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Linear and nonlinear exchange rate models:

the Euro-Dollar case

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Summary

Abstract

The thesis presents an application of exchange rate theories related to empirical literature. The study, adopting econometric approaches, started investigating about the hypothesis of Dollar-Euro weekly exchange rate stationarity. The first analysis implemented was the unit root tests for the weekly spot Dollar-Euro exchange rate and for three different weekly Dollar-Euro exchange rate time horizons, respectively one-month forward, three-months forward and one-year forward, for the period January 1999 – June 2016. As reported, the results proved that the weekly Dollar-Euro exchange rate has a unit root or is not stationary. Adopting the same three time horizons, different tests on exchange rate forecast accuracy were performed. The outcomes reveal that forward exchange rates are not able to predict the future spot exchange rate, with an increase of error with regard to time.

To obtain robust results, the market efficiency hypothesis (MEH) was implemented. Three time horizons were employed, but without favourable results.

Following the Meese and Rogoff's puzzle, structural exchange rate models with monthly data and macroeconomic variables were used to determine whether it is possible to beat the simple random walk. In this case, the exchange rate specification adopted was the monthly Euro-Dollar exchange rate, from January 1999 to June 2016 again. The selected structural models were the flexible-price model (Frenkel-Bilson), the sticky-price model (Dornbusch-Frankel) and the sticky-price portfolio model (Hooper-Morton). Proves demonstrated the poorly performance of the above ones compared to the random walk.

Finally, a nonlinear analysis with the same variables of the structural models was carried out to verify whether the random walk overperforms the structural nonlinear models. The nonlinear model used was the Artificial Neural Network (ANN), and findings report the random walk superiority again.

In concluding remarks, it is important to consider the behaviour of the currencies during last years, therefore of the exchange rates, with respect the in-sample outcomes of the study.

Introduction

The structural models developed during the last forty years and based on the determination of exchange rates by fundamental variables – as the flexible-price monetary models, the sticky-price monetary models and the portfolio balance models – had represented a cornerstone for the political and financial decisions. Nevertheless, the "heroic age of exchange rate theory"[1] did not survive long.

The pioneering study conducted by Meese and Rogoff (1983a, 1983b) revealed that the three structural models performed lower than the random walk in terms of root mean square error.

The turning point in favour of random walk accuracy compared with structural models introduced several doubts in the economic environment. A prominent literature investigated the Meese's and Rogoff's intuition, implementing their analysis with different time horizons tests. More recently, a lot of theories have developed new approaches based on high-frequency microeconomic variables models.

The present work is addressed to investigate into the predictability of the exchange rate by means of the market efficiency hypothesis and the linear and nonlinear models performances' comparison.

The first chapter examines the spot and forward weekly Dollar-Euro exchange rate, adopting unit root tests and then OLS and co-integration analyses to verify the market efficiency hypotheses given weekly time horizon variables.

In chapter two, monthly variables are involved to estimate four structural macroeconomic models and to test Euro-Dollar exchange rate, so to examine the in-sample forecast ability for each model.

Finally, chapter three investigates into the accuracy of Euro-Dollar exchange rate prediction through the artificial neural network (ANN) model and, therefore, the in-sample forecast ability of each linear and nonlinear models is verified in comparison with the simple random walk.

[1] Krugman (1993b, p.6)

Chapter 1 - The Dollar-Euro case: a weekly analysis

This weekly analysis is based on data provided by the WM-Reuters through Datastream. Data were downloaded by Excel and then analysed through the statistical programme Stata[2].

The variables involved in the experimental study are the following:

- A time variable from January 1999 to June 2016
- The spot exchange rate Dollar-Euro from January 1999 to June 2016
- The one month forward exchange rate Dollar-Euro weekly from January 1999 to June 2016
- The three months forward exchange rate Dollar-Euro weekly from January 1999 to June 2016
- The one year forward exchange rate Dollar-Euro weekly from January 1999 to June 2016

1.1 Test of non-stationarity of weekly spot dollar-euro exchange rate, one-month weekly forward dollar-euro exchange rate, three-month weekly forward dollar-euro exchange rate and one year weekly forward exchange rate, from January 1999 to June 2016

The following analysis is based on the spot Dollar-Euro exchange rate, the one month forward Dollar-Euro exchange rate, the three months forward Dollar-Euro exchange rate and the one year forward Dollar-Euro exchange rate. The time of variable weekly spot Dollar-Euro exchange refers to the period January 1999 - June 2016, as the time variable availability of forward variables, that is from January 1999 to June 2016. The analysis is based on weekly data.
The AIC Criterion, BIC Criterion, FPE Criterion, HQIC Criterion and SBIC Criterion, computed using the VAC lag-order selection statistics (pre-estimation) and VEC lag-order selection statistics (pre-estimation), suggested one lag for the tests of the weekly spot Dollar-Euro exchange rate, weekly one month forward Dollar-Euro exchange rate, weekly three months Dollar-Euro exchange rate and weekly one year Dollar-Euro exchange rate.
I started from Augmented Dickey-Fuller test for unit root.

Table 1 – Augmented Dickey-Fuller unit root and non-stationarity tests for weekly Dollar-Euro spot and forward from January 1999 to June 2016

Spot Dollar-Euro		One month forward Dollar-Euro		Three months forward Dollar Euro		One year forward Dollar-Euro	
Test statistics	5% critical value	Test statistics	5% critical value	Test statistics	5% critical value	Test statistics	5% critical value
-1.377	-2.860	-1.378	-2.860	-1.377	-2.860	-1.364	-2.860

Notes: Variables in natural logs.

The 5% critical value is less than the test statistic: all variables have a unit root or are not stationary.
To confirm the outcomes of the Augmented Dickey-Fuller tests, I applied the DF-GLS unit root test to each variable.

