# THE OUT-OF-SAMPLE FAILURE OF EMPIRICAL EXCHANGE RATE MODELS – A NONLINEAR PERSPECTIVE.

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## ABSTRACT

This study reports an estimation of the out-of-sample performance of univariate, multivariate, and non-linear parametric monetary models contributing to the analysis of the Meese Rogoff paradox for the empirical CHF/USD, GBP/USD and JPY/USD series. 20 years of monthly observations and five models are analysed. In line with the academic literature I find a random walk model to be the best univariate model to capture the unit root behaviour of FX-rates and to forecast the latter out-of-sample. Nonetheless, in contrast with the general academic literature I do not find multivariate models to underperform a random walk model when forecasting FX-rates out of sample. Rather, I find that a vector error correction model representing the cointegration evidence among macroeconomics fundamentals and FX-rates marginally outperforms a random walk model for all the country series and estimation lags. Finally, the consideable out of sample performance of the generalized structured model points to non stable macroeconomic effects in time and non linear macroeconomic effects important to model in monetary models empirical studies.

***Keywords*** FX-rates · Monetary Models · Meese- Rogoff Puzzle · Cointegration · Generalized Tree Structured Model

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# 1 Introduction

Many approaches tried to model FX-rates since the start of a free-floating system after Bretton Woods in the 1970s. Monetary models, linking macroeconomics variables to FX-rates were the first to emerge and due to their compelling theoretical intuition soon became the reference in the field. Nonetheless, the enthusiasm for such elegant models was diminished by two seminal works. Meese and Rogoff (1983a, [1]) and Meese and Rogoff (1983b, [2]) demonstrated how none of the different monetary models could beat a random walk without a drift in modeling FX-rates out of sample. After the evidence was presented the opinion divided into four distinct diverging groups. Some authors, such as Kugler and Kräger (1993, [3]), argued for a sample issue and confined the problem to the specific historical period, other authors, such as Lucas (1976, [4]), Engle and Hamilton (1989, [5]), Hsieh (1992, [6]) and Chinn (1991, [7]), argued for the limit of the linear models to approach monetary models, other authors argued for the fail of monetary models and their underlying PPP assumptions documented in Taylor and Taylor (2004, [8]) and, finally, a last current of authors such as Frankel, Galli, and Giovannini (1996, [9]), Lyons (2001, [10]) and Sarno and Taylor (2001, [11]) started to approach the issue in an innovative way turning towards micro-based models that aim to capture the complexity of market information asymmetries and investors heterogeneity. [1]

While all the above-mentioned different reactions contributed to a further understanding of FX-rates properties I question whether the runaway from linear monetary models is justified given the methodological approach presented in the studies of Meese and Rogoff, the small sample of use and the lack of a co-integration analysis later formalized by Granger and Engle (1987, [13]). Moreover, given the focus of the academic literature on understanding the non-linear relation between macroeconomics fundamentals and FX-rates by inferring alternating conditional expectation optimal transformations introduced by Breiman and Friedman (1985, [14]) and through the markov switching models introduced by Hamilton (1989, [15]), I question whether a simple parametric model such as the generalized tree structured model introduced by Audrino and Bühlmann (2001, [16]) allowing to capture both time dependent structural breaks in the series such as the dot com bubble or the Japanese bank crises of the 1990s as well as policy regime changes identifiable with the current state of macroeconomics fundamentals might be beneficial for the analysis of FX-rates modeling.

This methodological study stands therefore as a revision of the out of sample failure of foreign exchange rates testing whether macroeconomics variables are indeed incapable of explaining FX-rates movements. This is achieved firstly by fitting the parametric models to a comprehensive self collected data set enlarged in size compared to the one used so far in the academic literature. Secondly, by applying an innovative estimation technique that allows to explore the more nuanced field of non-linear modeling by endogenously selecting optimal structural breaks for fitting parametric models.

Specifically, this study aims to explore the above at a monthly lag frequency on a data set ranging from 1986 to 2006. This period allows for a consistent estimation of all of the necessary parameters given the chosen models. Moreover, it avoids modeling the most recent financial crises where structural breaks are present in the series according to the preliminary CUSUM test applied on the times series.
As in Meese and Rogoff (1983a and 1983b, [1, 2]) I explore the out of sample forecasting performance of foreign exchange rates for three major monetary models. Firstly, the monetary models presented by Frenkel (1976, [17]) and Mussa (1976, [18]) claiming a link among monetary mass differentials, interest rates differentials, output gap and

[1] See Balliu and King (2005, [12]) for a general survey of FX-rates modeling in time.

FX-rates. Secondly the sticky price model where prices adjust sluggishly to macroeconomics shocks, exchange rates overshoot and inflation rates differential determine the long run behaviour of FX-rates (Dornbush 1976, [19]). Finally, a portfolio balance model claiming for the importance of monetary flows and net current account differentials as a key determinant for FX-rates changes as in Hooper and Morton (1982, [20]).
Based on such monetary models six different stochastic models are analyzed in order to forecast FX-rates. Three of them are presented in the seminal work of Meese and Rogoff (1983a, [1]) and represent the benchmark to verify whether the results of the paper hold for the time frame of interest. These models are a simple random walk forecast, an OLS estimation without inclusion of lagged terms and a vector auto-regressive model. On the top of these models I analyze the performance of transfer models discussed in Montgomery and Weatherby (1980, [21]) and the vector error correction model representation of the co-integration relationship between macroeconomic variables and FX-rates proposed by Granger and Engle (1987, [13]) as well as the previously mentioned generalized tree structure model of Audrino and Bühlmann (2001, [16]).

If the results are in line with the seminal papers of Meese and Rogoff in the case of univariate models, the picture resulting from a multivariate fit contradicts the results of the reference papers. I do not find enough evidence to support the claim of an underperformance of multivariate linear models in comparison to a simple random walk model. Moreover, I find a strong evidence for co-integration among macroeconomic series and FX-rates for all of the analyzed country series. This suggests a long term stable relation between the fundamentals and the FX-rates rejecting the claim of Meese and Rogoff about a weak relation between the two. Consistently with the last claim, I do find that a vector error correction model representation of the co-integration relation between macroeconomic series and FX-rates outperforms the out-of-sample forecast of FX-rates at all lags and for all of the country series. Finally, the applied generalized tree structure model parametric evaluation statistically outperforms all of the presented linear models for all country series analyzed suggesting the importance of modeling non-linear terms in modeling FX-rates and furthter contributing to the controversial debate of the necessity of modeling non linear terms for the monetary modeling of FX-rate series. An important breakthrough is moreover to notice how both of the analyses results are consistent. Both underline the special importance of modeling a long term stable relation between macroeconomics monetary mass and foreign exchange rates either trough a vector error correction model or a regime shift strengthening the hypothesis that a link between monetary models and FX-rates does indeed exist at monthly lag frequency given a long enough sample period that allows for a reliable multivariate endogenous model estimation as well the possibility to capture important nonlinearities in the macroeconomics fundamentals influence of FX-rates.

The paper continues as follows. Section 2 outlines the methodological approach and describes the techniques used for the empirical analysis and the out-of-sample forecast. Section 3 continues by introducing the data set used and the chosen proxies to capture the macroeconomic fundamentals of interest, Section 4 reports the main results of the empirical analysis and Section 5 concludes the findings.

## 2 Methodology

### 2.1 Structural Model

The basic structural model encompassing all of the different monetary models discussed in the introductory session is of the following form:

$$s = \beta_0 + \beta_1(m - m^*) + \beta_2(y - y^*) + \beta_3(r - r^*) + \beta_4(\pi - \pi^*) + \beta_5(TB - TB^*) + \varepsilon \tag{1}$$

where $s$ represents the logarithm of the indirect quote of FX-rates, i.e. the foreign exchange value of a dollar unit, $m - m^*$ represents the logarithm of the U.S. and foreign country money mass supply ratio, $y - y^*$ represents the logarithm of the U.S. and foreign GDP level ratio, $r - r^*$ represents the short term U.S./foreign country interest rate differential, $\pi - \pi^*$ represents the U.S./foreign country inflation rate differential, $TB - TB^*$ represents the U.S. foreign country current account differential. Finally, $\varepsilon$ represents the zero expectation i.i.d. error term capturing all of the other factors not expressed in the model.

The model above encompasses all of the monetary models previously discussed. Specifically, the most basic monetary model, the Frenkel-Bilson model logically inferred from the relative PPP proposition, assumes $\beta_4 = \beta_5 = 0$. The Dornbusch model that allows for a sluggish price adjustment behaviour and predicts FX-overshooting assumes $\beta_5 = 0$. Finally the Hooper-Morton model poses no restrictions on the coefficients of equation 1. Such a structural model is consequently estimated on four different parametric models of interest, which will be discussed next.

### 2.2 Univariate Models

The most basic model that is tested is an OLS model as in the benchmark papers of Meese and Rogoff (1983a, 1983b, [1, 2]). In this model the coefficients of equation 1 are computed without taking into account any lagged effect. On the other hand, a second more flexible model is modeled to capture possible lagged effects of the macroeconomics fundamentals. Opposed to the Meese and Rogoff papers where the authors decided to capture the possibility of lagged terms by incorporating exponentially smoothed autoregressive model giving a higher importance on more recent observations I decided to apply the transfer function models widely spread in the fields of engineering such as control systems and electronic circuits. These models have been poorly discussed in the field of economics with the exception of Tustin (1957, [22]) that tried to make the point for applying the models in the economic modeling field.

