.60	2.02	0.47	783.45	8.71	0.52
Jan-13	955.81	8.73	0.95	982.48	7.30	0.04
Feb-13	850.60	9.90	0.71	346.88	7.66	0.37
Mar-13	25.57	15.60	0.27	810.65	1.76	0.15
Apr-13	864.47	12.98	0.12	615.22	0.92	0.60

Table F-9: Optimized SVR parameters for Spain

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