[2] See http://www.stata.com – Stata/SE/12

Table 2 – DF-GLS unit root test for weekly spot and weekly forward Dollar-Euro exchange rates

	Spot Dollar-Euro		One month forward Dollar-euro		Three months forward Dollar-Euro		One year forward Dollar-Euro	
Lags	Tau test statistics	5% critical value	Tau test statistics	5% critical value	Tau test statistics	5% critical value	Tau test statistics	5% critical value
20	-1.521	-2.827	-1.518	-2.827	-1.508	-2.827	-1.462	-2.827
19	-1.500	-2.829	-1.497	-2.829	-1.486	-2.829	-1.436	-2.829
18	-1.563	-2.831	-1.560	-2.831	-1.551	-2.831	-1.503	-2.831
17	-1.486	-2.833	-1.483	-2.833	-1.472	-2.833	-1.421	-2.833
16	-1.513	-2.835	-1.511	-2.835	-1.500	-2.835	-1.443	-2.835
15	-1.480	-2.836	-1.477	-2.836	-1.468	-2.836	-1.417	-2.836
14	-1.545	-2.838	-1.544	-2.838	-1.539	-2.838	-1.501	-2.838
13	-1.495	-2.840	-1.495	-2.840	-1.490	-2.840	-1.452	-2.840
12	-1.444	-2.842	-1.443	-2.842	-1.437	-2.842	-1.404	-2.842
11	-1.501	-2.843	-1.497	-2.843	-1.489	-2.843	-1.451	-2.843
10	-1.353	-2.845	-1.351	-2.845	-1.343	-2.845	-1.311	-2.845
9	-1.382	-2.874	-1.379	-2.847	-1.369	-2.847	-1.329	-2.847
8	-1.463	-2.848	-1.458	-2.848	-1.447	-2.848	-1.404	-2.848
7	-1.452	-2.850	-1.450	-2.850	-1.441	-2.850	-1.402	-2.850
6	-1.489	-2.852	-1.486	-2.852	-1.477	-2.852	-1.436	-2.852
5	-1.506	-2.853	-1.504	-2.853	-1.496	-2.853	-1.459	-2.853
4	-1.522	-2.855	-1.521	-2.855	-1.513	-2.855	-1.472	-2.855
3	-1.453	-2.856	-1.452	-2.856	-1.446	-2.856	-1.409	-2.856
2	-1.473	-2.858	-1.472	-2.858	-1.467	-2.858	-1.433	-2.858
1	-1.488	-2.859	-1.488	-2.859	-1.444	-2.859	-1.415	-2.859

Notes: DF-GLS applied k(lags) according to the method proposed by Schwert (1989): $k_{max} = [12 \cdot (T/100)^{1/4}]$; in these four cases 20 lags for all variables.

The four cases demonstrated that the null hypothesis of unit root or stationary is rejected at the 5% level for all 20 lags.

The last unit root tests adopted were the Phillips-Perron tests.

Table 3 - Phillips-Perron unit root and non-stationarity test for weekly spot Dollar-Euro

		5% critical value
Z(rho) test statistics	-4.046	-14.100
Z(t) test statistics	-1.402	-2.860

Table 4 – Phillips-Perron unit root and non-stationarity test for one month weekly forward Dollar-Euro

		5% critical value
Z(rho) test statistics	-4.045	-14.100
Z(t) test statistics	-1.402	-2.860

Table 5 - Phillips-Perron unit root and non-stationarity test for three months weekly forward Dollar-Euro

		5% critical value
Z(rho) test statistics	-4.029	-14.100
Z(t) test statistics	-1.400	-2.860

Table 6 - Phillips-Perron unit root and non-stationarity test for one year weekly forward Dollar-Euro

		5% critical value
Z(rho) test statistics	-3.936	-14.100
Z(t) test statistics	-1.385	-2.860

These last tests, once again, rejected the null hypothesis of a unit root at all common significance levels. Evidences form all statistical analysis treated in both periods, from January 1992 to June 2016 (see previous paragraph) and from January 1999 to June 2016, demonstrated that the best prediction of the exchange at time $t+1$ is the exchange rate at a time t, or rather that the variable weekly spot Dollar-Euro exchange rate can be approximated at a random walk variable.

1.2 Statistics forecast accuracy tests of weekly spot dollar-euro exchange rate, one-month weekly forward dollar-euro exchange rate, three-month weekly forward dollar-euro exchange rate and one year weekly forward exchange rate, from January 1999 to June 2016

The following evaluations are developed using the forecast error variables generated by:

$$e_t = s_t - f_t \tag{1.1}$$

Where e_t is the forecast error, s_t is the spot Dollar-Euro exchange rate and f_t is the weekly forward Dollar-Euro exchange rate.
Introducing the student's t test of one-sample mean-comparison test for all three forecast error variables I have applied two necessary assumptions:

1. The hypothesized mean of the forecast errors is zero;
2. The data are normally distributed.

The Jarque-Bera test is used to check the normality distribution assumption for the three forward exchange rates.

Table 7 - Jarque-Bera test of forward for weekly Dollar-Euro exchange rates

	One month forward residuals	Three months forward residuals	One year forward residuals	Observations
Pr(Skewness)	0.0000	0.0000	0.0000	913
Pr(Kurtosis)	0.001	0.0001	0.0006	
Prob>chi2	0.0000	0.0000	0.0000	
Adj chi2(2)	56.51	56.98	59.18	

In the three Jarque-Bera tests the (Prob>chi2) is less than 0.05 critical value, for this reason I rejected the null hypothesis of normality for the three variables.
Given the no normal distribution of data I have implemented the t-test statistics with hypothesized mean of forecast errors equal to zero.

Table 8 - One-Sample t-test of one month forecast error with hypothesized mean equal to zero

		One month forecast error
Observations		913
Mean		0.3681812
Standard Error		0.0101276
Standard Deviation		0.306015
95% Confidential Interval	Lower	0.348305
	Upper	0.3880573
t-value		36.3542
Degrees of freedom		912
Hypothesis: mean < 0		Pr (T < t) = 1.0000

Hypothesis: mean = 0	Pr (ǀTǀ = ǀtǀ) = 0.0000
Hypothesis: mean > 0	Pr (T > t) = 0.0000

Table 9 - One-sample t-test of three months forecast error with hypothesized mean equal to zero

		One month forecast error
Observations		913
Mean		0.3686742
Standard Error		0.010118
Standard Deviation		0.3057234
95% Confidential Interval	Lower	0.348817
	Upper	0.3882314
t-value		36.4376
Degrees of freedom		912
Hypothesis: mean < 0		Pr (T < t) = 1.0000
Hypothesis: mean = 0		Pr (ǀTǀ = ǀtǀ) = 0.0000
Hypothesis: mean > 0		Pr (T > t) = 0.0000

Table 10 – One-sample t-test of one year forecast error with hypothesized mean equal to zero

		One month forecast error
Observations		913
Mean		0.3715516
Standard Error		0.0100567
Standard Deviation		0.3038734
95% Confidential Interval	Lower	0.3518145
	Upper	0.3912886
t-value		36.9455
Degrees of freedom		912
Hypothesis: mean < 0		Pr (T < t) = 1.0000
Hypothesis: mean = 0		Pr (ǀTǀ = ǀtǀ) = 0.0000

Hypothesis: mean > 0	Pr (T > t) = 0.0000

The t-test(s) affirmed one more time the errors in forecast: in all three t-tests I rejected the null hypothesis.
A comparison of Root Mean Square Error of the three regression models was adopted to verify the forecast accuracy, computed thanks the square of the forecast error of the exchange rates

Table 11 – RMSE in forecast error of weekly Dollar-Euro exchange rates

	Forecast error one month exchange rate	Forecast error three months exchange rate	Forecast error one year exchange rate
RMSE	0.47864392	0.47883724	0. 47988384

As expected, by increasing the time in forecast exchange rates, the RMSEs increase too.
Ascertained the forecast error in exchange rate, the next section investigates about distribution of variables, using the Skewness-Kurtosis test (Jarque-Bera test). A robust regression is applied to shorten the limitations of dependent and independent variables, and even to solve problem of heteroscedasticity. From each robust regression, I generated three new variables of predicted residuals.
The results obtained from these tests are shown in the following table.