Transfer function models relates a given set of inputs to an output variable through the following general formula

$$Y_t = \mu + \frac{(\omega_0 + \omega_1 B^1 + \cdots + \omega_s B^s)}{1 - \delta_1 B^1 - \cdots - \delta_r B^r} X_{t-b} + \varepsilon_t \tag{2}$$

where $X$ represent a matrix of exogenous terms, $\mu$ the optional term modeling the mean of the series and $\varepsilon$ the non-captured variation in the series. Moreover the above ratio represents the transform function of the regressors matrix and is especially characterized by the order of the denominator and nominator terms.

$r$, the order of the denominator term, expresses the rate of the decay pattern, where a higher term indicates a slower decay. $s$, the order of the nominator term, expresses the persistence of so called unpatterned spikes, that is the persistence of effects that are not captured in the decay pattern. Finally, the $b$ term in the matrix of input represents the dead time,

that is the time it takes for the dependent variable to react to some changes in the input matrix. This is of primary importance as it might very well be that some shift in macroeconomic fundamentals just begins to display effects after a certain amount of time when the economic agents begin to perceive the change.
Due to the flexible nature of the latter model, I believe that it is better suited and preferable to capture the true nature of distributed lags present in the structural model of equation 1 in comparison with the smoothed autoregressive model, applied by Meese and Rogoff, with the arbitrarily chosen smoothing term of 0.95 (See Meese and Rogoff (1983a pp. 7, [1])).

### 2.3 Multivariate Models

The above discussed models rely on the exogeneity of the independent variables. If the assumption fails, the model are biased and lead to misleading conclusion as the independence of the sample distribution is not guaranteed. In practice this poses an issue for the estimation of the structural model of equation 1.

While some variables as the monetary mass and the output gap are commonly treated as exogenous variables in the underlying monetary models the practice suggests that such macroeconomic variables might very well be influenced by the movements of FX-rates. On the top of it other variables such as short-term interest rates differentials are treated as endogenous even in the underlying monetary models and therefore require a different estimation compared to the one outlined in the previous section.

To obviate the above issues Meese and Rogoff (1983a and 1983b, [1, 2]) analyzed the structural model of interest through a vector autoregressive model firstly introduced by Sims (1980, [23]). In the general case the model consists of a system of equations in the form

$$y_t = \Phi_0 + \Phi_1 y_{t-1} + \Phi_2 y_{t-2} + \cdots + \Phi_n y_{t-n} + \varepsilon_t \tag{3}$$

where $y$ is a vector containing the endogenous variables of interest, $\Phi_0$ is a vector of constants, $\Phi_1, \ldots, \Phi_n$ are matrices describing the effect of lagged endogenous variables on the levels of the current variables and $\varepsilon$ captures the equations specific error term. The resulting model will capture the endogeneity present in the monetary structural model allowing for a consistent OLS estimation as far as the error terms in the equations are uncorrelated.

Despite the described vector autoregressive model manages well to model the endogeneity of macroeconomic variables I question whether the restricted form of it could yield more efficient and more reliable estimates capturing the FX-rates and the monetary models relation. This is especially motivated by the cointegration theory developed by Engle and Granger (1987, [13]) and the well known evidence of non stationary macroeconomics times series [2]. Moreover, the importance of such method is underlined by the evidence of Phillips (1986, [25]) that set down the theoretical fundamentals showing how parameter estimates of cointegrated series do not converge in probability and do not converge to any non-degenerate distribution in the asymptotic case if the case of a misspecified OLS estimate as potentially is equation 3.

I propose therefore a test for cointegration among the macroeconomic and the FX-rates series based on Johansen (1991, [26]) and I consequently estimate a vector error correction model of the form

[2] See for instance Gil-Alana and Robinson (1997, [24])

$$\Delta y_t = \Pi y_{t-1} + \sum_{i=1}^{p-1} \Phi^* \Delta y_{t-i} + \varepsilon_t$$
$$\Phi^* = -\sum_{i=j+1}^{p} \Phi_i, \;\; j = 1, \ldots, p-1 \tag{4}$$
$$\Pi = -(I - \Phi_1 - \cdots - \Phi_p)$$

where $\Pi y_{t-1}$ of equation 4 represent the error correction term and $y_i$ and $\Phi$ refer to the variables described in the unrestricted vector autoregressive model of 3.

### 2.4 Generalized Tree Structured Model

This section further discuss a final methodology allowing to endogenously determine the optimal partitioned space for capturing the non-linear structure present in the series. As outlined by Audrino and Bühlmann, while the general idea of generalized tree structureed models is comparable to the one of self-exciting threshold autoregressive (SETAR) models of Tong (1983, [27]) and CART models of Breiman (2017, [28]) the estimation of the model and the model fit differs. In this sense, the generalized tree structured model reselbles SETAR and CART models as it aims at deriving the set of threshold variables that best capture the different regimes in the time series and modeling those by local parametric models. Nonetheless it differs from the two in the way in which the partitioned space, and therefore the threshold splits are derived as well as in how the final parametric model is fitted.
While the SETAR models are autoregressive self-exciting models, and therefore search for the best partition by determining the relation between a lagged autoregressive variable and the theshold variable, the generalized tree structure models are more general in the sense that the partition space may be identified based on any external factors independently whether it fits in the parametric model or not. Additionally the parametric model is not restricted to be an autoregressive model but is rather limited by the only restriction of being a fully specified parametric model such that a likelihood estimation is possible. In this regard the generalized tree structure model resembles more the previously mentioned CART models with the difference that while CART models estimation technique leverages the minimization of the squared sum of residuals, the generalized tree structured models leverages likelihood estimation being therefore applicable to deterministic models such as GARCH models and better suited for modeling not-normal distributed error terms.

An exact definition of the generalized tree structured model might be found in Audrino and Bühlmann (2001, [16]) and can be summarized through the follwing steps.

*Step 1:* Estimate the global parametric model by the maximum likelihood method over the entire data set space $\mathcal{D}$ with the optimization technique of choice.

*Step 2:* Define a set of observable variables $\mathcal{S}$ that might help to proxy regimes changes or structural breaks in the underlying parameteric model.

*Step 3:* For each variable $s_j \in \mathcal{S}$ get threshold values $\overline{s}_{j,m}$, where $m$ corresponds to the mth quantile of the empirical distribution of the variable $s_j$. Usually the $m$ are selected to be the $1/n, \; n = 1, 2, ..., 16$

empirical quantiles. Finally partition the overall data set space into overlapping $\mathcal{P}_{j,m} := \mathcal{P}_{j,m}^{right} \cup \mathcal{P}_{j,m}^{left}$ sets, where $\mathcal{P}_{j,m}^{right} := \{d \in \mathcal{D} \mid s_j < \overline{s}_{j,m}\}$ and $\mathcal{P}_{j,m}^{left} := \mathcal{P}_{j,m} \setminus \mathcal{P}_{j,m}^{right}$.

*Step 4:* Fit a parametric model on each of the defined $\mathcal{P}_{j,m}$ sets. Define the optimal partitioned data set by the $\mathcal{P}_{j,m}^{optimal}$ maximizing the overall maximum likelihood in sample and note the optimal threshold variable $\overline{s}_{j}^{optimal}$. You will have have obtained a new partitioned space where $\mathcal{D} = \mathcal{P}_{j,m}^{optimal,right} \cup \mathcal{P}_{j,m}^{optimal,left}$

*Step 5:* Grow the tree. This means to treat each of the partitioned data sets in the terminal nodes of the tree as the original data set $\mathcal{D}$ and to iterate *Step 2-4*. The next partitioned space is then selected by choosing the best performing partitioned space among the terminal nodes optimal partitioned spaces. Subsequentially the tree continues to grow until the resulting partitioned space contains too little observations for a reliable estimation of the parametric model of interest.

*Step 6:* Prune the tree. This means to reduce the dimension of the tree and the number of the partitions $\mathcal{P}$ according to some information criteria. The information criteria should guard against over-fitting and guarantee that a binary partition is added just upon a sufficient increase in likelihood. The extent to which the sufficiency condition is defined depends on the choice of information criteria and it is left to the discretion of the end user.

Given the methodological understanding of the model I turn to the case specific application of the model.

The generalized structured tree model is used in combination of three parametric models. The first is the OLS structural model of 1, the second is the vector autoregressive model specified by 3 and the final model is the vector error correction model of equation 4. Where, the latter two models are selected especially due to their increased out of sample performance in comparison to univariate models. Due to the different parameter size of the models I decided to modify the stopping criteria for the univariate and multivariate models. While the stopping criteria for univariate models will be a partitioned data set encompassing less than 40 observations the threshold for the multivariate models was set at 70 and 80 observations respectively to allow a sufficient number of observations for the parametric fit and allow for a robustness check of the model by checking at the varying performance in the stopping criteria.

Moreover, for the set of observable variables over which to search for the optimal partition I decided to include all of the macroeconomics fundamentals differentials outlined in the structural model described in 2.1 adding a time variable that should be able to capture general structural breaks in time important to model for the sample data set of choice.

Finally the AICc information criteria discussed by Cavanough (1997, [29]) was chosen as the information criteria for pruning the tree. This information criteria expands on the most known AIC information criteria by including a correction term useful to avoid the small sample over-fitting issue discussed in Mcquarrie (1998, [30]).

$$
\begin{gathered}
AIC = 2k - 2ln(\hat{L}) \\
AICc = AIC + \frac{2k^2 + 2k}{n - k - 1}
\end{gathered}
\tag{5}
$$

### 2.5 Forecasting Approach

The five described models are validated by looking at their ability to forecast FX-rates out of sample in comparison to a random walk model without drift. In this sense the 234 observations sample is split in a training and a validation sample. Three fourth of the total observations are training the four models while the remaining fourth of the observations is used for the out of sample validation.