Table 12 - Jarque-Bera test of forward for weekly Dollar-Euro exchange rates residuals

	One month forward residuals	Three months forward residuals	One year forward residuals	Observations
Pr(Skewness)	0.000	0.000	0.0000	913
Pr(Kurtosis)	0.000	0.000	0.000	
Prob>chi2	0.0000	0.000	0.000	
Adj chi2(2)	41.42	44.44	58.02	

In all Jarque-Bera tests the (Prob>chi2) is less than 0.05 critical value, therefore I rejected the null hypothesis of normality for all residual variables.
Finally, I was interested in the interactions among residuals of spot variable and forward variables. The Durbin-Watson test was applied at the robust regression to discover whether and which serial correlation exists in the residuals.

Table 13 –Durbin-Watson tests of weekly Dollar-Euro exchange rate residuals

	Spot Dollar-Euro exchange rate	One month forward Dollar-Euro exchange rate	Three months forward Dollar-Euro exchange rate	One year forward Dollar-Euro exchange rate
D-W test	0.0082346	0.0082415	0.0082277	0. 0080873

The Durbin-Watson statistics results indicated the presence of positive serial correlation in the residuals.

Again, the tests developed on forecast errors proved that the forecasts of the exchange rate, with different time horizons, failed to predict the spot exchange rate at time t.
Whereby the errors on average are not zero and even they are correlated. The outcomes reveal that forward exchange rates over- or under-predict the future spot exchange rate, however this inconsistency is not inevitably an evidence of exchange market inefficiency. If forward exchange rate at time t were under-predict its spot exchange rate at time $t+1$ this may be a result of the existence of a positive risk premium tied to the foreign currency.
For these reasons, the following tests of market efficiency hypothesis were implemented.

1.3 Dollar-Euro market efficiency hypothesis

Following the reasoning of previous sections, the market efficiency hypothesis was adopted in order to analyse the exchange rate. This approach, based on the rational expectations hypothesis (REH), suggests that rational agents do not make systematic errors when making their predictions (Pilbeam, 2006).
Endorsed this conjecture, following the approach adopted by Meese and Singleton (1982), Cumby and Obstfield (1984), Hansen and Hodrick, it is assumed that the future exchange rate is determined by:

$$(s_{t+1} - s_t) = \alpha_0 + \alpha_1 (f_t - s_t) + \mu_{t+1} \tag{1.2}$$

The ensuing tests were developed to verify the abovementioned assumption.

Table 14 - Dollar-Euro market efficiency test with detrended data

	One month forward Dollar-Euro exchange rate	Three months forward Dollar-Euro exchange rate	One year forward Dollar-Euro exchange rate
α_0	0.00090803	0.00227804	0.00088147
α_1	0.00229359	0.00090342	0.00220124
R^2	0.0024	0.0023	0.0021
RMSE	0.01445	0.01445	0.01445
DW	1.91839	1.91839	1.918411
Observations	855	855	855

Notes: variables are in natural logs. Hypothesis is that $\alpha_0 = 0$ and $\alpha_1 = 1$. Regressions are estimated by OLS. Triple asterisks denote a 1% level of significance. DW is the Durbin-Watson statistics.

Table 15 – Jarque-Bera test of residuals forward for weekly Dollar-Euro exchange rates with detrended data

	One month forward residuals	Three months forward residuals	One year forward residuals	Observations
Pr(Skewness)	0.1180	0.1181	0.1185	
Pr(Kurtosis)	0.0009	0.0009	0.0009	
Prob>chi2	0.0020	0.0020	0.0020	855

Adj chi2(2)	12.45	12.44	12.40	

Table 16 - Augmented Dickey-Fuller unit root and non-stationarity tests of residuals for forward for weekly Dollar-Euro with detrended date

One month forward Dollar-Euro residuals		Three months forward Dollar-Euro residuals		One year forward Dollar-Euro residuals	
Test statistics	5% critical value	Test statistics	5% critical value	Test statistics	5% critical value
-28.061	-2.860	-28.061	-2.860	-28.062	-2.860

Notes: Variables in natural logs. Zero lags selected according to FPE, HQIC, AIC and SBIC criterion.

As stated by the results reported in table 14, I rejected the null hypothesis of Dollar-Euro exchange rate market efficiency. Both coefficient α_0 and α_1 are not significant, the R^2 showed a low level of goodness of fit and the RMSE value is small. Furthermore, the Durbin-Watson statistics demonstrates that there is no first-order serial correlation in the residuals. Table 15 supports the no MEH through the no normal distribution of residuals (Prob>chi2 less than 0.05).
Once again, the Augmented Dickey-Fuller tests rejected the null hypothesis of unit root for residuals for all regressions. These outcomes reveal that taking account of the trend in the exchange rate, agents have on average mispredicted the direction of the exchange rate (Pilbeam, 2006).

Chapter 2 - The Euro-Dollar case: structural exchange rate models with monthly data

To verify structural models of exchange rate determination, macroeconomic variables were involved with monthly horizon. The theories stated that exchange rates are established by fundamental variables, but these variables do not suggest to foresee the future exchange rates, approximating them as random walks. As described by Meese and Rogoff (1982), who studied firstly this phenomenon. "*While a large number of studies have subsequently claimed to find success for various versions of fundamentals-based models, sometimes longer horizons and over different time periods, the success of these models has not proved to be robust*" (West & Engel, 2005).
The adopted structural models include the flexible-price (Frenkel-Bilson) and the sticky-price (Dornbusch-Frankel) monetary models, and the sticky-price model which incorporates the current account (Hooper-Morton). The data used in the empirical tests about the exchange rate models are provided by ECB (European Central Bank) dataset, by FRED of St Louis dataset (Federal Reserve Economic Data) and by WM-Reuters through Datastream.
Because the availability of macroeconomic variables is related to larger horizons of time, the date used to test the exchange rate models are monthly, specifically from January 1999 to June 2016.
Since the monthly GDP date is not available, industrial production index has been used as proxy. M2 is the monetary aggregate adopted for the following tests, since it fits better than M1. The definition of exchange rate of the following models is $Euro/Dollar$. All of the structural models posit that the exchange rate exhibits first-degree homogeneity in the relative money supplies, or $\alpha_1 = -1$ (Rogoff & Meese, 1983).

The United States data series are the following:

- m, M2 money stock. Seasonally adjusted M2;
- p, Consumer price index. The consumer price index for all urban consumers. Seasonally adjusted, (1982-1984=100);
- $\dot{p}$, Inflation. The rate of increase of the consumer price index;
- y, Industrial productivity index. Seasonally adjusted (2012=100);
- TB, Trade balance. The series is equal to the difference between export and import divided by the sum of the export and import. Seasonally adjusted;
- r, Interest rate. Three-month treasury bill rates, second market rate;
- s, Dollar-Euro foreign monthly exchange rate.

The variables involved for the Euro Area are:

- m^*, M2 money stock. Working day and seasonally adjusted;
- p^*, Consumer price index. HICP - overall index. Working day and seasonally adjusted (2015=100);
- $\dot{p}^*$, Inflation. The rate of increase of the consumer price index;
- y^*, Industrial production index. Working day and seasonally adjusted, Euro area 19;
- TB^*, Trade balance. The series is equal to the difference between export and import divided by the sum of the export and import. Working day and seasonally adjusted (2010=100);
- r^*, Interest rate. Three-month euribor (Euro interbank offered rate).

2.1 The Euro-Dollar random walk

The random walk theory suggests that the exchange rate changes have the same distribution and are independent of each other, so the past movement or trend of an exchange rate is wrong predictor of the future movement, in other words the exchange rates follow a random and unpredictable path. Following this theory, the value of the exchange rate at time *t* is the best predictor of the value of the exchange rate at time *t+1*.
The findings of the tests are reported in the following tables.

Table 17 - Random walk

$s_{t+1} = \alpha_0 + \alpha_1 s_t + \mu_{t+1}$	
Period	1999M1 – 2016M6
α_0	0.00326126
α_1	0.98189106***
R^2	0.9637
RMSE	0.02959
DW	1.926836
Observations	210

Notes: variables are in natural logs. Hypothesis is that $\alpha_0 = 0$ and $\alpha_1 = 1$. Regression is estimated by OLS. Triple asterisks denote a 1% level of significance. DW is the Durbin-Watson statistics.

Table 18 - Jarque-Bera test of residuals of random walk

	J-B test	Observations
Pr(Skewness)	0.0003	210
Pr(Kurtosis)	0.0666	
Prob>chi2	0.0010	
Adj chi2(2)	13.73	

Table 19 - Augmented Dickey-Fuller unit root and non-stationarity tests of random walk

Test statistics	1% critical value	5% critical value	10% critical value	Observations
-1.457	-3.474	-2.883	-2.573	208

Notes: Variables in natural logs. One lag selected according to FPE, AIC, HQIC and SBIC criterion.

Table 20 - RESET test of random walk

Ho: model has no omitted variables	
F (3, 205)	1.90
Prob > F	0.1309

Table 21 - White test of random walk

Ho: homoscedasticity - Ha: unrestricted heteroscedasticity	
chi2(2)	0.93
Prob > chi2	0.6293

The outcomes are inclined to accept the random walk. As presented in table 17, the coefficient α_0 does not diverge from zero, furthermore the coefficient α_1 does not significantly deviate from 1. The R^2 reveals a quasi-perfect goodness of fit, and the Durbin-Watson shows quasi-no first-order correlation. The Jarque-Bera test (table 18) on residuals exhibits that residuals do not follow a normal distribution (Prob>chi2 less than 0.05). Concerning the Augmented Dickey-Fuller unit root and non-stationarity tests of random walk, at 1%, 5%, and 10% the critical values are less than the test statistic: the variable s_{t+1} has a unit root or are not stationary.

In the light of the Ramsey specification test (RESET) for omitted variables, the model does not suffer from omitted variable [given that (Prob > F) > 0.05], supporting the conclusion that all relevant variables are included in the model. Appling the White test, I accepted the null hypothesis of homoscedasticity [(Prob > chi2) > 0.05], in other words the homogeneity of variance.

As the theory suggests, the results of all tests are favourable to the random walk model. The outputs are coherent with the findings in first chapter, more precisely I accepted the hypothesis of unit root again. Anyway, the random walk approach, despite of the positive outcomes, needs to be compared with the following structural models to demonstrate its superiority.

2.2 The Euro-Dollar flexible-price monetary model

The model was developed by Frenkel (1976), Mussa (1976) and Bilson (1978), and it hypothesizes that the purchasing power parity is continuous in time. Furthermore, the model represents an interesting addition to exchange rate theory, given the introduction of money stocks as determinants of the relative prices.

The flexible-price monetary models assume that prices in an economy are fully flexible, bonds are perfectly substitutes and, moreover, that the domestic demand for money in relation to the supply of money is one of the fundamentals for the exchange rate determination. From these assumptions, countries with high monetary growth generate high inflationary expectation, which means a reduction in the demand to hold real money balances, that is an increase of goods' expenditure, so a rise of domestic price level and depreciation pressures, with the aim to maintain the purchasing power parity.

The introduction of the role of money supplies, so of the inflationary expectation, represents the most important addition of the model, compared with the previous exchange rate theories. A summary of the results is shown in the following tables.

Table 22 - The flexible-price monetary model

$s_t = \alpha_0 + \alpha_1(m - m^*) + \alpha_2(y - y^*) + \alpha_3(\dot{p} - \dot{p}^*) + \mu_{t+1}$	
Period	1999M1 – 2016M6
α_0	1.4021013***
α_1	-0.00014281***
α_2	0.02184111***
α_3	-0.11145226
R^2	0.0887
RMSE	0.173
DW	0.0743061
Observations	209

Notes: variables are in natural logs. Hypothesis is that $\alpha_0 = 0, \alpha_1 = -1$, $\alpha_2 > 0$ and $\alpha_3 < 0$. 1999M1 missing observation of $(\dot{p} - \dot{p}^*)$ variable. Regression is estimated by OLS. Triple asterisks denote a 1% level of significance. DW is the Durbin-Watson statistics.

Table 23 - Jarque-Bera test of residuals of flexible-price monetary model

	J-B test	Observations
Pr(Skewness)	0.0940	209
Pr(Kurtosis)	0.1995	
Prob>chi2	0.1056	
Adj chi2(2)	4.50	

Table 24 - Augmented Dickey-Fuller unit root and non-stationarity tests of flexible-price model

Test statistics	1% critical value	5% critical value	10% critical value	Observations
-1.683	-3.475	-2.883	-2.573	205

Notes: Variables in natural logs. One lag selected according to AIC, HQIC and SBIC criterion.