In comparison to Meese and Rogoff (1983b, [2]) I do not try any restricted estimation based on the theoretical monetary models literature. I rather estimate unrestricted versions for all of the models outlined with the exception of the vector error correction model described in 4, given the by product VAR model restriction imposed by the latter.

To select the best performing monetary model I use a two step approach. Firstly, I estimate the four parametric models according to the most general structural model described in 1. Secondly I perform Wald tests to check whether there is in sample evidence for using restricted models. Based on positive evidence I proceed by running restricted models out of sample and look for an increased performance.

The out of sample performance of the different models is measured by applying a rolling out-of-sample forecast in analogy to the benchmark papers. This consists of a re-estimation of the five outlined models for each new forecasting point. Given the decision to estimate the out of sample model performance at one, three, six and twelve months lags the rolling forecast technique involves a model reestimation at respective frequencies. Important is to underline how the results of the Wald tests are extended for each of the subsequent model estimation in the rolling forecast. This means that given the statistically significant evidence for the Null of a restricted model in the first three fourth of the sample the same restricted model is used for the subsequent model estimations.

Explicitly, this approach intends to fit a structural model containing all of the macroeconomics series in the first 176 observations - from September 1986 to April 2001 - and perform Wald tests to verify whether a restricted monetary model is supported in the sample. Based on such restults the rolling forecast method intends to estimate the next point forecast at 1, 3, 6 and 12 month lags and shift the data sample of one period such that a new model is estimated for the October 1986 to May 2001 series. According to the new parametric fit, point forecast at 1, 3, 6 and 12 months are estimated and the method iterated until the last out of sample observation for February 2006 is reached.

Finally, it is important to underline that as in the benchmark papers, I allow the univariate models described in 2.2 a richer set of information compared to the random walk. Specifically, the random walk and the multivariate model use the $\mathscr{F}_{t-1} = F_0, \ldots, F_{t-1}$ information set, where $F_i$ represents a set containing all of the available information at timepoint $i$. By contrast the univariate models dispose of $\mathscr{F}_t \setminus s_t$, where $s_t$ represents the FX-rate at time point $t$. In simple terms this means that I am going to give the univariate models the advantage of using the actual realizations of macroeconomics variables without the need to estimate them, therefore outlying the possibility of poor out-of-sample fit due to poor macroeconomic fundamentals estimation.

Based on the obtained rolling forecasts three statistics are computed to compare the model fit. These are the root mean squared error (RMSE), the mean absolute error (MAE) and the mean directional accuracy (MDA). A particular importance is assigned to the MAE results given Westerfield (1977, [31]) that analyzed the empirical exchange rates distribution finding evidence for FX-rates non-normal stable-Paretian distributions with infinite variance.
Opposed to Meese and Rogoff (1983a and 1983b, [1, 2]) I decided to further explore the point estimators of the above mentioned statistics by computing a model confidence set (MCS) as described in Hansen et al. (2011, [32]). The idea of the latter consists of a procedure yielding a model set, $\mathcal{M}^*$, built to contain the best model with a chosen level of confidence. The exact procedure is based on an equivalence test $\delta_m$ and an elimination rule $\epsilon_m$, consistent with the chosen confidence level. In a first step the competing models are compared with each other. If $\delta_m$ does not support evidence for the equal performance of the models, $\epsilon_m$ is applied, the poorly performing models are discarded, and the general problem reiterated until $\delta_m$ is accepted for all of the surviving models.
In this paper I decided to make use of superior predictive ability test of Hansen (2005, [33]) and to obtain p-values for the equal predictive hypothesis of models according to a bootstrap implementation outlined by Hansen et al. (2011, [32]).

## 3 Dataset

The dataset, comprehensively discussed in Appendix A 6 consists of monthly observations over 21 years ranging from January 1986 to January 2006. All the time series of use are selected in accordance with the underlying monetary structural model 1 and are consistent with the series first utilized by Meese and Rogoff (1983a, [1]). Three different FX-rates series are analyzed, namely the JPN/USD rate, the GBP/USD rate and the CHF/USD rate. With respect to the independent variables of the structural model, I decided to work with the 3-months treasury bills to capture the short term interest rates differentials. The only exception were of CH series where I worked with the 3-month US-CH LIBOR spread due to missing reported publicly available data for the seasonally unadjusted short term treasury rates at monthly lag.
For measuring money mass differentials, I worked with the M1 and M3 measures testing the both given the important difference among the two and the lack of theoretical models to favour one measure above the other. I obtained stronger results for the M3 series and therefore proceeded to report the results obtained through such measure in the paper.
For measuring the inflation rate differentials important for the Dorbusch model I worked with consumer price indices and for measuring the trade balance I worked with the net trade amount for goods as a proxy for the current account balance. The trade balance is indeed just a rough approximation given the fraction of traded goods in comparison to the total amount of trade that includes services and monetary transfers. Nonetheless I preferred such measure from an interpolation of the quarterly published current account balances.
Finally, I worked with the unemployment rate to capture the output differential of the economies as such variable reflects well the fluctuations in output levels, i.e. the quantitiy of interest, leaving the constant term in equation 1 to capture the other information present in the output measure such as the size of the economies.

As in our reference papers I decided not to work with seasonal time series in order to avoid the possible bias introduced by different seasonal adjustments to the structural parameters documented in Sims (1973a and 1973b, [34, 35]).

Henceforth I decided to approach our model validation by fitting the models on seasonal adjusted and detrended time series.

With respect to the time series adjustments I proceeded by detrending the series exploring three different possibilities. Firstly, detrending via differentiation, secondly detrending through a linear time trend and thirdly detreding through a moving average filter. Detrending through differencing proved to be the most effective due to the quadratic behaviour displayed by the series. This approach was therefore applied to all of the series. The obtained mean stationary series were consequently inspected for the presence of seasonality. This was done using spectral peaks derived from the fast-Fourier transform and the correspondigly power density to detect seasonality in accordance with Nerlove (1964, [36]). The two most common seasonalities in the stationary times series were subsequently captured by modeling fourier terms, where the number of fourier terms was chosen based on the standard Akaike criteria of 5. New seasonal adjusted times series were finally computed by factoring the modeled seasonality out thorough the following form:

$$y^{adjusted} = y^{unadjusted} - \sum_{k=1}^{K}[\alpha_k \sin(\frac{2\pi kt}{m}) + \beta_k \cos(\frac{2\pi kt}{m})] - \sum_{j=1}^{J}[\alpha_j \sin(\frac{2\pi jt}{m}) + \beta_j \cos(\frac{2\pi jt}{m})] \tag{6}$$

where $K$ and $J$ represent the optimal number of fourier terms to include to capture the two seasonalities according to the AIC information criteria and $a_k, a_j, b_k, b_j$ the optimal estimated coefficients to model the seasonality in the series.

Finally the newly generated seasonal adjusted series were tested for seasonality according to the seasonal unit roots tests presented by Canova and Hansen (1995, [37]) and Wang and Smith (2006, [38]) and the process above reitered until no evidence of seasonality could be found for any of the seasonal lags suggested by spectral peaks.

# 4 Empirical Results

## 4.1 Univariate Models

The results for the univariate model fit are presented in table 1. For all of the univariate models described in section 2.2 a Wald test assessing the empirical evidence for a restricted structural model is computed. I find that the joint Null of the Frenkel-Bilson model cannot be rejected on a 1% confidence level for the simple OLS modeling of FX-rates. We proceeded therefore to estimate the out of sample performance for the OLS applying both the most general structural model and the Frenkel-Bilson model.

For the transfer function model described in 2 the rate of decay, the persistence term and the dead lag were estimated at each model estimation in the rolling forecast. The optimal lags for the terms above where selected minimizing the Akaike information criteria (See Akaike (1998, [39]). I found a compelling evidence for modeling the differentiated series with one term in the nominator capturing the effect of unexpected shifts in the independent variables and two terms in the denominator capturing the general high persistence of FX-rates movements through time.

The results of table 1 confirm the one of the general literature where an OLS model vastly under-performs a random walk in the out of sample forecast of FX-rate at all tested lags.