Table 25 - RESET test of flexible-price model

Ho: model has no omitted variables	
F (3, 202)	4.01
Prob > F	0.0085

Table 26 - White test of flexible-price model

Ho: homoscedasticity - Ha: unrestricted heteroscedasticity	
chi2(2)	43.75
Prob > chi2	0.0000

The conclusions from the OLS regression are presented in table 22. The coefficient α_0 diverges significantly from zero, and the coefficient α_1 (money stock differential) does not deviate significantly from negative unity. α_2 (industrial production index differential) and α_3 (inflation differential) are congruent with the hypothesis. The R^2 reveals a no goodness of fit, and the Durbin-Watson shows negative first-order correlation. The Jarque-Bera test on residuals exhibits that residuals follow a normal distribution.
From the Augmented Dickey-Fuller test, at 1%, 5%, and 10% the critical values are less than the test statistic, affirming that the variable s_t has a unit root or are not stationary.
As reported by the Ramsey specification test (RESET) for omitted variables, the model suffers from omitted variable [given that (Prob > F) < 0.05]. As demonstrated by the White test, I rejected the null hypothesis of homoscedasticity [(Prob > chi2) < 0.05], or rather the homogeneity of variance. The conclusion from the tests are clearly not supportive to the flexible-price monetary model to determine the Euro-Dollar exchange rate.

2.3 The Euro-Dollar sticky-price Dornbusch monetary model

This model was applied to avoid the major deficiencies of the flexible-price monetary model, in other words that purchasing power parity hold continuously and that prices follow the exchange rate's trend. The Dornbusch model introduced the idea of exchange rate "overshooting". Therefore, the prices (in the good market) and the wages (in the labour market) are defined in "sticky-price" markets, and they slowly change towards the changes in money supply. However, "the exchange rate is determinate in a 'flex-price' market, and can immediately appreciate or depreciate in response to new developments and shocks" (Pilbeam, 2006).
Following the model, the exchange rate does not match with the price movements, so with the purchasing power parity condition. The findings of this model are summarized in the underlying tables.

Table 27 - The sticky-price Dornbusch monetary model

$s = \alpha_0 + \alpha_1(m - m^*) + \alpha_2(y - y^*) + \alpha_3(r - r^*) + \mu_{t+1}$	
Period	1999M1 – 2016M6
α_0	0.47298385***
α_1	-0.00019061***
α_2	3.8414851***
α_3	-0.0476116***
R^2	0.2381
RMSE	0.13626
DW	0.1391447
Observations	210

Notes: hypothesis is that $\alpha_0 = 0$, $\alpha_1 = -1$, $\alpha_2 > 0$ and $\alpha_3 > 0$. Regression is estimated by OLS. Triple asterisks denote a 1% level of significance. DW is the Durbin-Watson statistics.

Table 28 - Jarque-Bera test of residuals of sticky-price Dornbusch monetary model

	J-B test	Observations
Pr(Skewness)	0.0000	210
Pr(Kurtosis)	0.0001	
Prob>chi2	0.0000	
Adj chi2(2)	27.08	

Table 29 - Augmented Dickey-Fuller unit root and non-stationarity tests of sticky-price Dornbusch monetary model

Test statistics	1% critical value	5% critical value	10% critical value	Observations
-1.449	-3.474	-2.883	-2.573	207

Notes: two lags selected according to HQIC and SBIC criterion.

Table 30 - RESET test of sticky-price Dornbusch monetary model

Ho: model has no omitted variables	
F (3, 203)	8.82
Prob > F	0.0000

Table 31 - White test of sticky-price Dornbusch monetary model

Ho: homoscedasticity - Ha: unrestricted heteroscedasticity	
chi2(9)	69.57
Prob > chi2	0.0000

As reported in table 27, the coefficient α_0 is significantly close to zero. Although α_1 is aligned with the hypothesis, as well the coefficients α_2, nevertheless α_3 is incongruent with the assumed value. Also in this case, the R^2 demonstrates no goodness of fit. The Durbin-Watson analysis affirms a negative first-order correlation. Also in this model, the Jarque-Bera test on residuals shows no normality of distribution of them. From the Augmented Dickey-Fuller test, the s_t has a unit root or is not stationary. The RESET demonstrates that the model is affected by omitted variables [given that (Prob > F) < 0.05]. In the White test, given that (Prob > chi2) < 0.05, I rejected the null hypothesis of homoscedasticity. Clearly, the outcomes of all tests employed for the sticky-price Dornbusch model do no support the ability of the model to predict the Euro-Dollar exchange rate.

2.4 The Euro-Dollar sticky-price portfolio model

The perception of risk or risk-aversion in the determination of the exchange rate came relevant thanks to Jeffrey Frankel (1983 and 1984). The introduction of the no perfect substantiality of domestic and foreign bonds and of the significant role for the current account in the exchange rate determination represented the most important innovations compared to the previous monetary models (Pilbeam, 2006). These new features induced a significant policy implication in the exchange rate determination, especially for the foreign exchange operation adopted by central banks to purchase foreign currency bonds.
The following tables show the result of the analysis (as the sticky-price Dornbusch model, the natural logarithm was not applied to the variables).

Table 32 - The sticky-price portfolio model

$s = \alpha_0 + \alpha_1(m - m^*) + \alpha_2(y - y^*) + \alpha_3(r - r^*) + \alpha_4(\dot{p} - \dot{p}^*) + \alpha_5(TB - TB^*) + \mu_{t+1}$	
Period	1999M1 – 2016M6
α_0	0.53646372***
α_1	-0.00019***
α_2	3.8875093***
α_3	-0.04993245***
α_4	-1.9622507*
α_5	0.38835409
R^2	0.2650
RMSE	0.13477

DW	0.0847707
Observations	209

Notes: hypothesis is that $\alpha_0 = 0$, $\alpha_1 = -1$, $\alpha_2 > 0$, $\alpha_3 > 0$, $\alpha_4 < 0$ and $\alpha_5 > 0$. 1999M1 missing observation of $(\dot{p} - \dot{p}^*)$ variable. Regression is estimated by OLS. Triple asterisks denote a 1% level of significance. DW is the Durbin-Watson statistics.

Table 33 - Jarque-Bera test of residuals of sticky-price portfolio model

	J-B test	Observations
Pr(Skewness)	0.0000	209
Pr(Kurtosis)	0.0013	
Prob>chi2	0.0000	
Adj chi2(2)	23.38	

Table 34 - Augmented Dickey-Fuller unit root and non-stationarity tests of sticky-price portfolio model

Test statistics	1% critical value	5% critical value	10% critical value	Observations
-1.502	-3.475	-2.883	-2.573	204

Notes: five lags selected according to FPE and AIC criterion.

Table 35 - RESET test of sticky-price portfolio model

Ho: model has no omitted variables	
F (3, 200)	9.69
Prob > F	0.0000

Table 36 - White test of sticky-price portfolio model

Ho: homoscedasticity - Ha: unrestricted heteroscedasticity	
chi2(20)	104.12
Prob > chi2	0.0000

According to the sticky-price portfolio model we would expect $\alpha_0 = 0$, $\alpha_1 = -1$, $\alpha_2 > 0$, $\alpha_3 > 0$, $\alpha_4 < 0$ and $\alpha_5 > 0$. The summary of the results, reported in table 32, shows convergence from expectations, above all for the industrial productivity index variable, and, not surprising, the R^2 is near to zero. However, the interest rate differential coefficient represents an exception from the envisaged value. The Jarque-Bera test affirms the no normal distribution of residuals, and the Durbin-Watson shows a quasi-perfect first order negative correlation. The Dickey-Fuller test demonstrates that s_t has a unit root or is not stationary, and the Ramsey test outcome confirm the model's suffering for omitted variables. Again, the White test rejects the null hypothesis of homoscedasticity. One more time, evidences from the analysis are not favourable to the sticky-price portfolio model as predictor of the Euro-Dollar exchange rate.

2.5 Euro-Dollar exchange rate models: in-sample prediction

The in-sample accuracy was measured by root mean square error.
In agreement with the RMSEs reported in table 37, the model that outperforms the others is the random walk, followed by the sticky-price Dornbusch model, the sticky-price portfolio model and finally by the flexible-price monetary model.

Table 37 – In-sample predictions

Model	RMSE	Observations
Random walk	0.02959	210
Flexible-price monetary model	0.17300	209
Sticky-price Dornbusch model	0.13626	210
Sticky-price portfolio model	0.13477	209

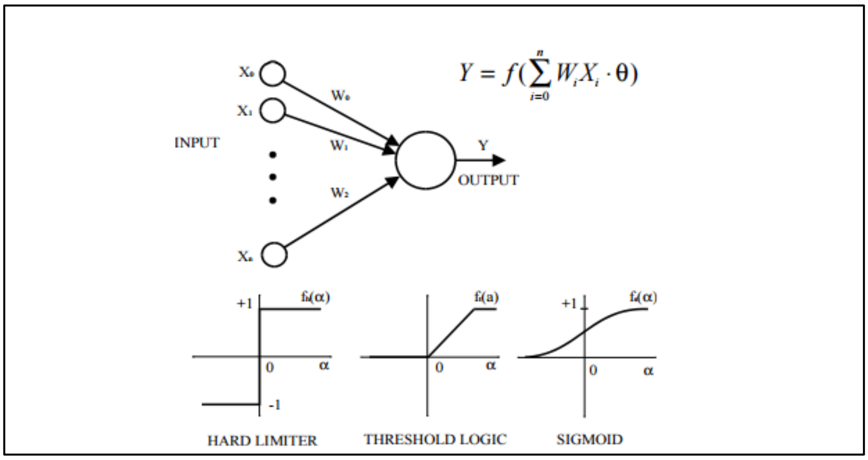
Note: RMSE is the root mean square error.

From the table above, regarding the comparison between structural models using the RMSE as a measure of accuracy, we can conclude that the random walk approach is the best suited to predict the Euro-Dollar exchange rate. The sticky-price portfolio model performed minimally better than the sticky-price Dornbusch model, and finally flexible-price monetary model had the worst performance. In both monetary models the interest rate differential coefficients diverge from the hypothesis. One explanatory factor is that the investors no longer regard the domestic and the foreign bonds as perfect substitutes, namely the uncovered interest parity condition no longer holds (Pilbeam, 2006). In other words, the unexpected results can be explained thanks to the risk premium.
On the other hand, the exchange rate expectations, probably, played a crucial role in the coefficients' divergence from the hypothesis of the monetary models.
To demonstrate the rigor of the analysis a comparison between the above structural models and the Artificial Neural Network (ANN) represents the best solution to examine the ongoing economic theories of exchange rate determination. As a yardstick, the Root Mean Square Error was adopted to comparison and the variables involved for each ANN test were the same as the previous models.

Chapter 3 - Nonlinear model analysis: a linear and nonlinear monthly Euro-Dollar exchange rate models' comparison

Modelling and forecasting exchange rate is usually studied by the regression technique. Therefore, I used the Artificial Neural Network (ANN), a highly flexible form of non-linear models, to forecast the same. Artificial Neural Network (ANN) is a rising computational analysis that provides a new path for exploring dynamics of various economic and economic applications. The ANN is an information process technique for modelling mathematical relationships between input variables and output variables. This training process adopts a training algorithm which adjusts the weights to obtain the global minimum error.
Applying the same structural models' line of reasoning, the present study uses feed-forward back propagation neural technique for forecasting the Euro-Dollar exchange rate. In general, ANN structure is composed of three layers: input layer, hidden layer and output layer. Each layer has a certain number of processing elements called neurons. Signals are passed among neurons over connection links. Each connection link has an associated weight, which, in a typical neural net, multiplies the signal transmitted. Each neuron applies an activation function (usually nonlinear) to its net input (sum of weighted input signals) to determine its output signal (Pradhan & Kumar, 2010). The results depend strongly on the ANN architecture. Figure 1 shows the simplest node, which sums N weighted inputs and conveys the outcome further. The node is characterized by an internal threshold or offset θ and by its type of specified nonlinearity. Moreover, the figure reports three common types of non-linearity used in ANNs: hard limiters, threshold logic elements, and sigmoid.

Figure 1 - Computational element or node with *N* inputs and one output (weighted sum of inputs). Three representative examples of non-linearities are shown below



Source: (Gradojevic & Yang, 2000)

3.1 Artificial Neural Network through structural models' variables

The variables involved in this study, as the previous structural models, are the following.

For the United States:

- m, M2 money stock. Seasonally adjusted M2;
- p, Consumer price index. The consumer price index for all urban consumers. Seasonally adjusted, (1982-1984=100);
- $\dot{p}$, Inflation. The rate of increase of the consumer price index;

- y, Industrial productivity index. Seasonally adjusted (2012=100);
- TB, Trade balance. The series is equal to the difference between export and import divided by the sum of the export and import. Seasonally adjusted;
- r, Interest rate. Three-month treasury bill rates, second market rate;
- s, Dollar-Euro Foreign Monthly Exchange Rate.