In contrast, transfer function models performed much better in modeling FX-rates out of sample. While the model still under-performs a random walk in forecasting the FX-rates of the countries of interest at 1 month lag, the evidence at

Table 1: Mean Absolute Error – Univariate Models Equal Predictive Ability p-value in Parenthesis

| | | Univariate Models | | |
|---|---|---|---|---|
| Lag | Model | Switzerland | United Kingdom | Japan |
| MAE 1 | Random Walk | 0.0193 (0.503) | 0.0168 (0.506) | 0.0162 (0.506) |
| | Transfer Function Model | 0.0205 (0.119) | 0.0176 (0.128) | 0.0173 (0.228) |
| | OLS - unrestricted | 0.0234 (0.031) | 0.0211 (0.053) | 0.0194 (0.192) |
| MAE 3 | Random Walk | 0.0390 (0.307) | 0.0330 (0.093) | 0.0291 (0.534) |
| | Transfer Function Model | 0.0384 (0.499) | 0.0341 (0.094) | 0.0280 (0.111) |
| | OLS - unrestricted | 0.0603 (0.133) | 0.0443 (0.143) | 0.0497 (0.000) |
| MAE 6 | Random Walk | 0.0580 (0.483) | 0.0495 (0.785) | 0.0439 (0.484) |
| | Transfer Function Model | 0.0581 (0.468) | 0.0498 (0.526) | 0.0442 (0.396) |
| | OLS - unrestricted | 0.0789 (0.003) | 0.0531 (0.486) | 0.0669 (0.000) |
| MAE 12 | Random Walk | 0.0964 (0.171) | 0.0584 (0.726) | 0.0753 (0.505) |
| | Transfer Function Model | 0.0954 (0.489) | 0.0598 (0.678) | 0.0752 (0.147) |
| | OLS - unrestricted | 0.1210 (0.000) | 0.0744 (0.523) | 0.1001 (0.000) |

higher lags is rather mixed and it seems the two models performs equally in forecasting FX-rates out of sample. This is confirmed by the superior predictive test of Hansen (2005, [33]) and the p-value reported in parenthesis in table 1 obtained by the bootstrap method of Hansen (2011, [32]). For all of the models the equal predictability hypothesis of the unrestricted and restricted OLS model is rejected with 5% confidence.

Two possible causes for such observations might exist. While on one hand the increased forecast performance at higher lags might be explained by the different information set provided to the two models as described in 2.5, on the other hand, the fact might be caused by an increasing importance of macroeconomic variables for explaining the long run behaviour of FX-rates movements.

Finally, the Null of equal predictability of the random walk model and the transfer function models in the superior predictability test could not be rejected with 10% confidence. This suggests the random walk model as the best univariate model to fit FX-rates out of sample given its parsimonious computation power combined with a restricted information set compared to the transfer function model as discussed in 2.5.

I observe no systematic difference when looking at RMSE. The picture of the latter looks similar to the results obtained looking at the MAE at all lags and for all models. No particularly important outliers in forecast errors seem to be of significant importance in the analysis. The final word is given to the directional accuracy measure defined as the average number of times the sign of the realized FX-rate difference is matched by an equivalent sign in the FX-rate forecast difference. The values for such statistics lie between 0.4-0.6 for all the frequencies and there does not seem to be systematic differences among the models.

### 4.2 Multivariate Models

The evidence from the previous section together with the general empirical literature suggests the presence of a unit root in the FX-rates. This was further confirmed by augmented Dickey-Fuller tests (Dickey and Fuller (1979, [40])) applied to the FX-rates and macroeconomics variables at the moment of detrending the series. There a statistically significant presence of unit roots could be found in the series in level. Dickey-Fuller tests were estimated once again after differentiating the series. All of the series but the US-JP interest rates differential and the US-UK unemployment rate differential proved to be stationary after such adjustment, which supports an evidence for an integration order of 1 for most of the series.

While in the previous section the FX-rate unit root was proved to be best modeled by a simple random walk model this section further expands the analysis by looking at the performance of multivariate models. Those may capture and efficiently estimate the relation among macroeconomics variables and FX-rates in the case of endogeneity among the series.

While the reference paper of Meese and Rogoff (1983a and 1983b, [1, 2]) attempted to use a multivariate model through a vector auto-correlation model I will analyze the extent of co-integration among the series using the results of the previous analysis showing a higher order integration for the macroeconomic and FX-rates series.

In order to do that I tested the hypothesis of co-integration for the macroeconomics variables and the FX-rates taking into account the trend displayed by the times series. The results of this analysis are based on the trace statistic for the computed eigenvector discussed in Johansen (1991, [26]). Running the Johansen co-integration test I obtained the results presented in table 2. All of the series display a profound evidence for the presence of two co-integration vectors at 5% percent confidence level.

Given the five series of macroeconomic fundamentals it is possible that the two co-integration relations might exist just among such variables and that a long term relation between the macroeconomic fundamentals and the FX-rate for the three different series does not exists. In order to test such a hypothesis I decided to first run Johansen tests verifying for co-integration between the FX-rate and the single macroeconomic variables. I then iterated the process by gradually adding macroeconomic variables until the estimation of a model included all of the variables present in the structural model as in 1. The results in this case confirm the hypothesis of co-integration between FX-rates and the macroeconomic variables. For the period analyzed I found strong evidence for co-integration among the FX-rate and macroeconomic fundamentals for the UK-US series. In such a case the Null of no co-integration could be rejected with 5% confidence for the FX-M3, FX-CPI, FX-Current Account, FX-interest rate series. The picture looks more fragmented in the case of the other series. In the case of the CH-US series evidence for co-integration is displayed between {M3, M1, Interest Rate} and the FX-rate respectively, while for the JP-USA series the Null of no co-integration can be rejected only for the FX-M3 series.

Given the evidence of co-integration relations among FX-rates and macroeconomic fundamentals the Granger's theorem postulates the existence of a vector error correction model representation as in 4. I selected the optimal lagged terms of

Table 2: Johansen Co-Integration Test – Trace Statistics

| | | | Quantiles Test Statistics | | |
|---|---|---|---|---|---|
| Series | | Trace Score | 90% | 95% | 99% |
| Structural JP-US | Co-integrated Series <= 3 | 26.46 | 28.71 | 31.52 | 37.22 |
| | Co-integrated Series <= 2 | 48.79 | 45.23 | 48.28 | 55.43 |
| | Co-integrated Series <= 1 | 87.80 | 66.49 | 70.60 | 78.87 |
| | Co-integrated Series = 0 | 138.18 | 85.18 | 90.39 | 104.20 |
| Structural CH-US | Co-integrated Series <= 3 | 25.97 | 28.71 | 31.52 | 37.22 |
| | Co-integrated Series <= 2 | 53.22 | 45.23 | 48.28 | 55.43 |
| | Co-integrated Series <= 1 | 85.88 | 66.49 | 70.60 | 78.87 |
| | Co-integrated Series = 0 | 145.12 | 85.18 | 90.39 | 104.20 |
| Structural UK-US | Co-integrated Series <= 3 | 26.94 | 28.71 | 31.52 | 37.22 |
| | Co-integrated Series <= 2 | 51.26 | 45.23 | 48.28 | 55.43 |
| | Co-integrated Series <= 1 | 88.47 | 66.49 | 70.60 | 78.87 |
| | Co-integrated Series = 0 | 178.10 | 85.18 | 90.39 | 104.20 |

it by estimating three different information criteria for the model fit. Specifically, I computed the Akaike, Quinn-Hannan (See Hannan and Quinn (1979, [41]) and Schwarz (See Schwarz (1978, [42]) information criteria for the models with diverse lag terms and for parsimony reasons selected the minimum lag number identified by any of the three models above. An analogous approach was used for determining the optimal lag terms of the benchmark multivariate model – a vector auto-regressive model in difference. Based on this approach multivariate models of term one, and with a smaller frequency also of term two, resulted in the model estimates of the rolling forecast method. This is an important result given the restricted sample size and the exponential increase of parameters in the number of lagged terms.

The results of the rolling forecast are presented in table 3. As in the case of the univariate fit and in line with the expectations, the error increases in the estimation lag. In contrast to Meese and Rogoff (1983a and 1983b, [1, 2]) I do not find evidence for a general under-performance of the vector auto-regressive models in predicting out of sample movements of foreign exchange rates in comparison to the simple random walk model. Especially in the short term when looking at the one month out of sample performance of vector auto-regressive models I find that the this marginally outperforms a random walk model. For higher term lags the evidence is rather mixed and the superiority of random walk models cannot be claimed. Moreover, important is to underline that in comparison to univariate models of 2.2, the multivariate models make use of the same information set $\mathscr{F}_{t-1}$ as the random walk models.

One possible explanation for the striking difference between the results reported in this paper and the one presented in Meese and Rogoff (1983a and 1983b, [1, 2]) may be resulting from the different sample size used for the reported study compared to the one used by Meese and Rogoff. In this sense, Meese and Rogoff worked with a sample size of 87 observations, using as few as 37 observations for fitting their models (See Meese and Rogoff (1983a Section 3 and

1983b Section 3.2, [1, 2]). It is therefore highly likely that the multivariate results of their study suffer from over-fitting issues leading the vector auto-regressive model to perform poorly out of sample.

Table 3: Mean Absolute Error – Multivariate Models
Equal Predictive Ability p-value in Parenthesis

| | | Multivariate Models | | |
|---|---|---|---|---|
| Lag | Model | Switzerland | United Kingdom | Japan |
| | Random Walk | 0.0193 (0.125) | 0.0168 (0.177) | 0.0162 (0.625) |
| MAE 1 | VAR | 0.0183 (0.207) | 0.0186 (0.178) | 0.0160 (0.170) |
| | VECM | 0.0176 (0.491) | 0.0174 (0.476) | 0.0153 (0.355) |
| | Random Walk | 0.0390 (0.392) | 0.0330 (0.495) | 0.0291 (0.529) |
| MAE 3 | VAR | 0.0394 (0.359) | 0.0333 (0.486) | 0.0292 (0.488) |
| | VECM | 0.0376 (0.624) | 0.0328 (0.016) | 0.0320 (0.770) |
| | Random Walk | 0.0580 (0.675) | 0.0495 (0.081) | 0.0439 (0.449) |
| MAE 6 | VAR | 0.0578 (0.666) | 0.0488 (0.504) | 0.0418 (0.575) |
| | VECM | 0.0580 (0.535) | 0.0483 (0.355) | 0.0434 (0.647) |
| | Random Walk | 0.0964 (0.258) | 0.0584 (0.232) | 0.0753 (0.458) |
| MAE 12 | VAR | 0.0974 (0.165) | 0.0603 (0.092) | 0.0763 (0.267) |
| | VECM | 0.0881 (0.507) | 0.0542 (0.676) | 0.0731 (0.573) |

Turning to the vector error correction model of equation 4 that models the co-integration relation previously described I can see from table 3 that the rolling forecast of such models beats the random walk model fit for all of the countries and at all lags when measured in terms of mean absolute error.