For the Euro area:

- m^*, M2 money stock. Working day and seasonally adjusted;
- p^*, Consumer price index. HICP - overall index. Working day and seasonally adjusted (2015=100);
- $\dot{p}^*$, Inflation. The rate of increase of the consumer price index;
- y^*, Industrial production index. Working day and seasonally adjusted, Euro area 19;
- TB^*, Trade balance. The series is equal to the difference between export and import divided by the sum of the export and import. Working day and seasonally adjusted (2010=100);
- r^*, Interest rate. Three-month euribor (Euro interbank offered rate);

To apply the ANN to the structural models, all data were normalized to the [0,1] interval using the following equation:

$$y_{inp,out} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{3.1}$$

Where:

- $y_{i,out}$ = the normalized value of the input or the output value;
- x_i = original input or output value;
- x_{min} = minimum original input or output value;
- x_{max} = maximum original input or output value.

To avoid overtraining, the ANN was trained using an early stopping technique, where datasets were divided into three subsets: 70% training set (to calculate the gradient and to update weights and biases); 15% validation set (the training is stopped if the validation error starts increasing) and 15% testing set (used to compare real and model output of our structural models).

As theory suggests, I applied the following key elements:

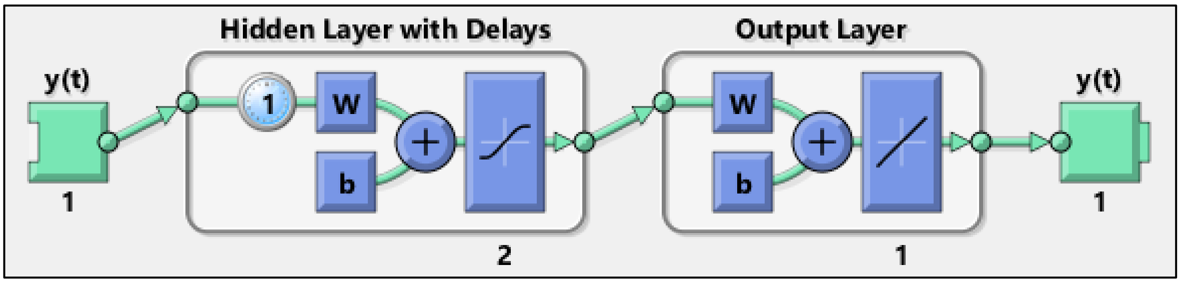
- two hidden neurons, to avoid the risk of overfitting;
- the Levenberg-Marquardt training algorithm, as the fastest method for training moderate-sized feed-forward neural networks;
- a sigmoid function, used commonly for financial markets time series data, which is nonlinear and keeps changing.

The network trainings and testing were performed using the software package Matlab[3], v. 9.1.0, Neural Networks Toolbox, The MathWorks Inc, because it contains a Neural Network Toolbox that is useful for training and testing a specific neural network (contrary to Stata).
Using the same variables previously applied for the structural models, this section investigates which models were suitable. By default, Matlab applies six validation checks. For the random walk comparison, the ANN

[3] See https://www.mathworks.com/

used was the non-linear autoregressive (NAR), useful to predict series y_t given d(delays) past values of y_t, with two hidden layers $d = 1$, as showed in the figure 2.

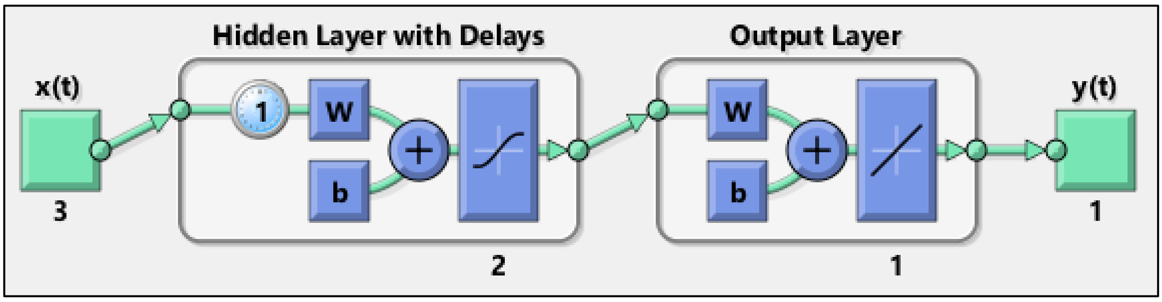
Figure 2 - Non-linear autoregressive



Source: Matlab, v. 9.1.0.

For the flexible-price model, the sticky-price Dornbusch model and the sticky-price portfolio comparison, the ANN used was the non-linear input-output, adopted to predict the series y_t given series x_t, with two hidden layers and one delay:

Figure 3 - Non-linear input-output



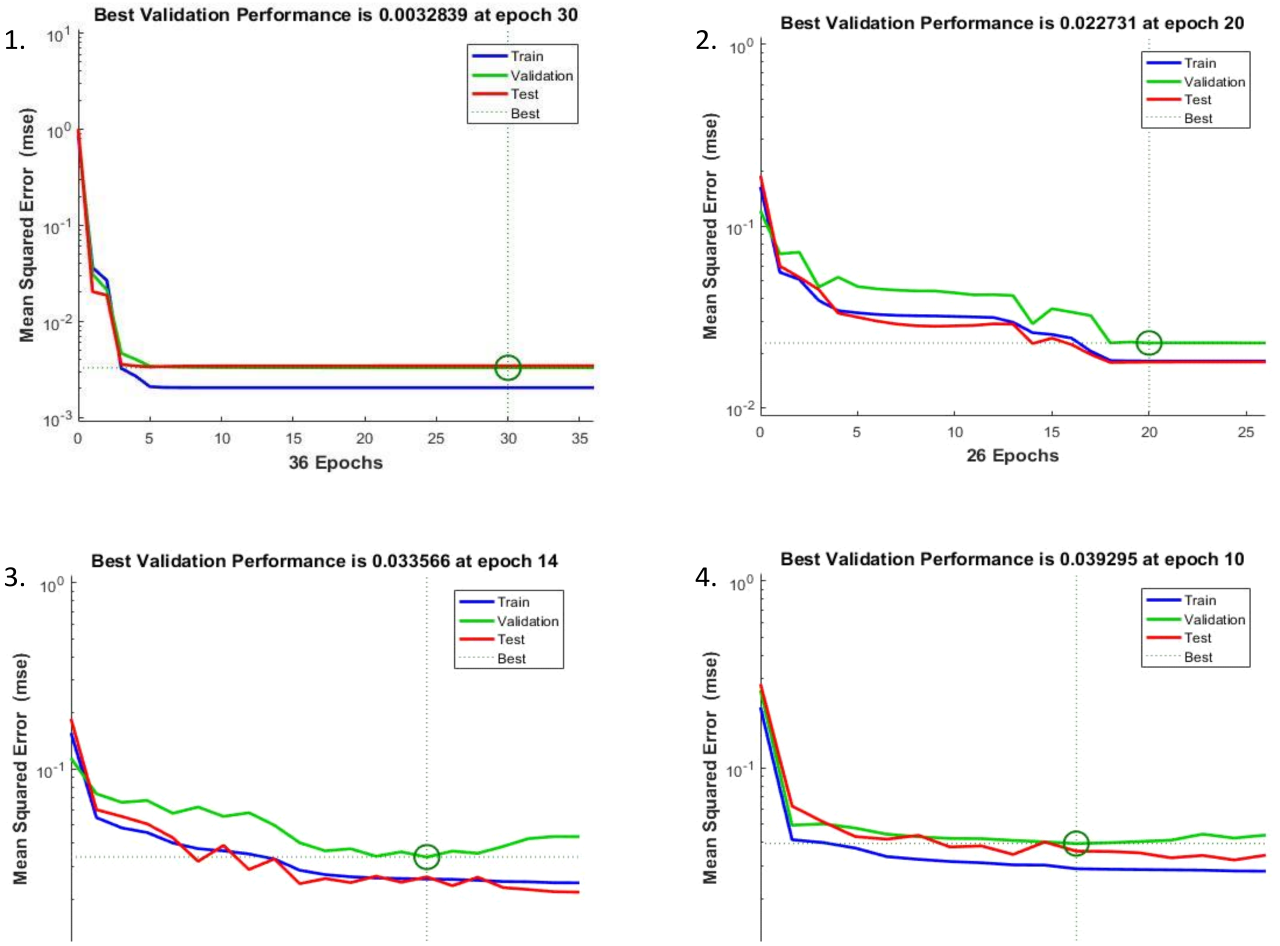
Note: x_t input variables change towards the structural model analysed.
Source: Matlab, v. 9.1.0.

The tables and the figure below report the results of the four tests:

Table 38 - Statistical performance of networks for the Euro-Dollar exchange rate - MSE

	Non-linear autoregressive, random walk variables	Non-linear input-output, flexible-price variables	Non-linear input-output, sticky-price Dornbusch variables	Non-linear input-output, sticky-price portfolio variables
MSE	0.0032839	0.022731	0.033566	0.033295

Figure 4 - Statistical performance of networks for the Euro-Dollar exchange rate - MSE and epochs



Notes: 1. refers to non-linear autoregressive, random walk variables; 2. refers to non-linear input-output, flexible-price variables; 3. refers to non-linear input-output, sticky-price Dornbusch variables; 4. refers to non-linear input-output, sticky-price portfolio variables.

Table 39 - Statistical performance of networks for the Euro-Dollar exchange rate – RMSE in-sample forecasting

	ANN - Non-linear autoregressive (random walk variables)	ANN - Non-linear input-output (flexible-price variables)	ANN - Non-linear input-output (sticky-price Dornbusch variables)	ANN - Non-linear input-output (sticky-price portfolio variables)
RMSE	0.057352	0.150768	0.183210	0.182469

Findings from the table 39 are favourable to non-linear autoregressive using the random walk approach, followed by the non-linear input-output using the flexible-price variables, non-linear input-output using the sticky-price Dornbusch variables and non-linear input-output using the sticky-price portfolio variables. As Meese and Rogoff (1983) suggested, even the random walk approach was tested with an artificial neural network, it achieves the best performance respect to the others.

3.2 Structural models and artificial neural networks: a RMSE comparative approach

The following table represents the focal point of the performances' comparison between structural models and artificial neural network models.

Table 40 – Structural models and ANNs models' performances, in-sample performances

	RMSE
Random walk	0.029590
ANN - Non-linear autoregressive (random walk variables)	0.057352
Flexible-price model	0.173000
ANN - Non-linear input-output (flexible-price variables)	0.150768
Sticky-price Dornbusch model	0.136260
ANN – Non-linear input-output (sticky-price Dornbusch variables)	0.183210
Sticky-price portfolio model	0.134770
ANN - Non-linear input-output (sticky-price portfolio variables)	0.182469

In both cases the random walk approach performed better than the other approaches. The random walk is superior in comparison to the non-linear autoregressive one. Surprising, the non-linear input-output model using the flexible-price variables is more accurate than the flexible-price model. For both sticky-price models, the structural model approach is the best in terms of RMSE.

One possible reason of the high value of RMSE in both ANN non-linear input-output sticky-price approaches is the increase of the structure of the neural network.

To conclude, the artificial neural network, especially in the case of flexible-price variables' use, can add values and possibilities to outperform the structural models to foresee the exchange rate.

The research therefore provides evidence to support the superiority of the structural exchange rate models towards the ANN non-linear models, except for the flexible-price model. The possibility to include in future comparison new micro and macro-economic variables can represent a starting point to further performances' analysis of exchange rate forecast.

The considerations highlighted above induce to a conclusive quote, which is basically methodological, that is the forcefulness of the integrated approach, based on the joint use of linear and non-linear methods of analysis to study the phenomenon of the forecasting exchange rate.

Conclusion

This dissertation tries to answer to the following question: how it is possible to beat the simple random walk? The methodology used to test the predictability of the exchange rate were different, and with various time horizons. The study started from the tests of non-stationarity, or unit root for the weekly spot Dollar-Euro exchange rate and for the three time horizons weekly forward Dollar-Euro exchange rate, respectively one month, three months and one year, in this case for the period January 1999 – June 2016. The tests demonstrated the non-stationarity, that is the unit root.
Subsequently, the analysis focused on the market efficiency hypothesis of weekly Dollar-Euro exchange rate, which showed the no market efficiency for one month, three months and one year forward weekly Dollar-Euro exchange rate, with an increase of error with respect to the time horizon.
From these findings, the research moved to study the so-called Meese and Rogoff puzzle. In these analyses the specification adopted was the monthly Euro-Dollar exchange rate, as well as the monthly horizons for the macroeconomic variables, from January 1999 to June 2016 again. According to the outcomes, the exchange rate at time t is the best predictor of the exchange rate at time $t + 1$, namely the random walk approach performs better than the structural models, which involves the combination of economic fundamentals to foresee exchange rate. Three structural models of monthly Euro-Dollar exchange rate were estimated and tested in terms of forecast accuracy against the simple random walk.
In particular, in in-sample forecast analysis the predictions based on the structural models underperform against the random walk in terms of RMSE.
From these considerations, an analysis based on nonlinear models using the same structural models' variables was adopted. The nonlinear model used was the artificial neural network (ANN), and the results demonstrated the superiority of the random walk once more.
Evidences support the finer performance of linear models than the nonlinear ones, with the exception of one structural model.
Despite the poor performance of nonlinear models, the outcomes open the way to new methodological approaches based on the research of new suitable variables to be included in integrated linear and nonlinear models of exchange rate prediction. The inclusion of other microeconomic and macroeconomic variables, with high and low frequencies, and the integration of currencies in the framework offer major advances in stage for future hybrid analyses of exchange rate forecast.

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