While the vector error correction model successfully outperforms the simple random walk model when looking at the MAE statistics, no statistically significant evidence for the difference among the two models is found when modeling a model confidence set as in Hansen (2011, [32]). Looking at the p-value of the Null Hypothesis of equal predictability, that results from a bootstrapped superior ability tests reported in parenthesis of table 3, the results are clear. All of the three models are indistinguishable in terms of their out of sample performance across all of the estimation lags and series.

### 4.3 Generalized Tree Structured Model

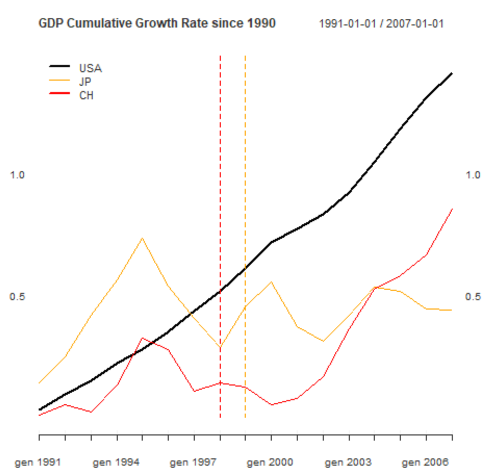
This section marks the final step in this analysis of the FX-macroeconomic fundamentals relation by presenting the results for a non-linear threshold model developed in accordance with the generalized tree structure discussed by Audrino and Bühlmann (2001, [16]) of section 2.4. It follows a discussion of the results of the generalized tree structured model in combination with a structural OLS fit without inclusion of lagged terms. Subsequently a word is given to the results of the generalized tree structured model applied in combination with the multivariate models discussed in section 2.

#### 4.3.1 Full Sample Optimal Partitions

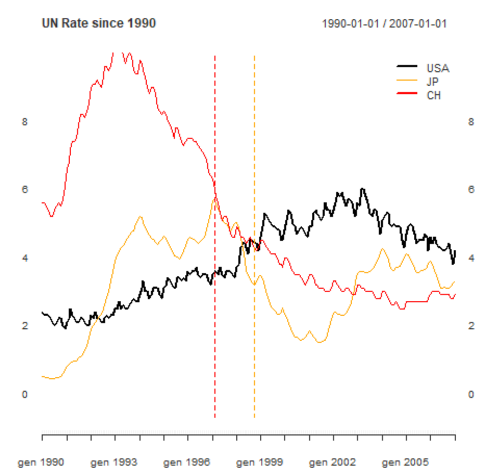
A first general overview of the generalized tree structured-structural OLS model is provided by the results of figures 2, 3 and 4 reporting the general tree structure with the corresponding optimal partitions.

We can infer from the figures how for Switzerland as well for Japan the data set is partitioned according to the time period of the observations. For the Swiss case the data is partitioned according to whether the observations occur prior to the 85th observation, i.e. February 1997. In contrast, in the case of Japan the partition occurs based on the 105th observation, i.e. October 1998. Interestingly for the Japan case the period matches well the *Lost 20 Years* of the economy that suffered an important economic slowdown after the banking crises of the 1990s and ultimately saw its GDP plummeting from 5.4 billion USD in 1995 to 4.5 billion USD in 2005.[3] In a similar way, the optimal Swiss partition is found for 1997, the year marking the start of the steep increase in employment after the unemployment crises of the 1990s and the sluggish economic growth where Switzerland ranked last among the European countries in terms of GDP growth as evidenced by Puhani (2003, [44]).

Figure 1: *Cumulative GDP growth since 1990 and Unemployment level. The dotted line represents the time threshold chosen by the generalized tree structured model to fit the parametric structural model.*




(a) GDP cumulative growth for United States, Japan and Switzerland between 1990 and 2007.




(b) Percentage of working force unemployment for United States, Japan and Switzerland between 1990 and 2007.

All of that further strengthens the generalized tree structured model that well managed to endogenously identify such important economic phases of the Swiss and Japanese economies once the time variable was included in the set of variables over which to search for structural breaks.

[3] See Saxonhouse (2003, [43]) for more.

Important is to notice that the time splits do not influence alone the parametric fit but stands rather in a tight relation with the other identified threshold splits. These differ for the Swiss and the Japanese time series. In fact, for the Japanese case the primary regime shift depends on the American-Japanese unemployment rate differential and the threshold value for the variable is found at the 25% empirical quantile of the series, i.e. at -0.2% points. This threshold captures the period between 1994 and 1997 that is characterized by the most rapid GDP downturn of the Japanese economy time series as it is possible to visualize in figure 1.

For the Swiss case a second partition is instead identified depending on the 37.5% quantile of the logarithm of the monetary mass ratio distribution, which very roughly represents the growth rate differential between the USD monetary mass and the Swiss monetary mass expressed in USD. No theoretical convincing reason could be found for the partition and an interpretation is left to the reader and to the economic historians.

Finally, turning to the GBP/USD generalized tree structured modeling, three optimal threshold splits are found giving rise to four different partitions of the data set space as visible from figure 4. The first and foremost important difference depends on the American-British 3-months treasury bills interest rate differential. For the variable the threshold is selected to be the 50% empirical quantile of the American-British interest rates differential – i.e. the median value corresponding roughly to 1.8% points. This is again an intuitive split given the importance of the financial centers in the two countries attracting a high amount of international capital and possibly driving FX-rates movements.

The space partitioned by the interest rates differentials is then further refined according to the monetary mass differential and four regimes are selected. On the left branch of the tree, the 43.75% quantile of the American monetary mass growth rate is selected. In the right branch the 56.25% quantile of the same variable is selected. This results into four regimes: (i) one characterized by higher than usual interest rate differentials and US-UK monetary mass high expansion, (ii) a second characterized by higher than usual interest rates differentials and mild US-UK monetary mass expansion, (iii) a third consisting of a lower than usual interest rates differential and a severe US-UK monetary mass contraction and, finally, (iv) a fourth regime of mild US-UK monetary mass contraction combined with lower than usual American-British interest rates differentials.

An interesting aspect to notice in all of the mentioned cases is how the macroeconomic variables chosen for partitioning the data set space are the ones that proved to be co-integrated with the FX-rate series according to the Johansen eigenvalue trace test statistic. To further investigate such an aspect the estimated parameters for the tree terminal nodes model fit were further inspected.

In general some key relations holds. For instance in UK case, when the interest rates differential is below the median value, and therefore the tree in the left branch, the foreign exchange rate differentials are estimated to be lower – due to the general lower estimated coefficients – in line with the macroeconomic theory and the co-integration relation discussed above. A similar results holds for the Swiss split, where the parameters of the terminal fit in node five of figure 2 estimate ceteris paribus a lower FX-rate change in comparison to the terminal fit in node 4 in line with the theory suggesting an appreciating currency in a decreasing relative money supply.

Before turning to the rolling forecast analysis it is therefore possible to claim that the obtained results for the generalized tree structured model are in general consistent with the monetary macroeconomic theory. Moreover, the interesting finding of parametric estimations that fits the reversal properties of the stable long run relation among macroeconomic fundamentals and the FX-rates documented in the previous section are a further important result of the generalized tree structured model that is worth to consider.

#### 4.3.2 Rolling Forecast Optimal Partitions

Turning to the analysis of the rolling forecast of the generalized tree structured model a first overview is available by looking at table 5. The table presents the number of optimal splits according to the pruned generalized tree structured model. As visible from the table, the number of optimal partitions diminishes in comparison with the results of the previous section and no time three partitions are selected to be optimal. The root of the result should not be searched in a poor likelihood fit of a third partition, but rather in the reduced sample size used for the estimation. If the previous section leveraged the entire sample for the estimation, the rolling forecast method makes use just of three fourth of the sample activating the 40 observations constraint at a earlier stage and inhibiting a third space partition due to unreliable parameter estimation.

Furthermore, it is interesting to notice the high number of times where one partition is chosen as optimal. This is both caused by the pruning action as well as from the small sample studied. It is namely noted how, for instance in the British case, the final 15 optimal splits are selected at the median value of the interest rate differential and how the two partitions of the data set cannot be further partitioned according to the quantiles and variables of choice without violating the number of observation constraints.

Tables 6–8 further report the number each combination of threshold variables and quantile value is chosen for the optimal first partition in the rolling estimation and are left to the interested reader.

Finally, table 9 in the appendix, reports the optimal partition tuples for the rolling generalized tree estimation. The partitioning stays generally stable over intervals of time. Moreover when looking at the usage rate, defined as the percentage of time a variable enters the rolling generalized tree estimation, it is possible to see the particular high value for the monetary mass in the Swiss case, reaching as high as 66,7%, and for the Japanese case, where the monetary mass is selected to be an optimal variable for partitioning the space in 73% of the cases. This confirms the importance of the monetary mass, further stressing how the difference in the monetary mass growth differentials well signal distinguished moments of the economies calling for a differentiated parametric fit and differentiated macroeconomic fundamentals influence. Nonetheless, the result seems not to be generally valid but rather dependent of the characteristics two economies analyzed. The analysis of the GBP/USD yield a different picture, with the monetary mass growth rate usage scoring as low as 2% in comparison with a usage rate of 100% for the interest rate difference, which interestingly was the UK-series showing the highest statistical significance for co-integration with the macroeconomic FX-rate series.

#### 4.3.3 Out-of-Sample Fit

The final results for the out-of-sample performance fit of the rolling generalized tree structured model estimation are presented in table 4. For the table the bootstrapped superior predictive ability p-values are omitted as being 0 for all of the models but the generalized tree structured model. The model confidence set procedure of Hansen (2011, [32]) rejects the Null of equal predictive between each of the model and the generalized structured tree performance with arbitrarily high confidence, eliminating iteratively all of the models by keeping just the generalized tree structured model as the best performing model.

Table 4: Mean Absolute Error – Generalized Tree Structure Model

| Multivariate Models | | | | |
|---|---|---|---|---|
| Lag | Model | Switzerland | Japan | United Kingdom |
| MAE 1 | Random Walk | 0.0193 | 0.0168 | 0.0162 |
| | VAR | 0.0183 | 0.0186 | 0.0160 |
| | VECM | 0.0176 | 0.0174 | 0.0153 |
| | GTS-OLS | 0.0082 | 0.0084 | 0.0101 |
| MAE 3 | Random Walk | 0.0390 | 0.0330 | 0.0291 |
| | VAR | 0.0394 | 0.0333 | 0.0292 |
| | VECM | 0.0376 | 0.0328 | 0.0320 |
| | GTS-OLS | 0.0089 | 0.0081 | 0.0096 |
| MAE 6 | Random Walk | 0.0580 | 0.0495 | 0.0439 |
| | VAR | 0.0578 | 0.0488 | 0.0418 |
| | VECM | 0.0580 | 0.0483 | 0.0434 |
| | GTS-OLS | 0.0075 | 0.0080 | 0.0099 |
| MAE 12 | Random Walk | 0.0964 | 0.0584 | 0.0753 |
| | VAR | 0.0974 | 0.0603 | 0.0763 |
| | VECM | 0.0881 | 0.0542 | 0.0731 |
| | GTS-OLS | 0.0078 | 0.0088 | 0.0095 |

Interestingly is to notice the performance of the generalized tree structured model out-of-sample. The model consistently and significantly reduce the out of sample error independently on whether the latter is measured in terms MAE or RSME terms. Moreover, it manages to increase the mean directional accuracy to levels ranging between 80%-90%, a 30%-40% increase.

When looking at table 4, the results are clear. The generalized tree structured model menages to increase the out of sample fit by around 50% on the one month lag out-of-sample estimation. Moreover, the performance of the model seems not to constantly deteriorate with an increasing out-of-sample estimation lag but stays rather constant, therefore strongly improving the out-of-sample-fit at higher lags.

#### 4.3.4 Multivariate model fit

Given the strong performance of the univariate parametric fit in the generalized tree structured model a multivariate generalized tree structured model estimation was tried with a vector error correction model and a vector auto-regressive model fit in the final nodes of the tree.

Given the high number of parameters in such multivariate models the criteria for further partitioning the tree was adjusted to 80+ observations. The generalized tree structured model could not go beyond one threshold variable and two partitions for the model due to the higher stopping criteria. Moreover, the out-of-sample performance deteriorated sensibly in comparison to the not partitioned multivariate models suggesting over fitting issues. The conclusion was further supported by the further worsen of performance of models with 70 observation stopping criteria threshold allowing to select threshold splits further in the tails of the empirical variable distribution.

Due to restricted sample size it is therefore not possible to draw sensible conclusions for the generalized tree structured model with multivariate model end-node parametric fit and the paper abstains therefore for conclusive remarks about the performance of the models leaving it as an interesting opportunity for research for the years to come.

## 5 Criticalities

The results outlined presented in the study underline the strong evidence for a long run stable relation among macroeconomic fundamentals and FX-rates.

The promising results from the generalized tree structured model further suggest the importance of capturing the stochastic process of FX-rates by incorporating different regimes based on the underlying macroeconomic situation. This result, together with the estimation of parameters in line with the reversal property that guarantees the long term stable relation among macroeconomic fundamentals and FX-rates might suggest how the adjustment process to the stable long run equilibrium is rather unstable through time and requires therefore a sluggish adjustment process as the one of alternating regime rather than a gradual, periodic, adjustment as the one modeled by the vector error correction model.

Despite, the above achievements some structural flows remain in the analysis. Starting, with a theoretical notice, it should be mentioned how all of the four currencies analyzed are considered to be safe haven currencies in the broad academic literature. This, implies that important movements for the series might be affected by important political events as documented by Ranaldo and Söderlind (2010, [45]) rather then by macroeconomic fundamental movements leading to a worsen performance of the structural monetary fit. Interesting would be in this sense to analyze the results for other less liquid FX-rates series and observe whether the results are in line with the one presented in the analysis as well as in the benchmark papers.

Moreover, some general issues remain with the macroeconomic proxies used in the analysis. Figure 1 shows how the unemployment rate and the gross domestic product growth are generally negatively correlated supporting the validity of proxy of choice, nonetheless, the possibility of further supporting the results by leveraging a linear interpolation of the GDP level or the crude oil consumption level subsist.

Finally, albeit the generalized tree structured model well managed to significantly outperform a random walk model, it should be further stressed the different information set leveraged by the model suggesting caution in claiming a claiming the superiority of the generalized tree structured model for modeling FX-rates out-of-sample.

## 6 Conclusion

The reported results generally confirmed the conclusions presented by Meese and Rogoff (1983a and 1983b, [1, 2]). None of the four models analyzed could improve with statistical significance the out of sample performance of a simple random walk model without drift when forecasting foreign exchange rates. Moreover, I found evidence for a statistically significant underperformance of OLS models compared to a random walk model.

When looking at the point estimation of out of sample error statistics I observed a mixed evidence for the vector autoregressive models and the transfer function models. Both models could sporadically yield more accurate results compared to the random walk model but generally underperformed the latter.

Given the evidence for cointegration among macroeconomic variables and FX-rates I estimated a vector error correction model which displayed promising results, outperforming a random walk model when looking at out of sample forecasting error statistics. These results were consistent among all estimation lags and country series. Nonetheless they did not display enough evidence for rejecting the Null of equal predictability with a random walk model based on the interval estimation through the model confidence test of Hansen (2011, [32]).

Therefore, I can conclude that our study does support the strength of a random walk model in comparison to univariate models for FX-rates estimation. It is also generally sound model for capturing the unit root behaviour observed in the FX-rates movements. Nonetheless, our study vastly contrasted with the results of Meese and Rogoff papers when analyzing multivariate models. The latter models were able to well capture the movements of FX-rates through a parametric model based on macroeconomic fundamentals suggesting an estimation failure due to a small sample bias in the results reported by Meese and Rogoff (1983a and 1983b, [1, 2]). Moreover the cointegration between macroeconomic fundamentals and FX-rates suggests that a stable long run relation between the two exists.

Based on our results I reject the claim of weak relation among macroeconomic variables and foreign exchange rates and I claim that the macroeconomic fundamentals should be considered as a primary determining factor driving the foreign exchange rates movements at monthly lag.

Finally, I note how the successful performance of the random walk models is explained by the long memory displayed by foreign exchange series that is visibile by analyzing autocorrelation plots for the series in virtually all time periods. In contrast to it, the comparable performance of macroeconomic models is explained by the long run relation and correlation among foreign exchange and macroeconomic variables and FX-rates. This is a remarkable achievement that leads us to claim for an underlying relation between fundamentals and FX-rates rejecting the exchange rate disconnect puzzle for the studied period.

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## Appendix A – Data

*Series: Unemployment rate.*

Description: Unemployment Rate: Aged 15-64: All Persons.

Source: Main Economic Indicators - complete database, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

*Series: 3-month Treasury Bills USA, percent annum.*

Description: 3-Month Treasury Bill - Secondary Market Rate

Source Board of Governors of the Federal Reserve System (US), 3-Month Treasury Bill: Secondary Market Rate [TB3MS], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/TB3MS`, April 13, 2019.

*Series: Treasury Bills UK.*

Description: Treasury Bills discount rate, percent per annum.

Source: Bank of England, Treasury Bill Discount Rate in the United Kingdom [TBDRUKM], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/TBDRUKM`, April 13, 2019.

*Series: Treasury Bills JP.*

Description: Interest Rates, Government Securities, Treasury Bills for Japan.

Source: International Monetary Fund, Interest Rates, Government Securities, Treasury Bills for Japan [INTGSTJPM193N], retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/INTGSTJPM193N`, April 13, 2019.

*Series: 3-month LIBOR.*

Description: 3-Month or 90-day Rates and Yields: Interbank Rates

Source: Organization for Economic Co-operation and Development, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

*Series: M3 USA & JP.*

Description: M3 comprises notes and coins in circulation outside banking corporations; demand and savings deposits, fixed and installment savings deposits, time deposits, and certificates of deposit of households, nonfinancial corporations, local governments, securities companies, Tanshi companies, and some other financial corporations such as securities finance companies with depository corporations in national and foreign currency; and nonresident deposits with banking corporations in national currency.

Source: International Monetary Fund, M3 for Japan, and US retrieved from FRED, Federal Reserve Bank of St. Louis; `https://fred.stlouisfed.org/series/MYAGM3JPM189N` & `https://fred.stlouisfed.org/series/MYAGM3USM052N`, April 13, 2019.

*Series: M3 CHF & UK.*

Description: M3 comprises notes and coins in circulation outside banking corporations; demand and savings deposits, fixed and installment savings deposits, time deposits, and certificates of deposit of households, nonfinancial corporations, local governments, securities companies, Tanshi companies, and some other financial corporations such as securities finance companies with depository corporations in national and foreign currency; and nonresident deposits with banking corporations in national currency.

Source: Organization for Economic Co-operation and Development, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

*Series: M1 UK & JP & CH.*

Description: M1 consists of: (1) currency outside the U.S. Treasury, Federal Reserve Banks, and the vaults of depository institutions; (2) traveler's checks of nonbank issuers; (3) demand deposits; and (4) other checkable deposits (OCDs), which consist primarily of negotiable order of withdrawal (NOW) accounts at depository institutions and credit union share draft accounts.

Source: Organization for Economic Co-operation and Development, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

*Series: CPI.*

Description: Consumer Price Index: All Items

Source: Organization for Economic Co-operation and Development, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

*Series: Trade.*

Description: Net Trade. Value of Goods.

Source: Organization for Economic Co-operation and Development, Main Economic Indicators (database), `http://dx.doi.org/10.1787/data-00052-en`, April 13, 2019.

## Appendix B – Figures

Figure 2: *Switzerland GTS Partitions*

*Full Sample 1986 –2006*

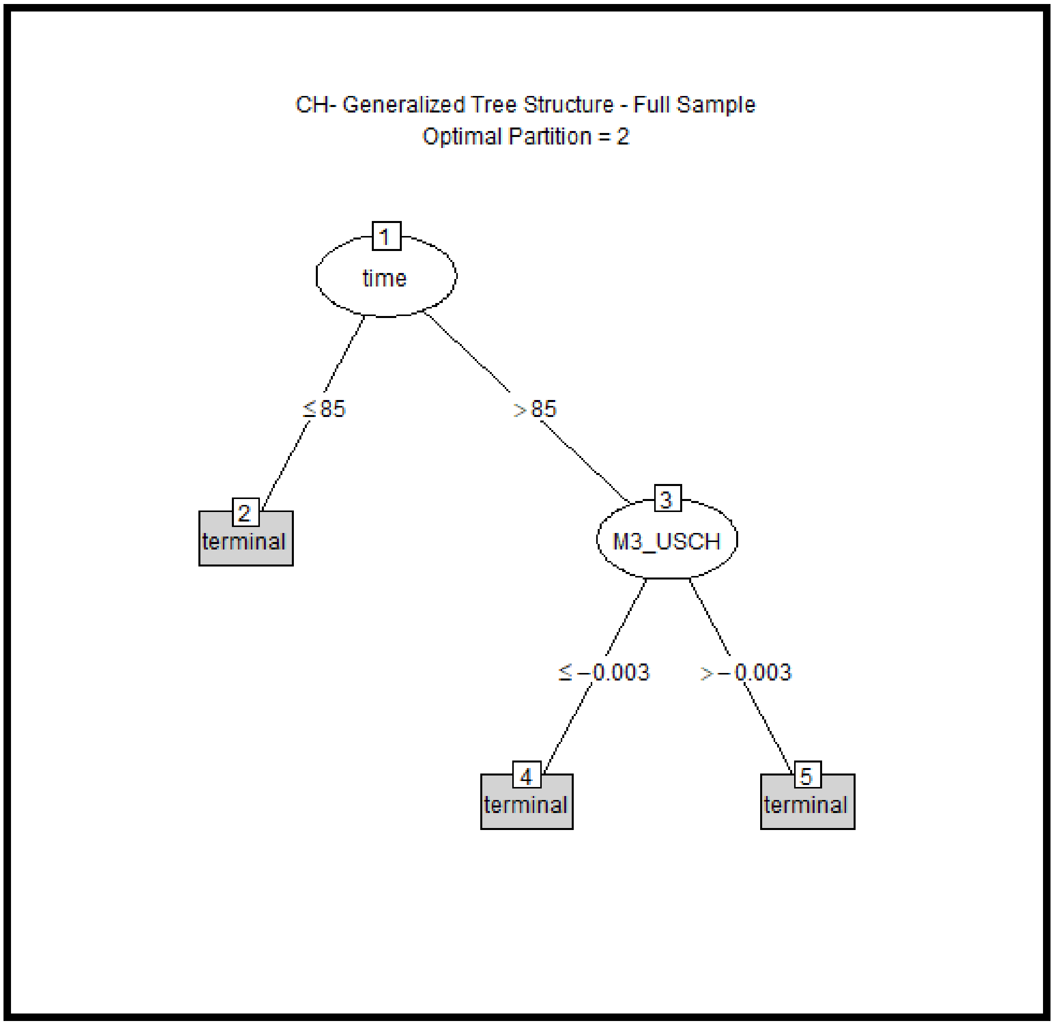


Figure 3: *Japan GTS Partitions*

*Full Sample 1986 –2006*

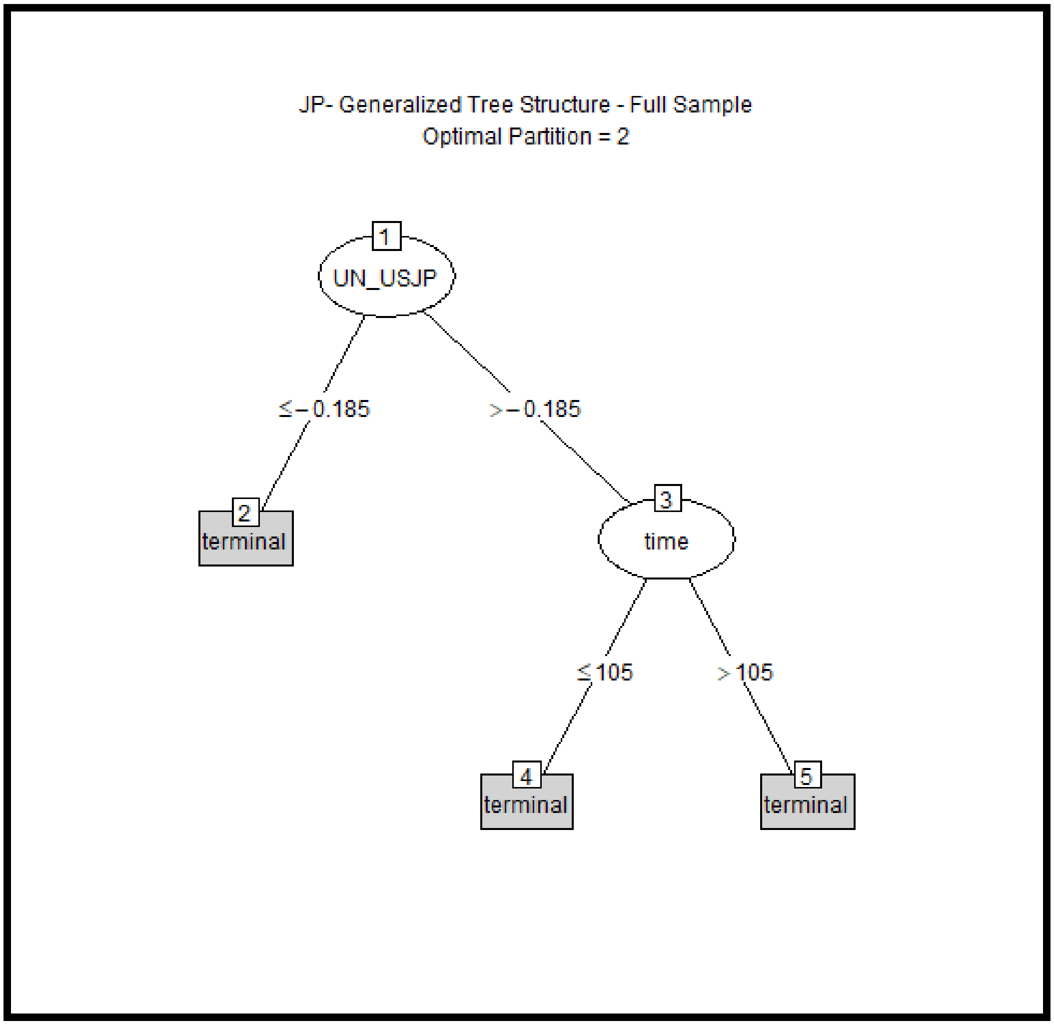
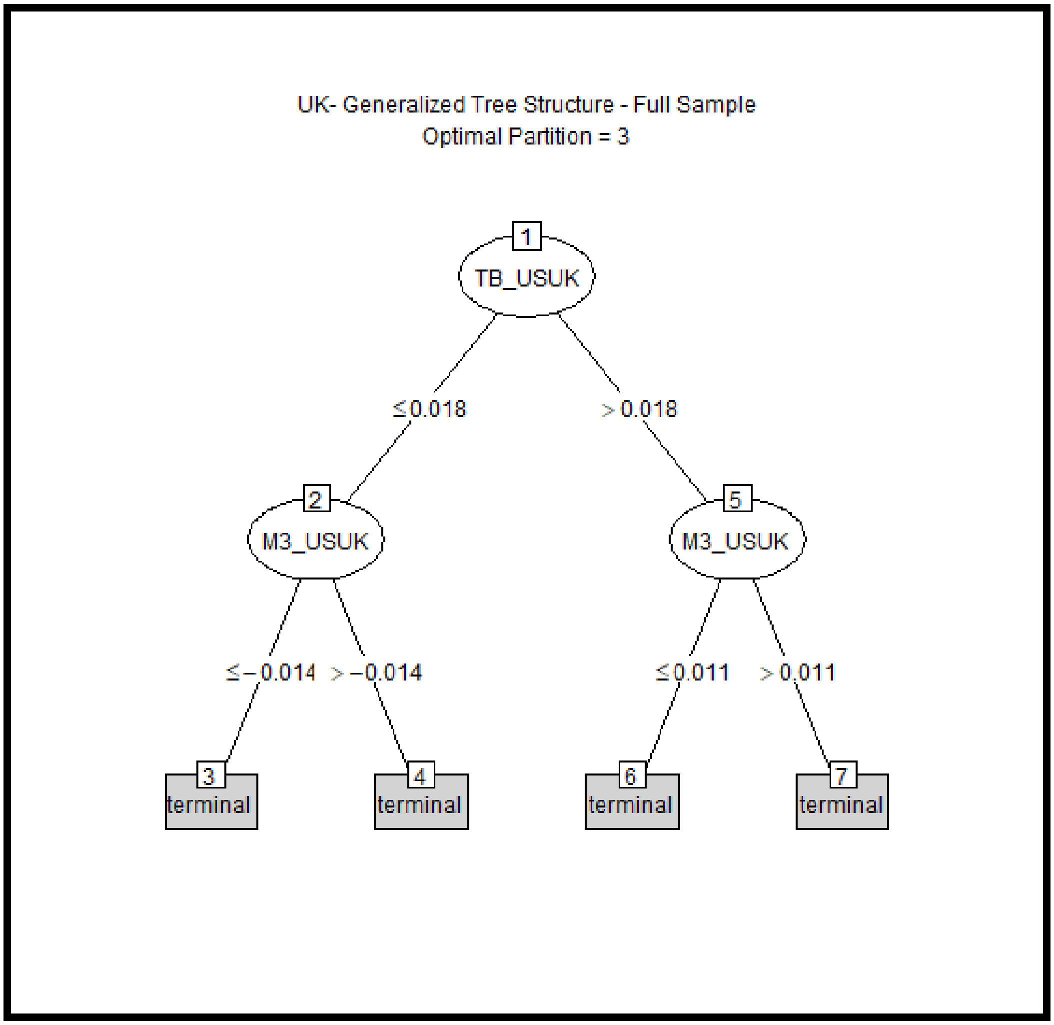


Figure 4: *United Kingdom GTS Partitions*

*Full Sample 1986 –2006*



## Appendix C – GTS Tablesw

Table 5: Generalized Tree Structured Model – OLS parametric fit
Optimal Number of Partitions in Rolling Forecasts

| Pruned Tree – Optimal Number of Partitions | | | |
|---|---|---|---|
| Lag | Switzerland | Japan | United Kingdom |
| Lag 1 | 1 Optimal Partition: 23 times | 1 Optimal Partition: 23 times | 1 Optimal Partition: 23 times |
| | 2 Optimal Partitions: 25 times | 2 Optimal Partitions: 25 times | 2 Optimal Partitions: 25 times |
| Lag 3 | 1 Optimal Partition: 23 times | 1 Optimal Partition: 21 times | 1 Optimal Partition: 21 times |
| | 2 Optimal Partitions: 23 times | 2 Optimal Partitions: 25 times | 2 Optimal Partitions: 25 times |
| Lag 6 | 1 Optimal Partition: 23 times | 1 Optimal Partition: 18 times | 1 Optimal Partition: 18 times |
| | 2 Optimal Partitions: 20 times | 2 Optimal Partitions: 25 times | 2 Optimal Partitions: 25 times |
| Lag 12 | 1 Optimal Partition: 20 times | 1 Optimal Partition: 13 times | 1 Optimal Partition: 15 times |
| | 2 Optimal Partitions: 17 times | 2 Optimal Partitions: 24 times | 2 Optimal Partitions: 23 times |

Table 6: Optimal First Partiton in Rolling Forecast – Switzerland

| Lag | Partition Variable | Partition Interval | Break Occurrences |
|---|---|---|---|
| Lag 1 | Monetary Mass M3 | 56.25% | 31 times |
| | Time | 37.5% | 1 times |
| | | 43.75% | 3 times |
| | | 50% | 6 times |
| | | 56.25% | 7 times |
| Lag 3 | Monetary Mass M3 | 56.25% | 29 times |
| | Time | 37.5% | 1 times |
| | | 43.75% | 3 times |
| | | 50% | 6 times |
| | | 56.25% | 7 times |
| Lag 6 | Monetary Mass M3 | 56.25% | 26 times |
| | Time | 37.5% | 1 times |
| | | 43.75% | 3 times |
| | | 50% | 6 times |
| | | 56.25% | 7 times |
| Lag 12 | Monetary Mass M3 | 56.25% | 20 times |
| | Time | 37.5% | 1 times |
| | | 43.75% | 3 times |
| | | 50% | 6 times |
| | | 56.25% | 7 times |

Table 7: Optimal First Partiton in Rolling Forecast – Japan

| Lag | Partition Variable | Partition Interval | Break Occurrences |
|---|---|---|---|
| Lag 1 | Trade | 56.25% | 10 times |
| | Unemployement | 31.25% | 12 times |
| | Monetary Mass M3 | 37.5% | 18 times |
| | | 43.75% | 5 times |
| | | 68.75% | 3 times |
| Lag 3 | Trade | 56.25% | 10 times |
| | Unemployement | 31.25% | 10 times |
| | Monetary Mass M3 | 37.5% | 18 times |
| | | 43.75% | 5 times |
| | | 68.75% | 3 times |
| Lag 6 | Trade | 56.25% | 10 times |
| | Unemployement | 31.25% | 8 times |
| | Monetary Mass M3 | 37.5% | 18 times |
| | | 43.75% | 5 times |
| | | 68.75% | 2 times |
| Lag 12 | Trade | 56.25% | 10 times |
| | Unemployement | 31.25% | 5 times |
| | Monetary Mass M3 | 37.5% | 18 times |
| | | 43.75% | 4 times |
| | | 68.75% | 4 times |

Table 8: Optimal First Partiton in Rolling Forecast – United Kingdom

| Lag | Partition Variable | Partition Interval | Break Occurrences |
|---|---|---|---|
| Lag 1 | Time | 31.25% | 3 times |
| | | 37.5% | 3 times |
| | Unemployement | 43.75% | 4 times |
| | Treasury Bills | 37.5% | 5 times |
| | | 43.75% | 7 times |
| | | 50.00% | 16 times |
| | | 56.25% | 10 times |
| Lag 3 | Time | 31.25% | 3 times |
| | | 37.5% | 3 times |
| | Unemployement | 43.75% | 4 times |
| | Treasury Bills | 37.5% | 5 times |
| | | 43.75% | 7 times |
| | | 50.00% | 14 times |
| | | 56.25% | 10 times |
| Lag 6 | Time | 31.25% | 3 times |
| | | 37.5% | 3 times |
| | Unemployement | 43.75% | 4 times |
| | Treasury Bills | 37.5% | 5 times |
| | | 43.75% | 7 times |
| | | 50.00% | 11 times |
| | | 56.25% | 10 times |
| Lag 12 | Time | 31.25% | 3 times |
| | | 37.5% | 3 times |
| | Unemployement | 43.75% | 4 times |
| | Treasury Bills | 37.5% | 5 times |
| | | 43.75% | 7 times |
| | | 50.00% | 11 times |
| | | 56.25% | 10 times |

Table 9: GTS Partition Analysis

| Lag | Rollling Forecast | Partition Tuples | Occurrences |
|---|---|---|---|
| Switzerland | 1-16 | Time – Consumer Price Index | 6 |
| | | Time – Monetary Mass 3 | 3 |
| | | Time – Interest Rates | 1 |
| | 18-48 | Monetary Mass 3 – Monetary Mass 3 | 6 |
| | | Monetary Mass 3 – Unempolyment | 16 |
| | | Monetary Mass 3 – Time | 5 |
| | | Monetary Mass 3 – Interst rates | 2 |
| | | Monetary Mass 3 – Trade | 2 |
| Japan | 1-18 | Monetary Mass 3 – Trade | 18 |
| | 19-24 | Trade – Monetary Mass 3 | 6 |
| | 25-48 | Unemployment – Trade | 13 |
| | | Monetary Mass 3 –Trade | 3 |
| | | Monetary Mass 3 –Time | 2 |
| | | Monetary Mass 3 –Unemployment | 1 |
| | | Trade – Monetary Mass 3 | 4 |
| United Kingdom | 1-6 | Time – Interest Rates | 6 |
| | 7-18 | Interest Rates – Monetary Mass 3 | 1 |
| | | Interest Rates – Unemployment | 6 |
| | | Interest Rates – Interst Rates | 4 |
| | | Interest Rates – Time | 1 |
| | 19-22 | Unemployment – Interest Rates | 4 |
| | 23-48 | Interest Rates – Interest Rates | 9 |
| | | Interest Rates – Time | 1 |

## Declaration of Authorship

I hereby declare:

- that I have written this writing sample thesis without any help from others and without the use of documents and aids other than those stated in the references
- that I have mentioned all the sources used and that I have cited them correctly according to established academic citation rules,
- that the topic or parts of it are not already the object of any work or examination of another course unless this is explicitly stated,
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Place: Milan (IT)

Signature: