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Exchange Rate Predictions: An Investigation of the Short-run Predictive Power of Fundamentals

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PREFACE AND ACKNOWLEDGEMENTS

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Abstract

Since the collapse of Bretton Wood system of fixed exchange rates, there have been many attempts to construct a model which can produce accurate and reliable forecasts of exchange rates. On the basis of these previous studies, the intent of this thesis is to construct three models capable to generate consistent and more accurate predictions than a driftless random walk model for the Euro/Dollar, Japanese Yen/Dollar, and Chinese Yuan/Dollar exchange rates. Considering past values of these exchange rates and price levels, determined by the CPI, I first built the Purchasing Power Parity model. However, since macroeconomic variables significantly influence exchange rates, I constructed a Monetary model and a Vector Autoregressive model in which are included macroeconomic fundamentals whose choice has been driven by the theoretical framework. All in all, the most important outcome of this research is that none of the models appeared to have a higher predictive power than the random walk model.

Keywords: *Exchange rates, Purchasing Power Parity, Monetary model, Vector Autoregressive model, In-Sample Predictions*

JEL Classification: F31, F37

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1. Introduction

The everyday life of each person involves and is influenced by cash. Every time that we go to the supermarket, or to a restaurant, or even to put gas on the car, we are embroiled in some kind of transaction in which money is required. However, is only when we travel abroad, and we are exposed to exchange rate variations that we really understand the importance of it. Let's consider, for example, a European citizen that decides to go to the U.S. for a journey. His/her budget might vary depending on exchange rates movements. For instance, one day 1,000 euros are worth 1,200 dollars but if the euro depreciates it might be worth 1,100 dollars or vice-versa, if it appreciates it would worth 1,300 dollars. Therefore, monitoring exchange rates and perfectly timing the exchange of money would allow the traveller to have a higher disposable budget.

Attempting to understand exchange rate movements and monitoring them is important not only for travellers, but also, and to some extent even more meaningful, for export/import companies and merchants (Evans, 2005). In fact, for a European exporter, a steady strengthening of euro would mean a decrease in the competitiveness of his products abroad. As a matter of fact, a strong euro would lead to a reduction in the demand for European products overseas. At the same time, imported products would become cheaper and this would cause a loss of competitiveness in the domestic market too. The other way around would arise whenever the euro depreciates: imported products will be more expensive since importers would have to pay more euros for the same amount of foreign currency, and, consequently, imported products will lose competitiveness with respect of locally produced commodities. To this will follow a soaring in export and a shrinking in imports.

Exchange rates movement is an important issue also considering macroeconomic analysis and market surveillance. Notwithstanding the important role covered by the exchange rate, forecasting it has been a longstanding challenge for academics. Since the collapse of Bretton Wood system of fixed rates, considerable interest has been devolved in forecasting exchange rate movements. However, despite a large number of studies and attention addressed to this topic, empirical results from many of the forecasting models have not yielded satisfactory results.

Motivated by the words of Sarno and Taylor (2002), who stated: "*Overall, the conclusion emerges that, although the theory of exchange rate determination has* *produced a number of plausible models, empirical work on exchange rates still has not produced models that are sufficiently satisfactory to be considered reliable and robust. In particular, although empirical exchange rate models occasionally generate apparently satisfactory explanatory power in-sample, they generally fail badly in out-of-sample forecasting tests in the sense that they fail to outperform a random walk*", this work aims to produce forecasts of exchange rates based on different models and factors which were proved to have an influence on exchange rate behaviours.

Research question

The rationale of this paper is multiple. Firstly, I am going to evaluate the performance of the Purchasing Power Parity model in predicting exchange rates of developed and emerging countries. Former researches (e.g. Haque et al. (2013)) showed that the absolute version of this model fails to provide accurate results. In this context, the relative Purchasing Power Parity model will be employed to assess this controversial issue.

Furthermore, I will focus on the research question: is there a forecasting model able to outperform a simple random walk model in the short run? Besides the relative Purchasing Power Parity, the forecast performance of a Monetary model and a Vector Autoregressive model will be tested. The forecasts of all these three models will be compared to those of a driftless random walk. For this purpose, three criterions, namely Mean Squared Forecast error (MSE), Direction of Change (DoC), and Forecast Error ratio (FE), are employed.

The remainder of this paper is organized as follow. In the next chapter, a literature review of previous relevant researches on forecasting exercises together with a theoretical background of each of the models tested in this paper is provided. Section 3 presents a detailed description of the exchange rate series used as dataset and other variables considered. The methodology employed to answer the research questions is described in section 4. Further, in section 5, an analytical investigation of the empirical findings is unveiled. The last section will conclude, providing a summary discussion, research limitations and suggestions for future researches.

2. Literature review

The difficulty of predicting the exchange rate movements has been a longstanding problem in international economics. Trying to understand which variables drive changes in exchange rates and build a model able to forecast their future movements is indeed crucial to evaluate the evolution of price competitiveness and export performance.

2.1 Is there a relationship between exchange rates and macroeconomic variables?

During the years, many different theoretical schools of thoughts focused on the pattern of exchange rates and the link between exchange rates and macro-variables. Some economists argue that it's almost impossible to predict future movements of exchange rates since there is not a definitive economic and statistical evidence of the reliability of the forecasting power of any economic variable. Others believe that inflation can be a leading indicator of future changes in the value of exchange rates.

As far as the first group of scholars is concerned, we should refer to, among the others, Krugman (1988), Flood and Rose (1995), and Obstfeld and Rogoff. The first author attributed the disconnection between exchange rate and prices volatilities to a circular logic. According to this logic, if a variation in the exchange rate value is immediately followed by changes in product allocation, the difference in the amount sold of these products would be so high that they would make the exchange rate decrease. The second authors investigated the effect of a floating regime versus a fixed one on exchange rate volatilities and the relationship between these volatilities and those of macroeconomic fundamentals (e.g. interest rates, money supply, relative prices). They found that, especially in the presence of floating exchange rate regimes, there isn't a strong trade-off between the volatilities of the two variables, given that while exchange rate volatilities appear to change dramatically, the volatility of macroeconomic variables does not.

Lastly, Obstfeld and Rogoff (2001) noticed that, during the short period, the rigidity of prices and macroeconomic variables makes them insulated from the exchange rate. Specifically, they analysed the 'Purchasing Power Parity puzzle' and the 'Exchange-rate disconnect puzzle'. They referred to the first puzzle as a way to explain how weak the connection between exchange rate and national price levels is.

By examining monthly data from 1973 to 1995 for Canada, France, Germany, Japan, and United States, they found, as many other authors, a mean half-life of 3 years. They argued that such long half-lives wouldn't be necessary a puzzle if the remarkable volatility of real and nominal exchange rates could have been explained without assigning an important role to monetary and financial shocks. But since these shocks are a predominant source of volatility, the puzzle relies on the fact that it is hard to ascribe these prolonged exchange deviations to another source of nominal rigidity. The second puzzle examined alludes to the weak relationship between the exchange rate and any macroeconomic aggregates. They referred to previous works (Meese and Rogoff (1983) and Baxter and Stockman (1989)) which demonstrated that standard macroeconomic exchange rate models display a weak forecast performance, even if compared to a naïve random walk model. Furthermore, they underlined the inexistent correlation between nominal and real exchange rate volatilities, due to the transition to floating exchange rate regimes, and fundamental macroeconomic variables volatilities.

On the opposite side, there were many studies that proved the existence of a relationship between exchange rates and macroeconomic fundamentals. Calvo and Reinhart (2000) asserted that, in emerging markets, exchange rate volatility has an injurious effect on the level of export and import, and thus it will influence inflation too. Furthermore, they showed that devaluations may also implicate a loss of access to international capital market. According to these authors, the entry barriers to the international capital market are driven by the fact that in most emerging countries the debt of both private and public sectors is mainly denominated in foreign currency.

Another important work that has to be taken into consideration is "*The behaviour of relative prices in the European Union: A sectoral analysis*". This study has been conducted by Chen (2004), who analysed the behaviour of prices against movements of exchange rates. The starting point of her work is the idea that the comparison of prices across different countries should be a way to investigate the extent of market integration and the consequent finding that prices of comparable goods, expressed in a common currency, fail to equate. The study is focused on output price indices of six major European countries between January 1981 and December 1997. The analysis consisted of two stages: firstly, she investigated the behavior of prices across different countries examining for the presence of unit roots in relative prices; secondly, she analysed the results of the multivariate unit root estimations to evaluate the impact of various macroeconomic factors that may explain differences in mean reversion across sectors and countries. The macroeconomic variables taken into account were differences in GDP per capita, degree of market concentration, existence of barriers and the tradability of products. The findings suggested that the higher volatility of the exchange rates tends to slow the speed of adjustment towards the equilibrium level. Thus, the higher the volatility is, the sticker prices are. Additionally, she evinced that differences on GDP per capita, as well as the presence of barriers, are significant in explaining the persistence of the failure of the law of one price across countries.

2.2 The beginning of exchange rates forecasting theories

The collapse of the Bretton Wood system of fixed exchange rates constituted the beginning of the floating exchange rate regime. After that moment, a considerable interest was devolved in forecasting exchange rate movements. However, notwithstanding the huge amount of studies carried in this field, empirical results from many different models have not yielded satisfactory and significant results.

Since the seminal paper of Meese and Rogoff (1983), the focus of many authors was directed in building a model able to beat the random walk in forecasting the exchange rate. In their paper, Meese and Rogoff argued that a variety of structural exchange rate models perform worse than a simple driftless random walk in out-of-sample forecasting exercises. In particular, they demonstrated that, during the floating period occurred after the collapse of the Bretton Wood system, structural post sample forecasts of foreign exchange rates are less accurate than those produced by a simple driftless random walk model that does not use any information about the fundamentals and merely forecasts the exchange rate to be unchanged. They conducted a monthly out-of-sample fit analysis considering the US dollar prices of Deutsche mark, pound and yen for the period that goes from November 1976 to June 1981. In the research, both structural models (flexible-price monetary model, sticky-price monetary model, and the sticky-price asset model) and univariate and multivariate time series models (long AR and unconstrained VAR models) were employed. The accuracy of the prediction was assessed by three criterions: root mean square error (RMSE), mean absolute error (MAE) and mean error (ME). Their results showed that at the 6- and 12-month horizons, predictions resulting from the driftless random walk model dominate those resulting from their regressions for all the currencies. Moreover, for two of the three currencies, the random walk performed better also at 1-month horizon. All models were based on the realized values of the fundamental in the forecast period. By assigning realized data in forming the forecast, they appear to have given a spurious advantage over the random walk model, making it even more remarkable that all the models generally produce worse results than a simple random walk model. According to these authors, the fact that structural models do not outperform the random walk prediction cannot be ascribed to the unpredictability of the explanatory variables as this uncertainty is handled by using realized values.

An extensive subsequent literature demonstrated the robustness of these results by using different data periodicity, currencies, models, and samples. Among the others, Cheung et al. (2005) examined the behavior of US dollar-based exchange rates of the Canadian dollar, British pound, Deutsche mark and Japanese yen and analysed the performance of five different structural models against the random walk model. The mean square error (MSE) criterion, used to assess the validity of the model, produced results that were not favorable for the structural models. In fact, more than half results were not significant, which means that it is not possible to differentiate the forecasting performance between structural and random walk models. Among the significant results, the vast majority validated the supremacy of a simple random walk model in forecasting exchange rate movements. Moreover, they concluded that a particular model may do well for one exchange rate but not for the others.

Similar results were achieved by Faust et al. (2003), who examined real-time forecasting power of exchange rate models based on macroeconomic fundamentals. The currencies analysed were Japanese yen, Deutsche mark, Canadian dollar, and Swiss franc versus US dollar for the period that goes from April 1988 to October 2000. Contrary to Meese and Rogoff (1983), they constructed the monetary and portfolio balance models using forecasts of future values of fundamentals rather than the realized values. Their results confirmed those of Meese and Rogoff, inasmuch the ratios of the root mean square error (RMSE) are generally greater than one, and increase as the forecast horizon increases. These results attest the failure of the monetary model.

During the years, there have been many attempts to overturn the idea that models based on macroeconomic fundamentals are not able to beat the random walk in forecasting the exchange rate. One of the first authors that obtained results in favour of monetary models was Mark (1995). The scope of his paper was to present evidence that long horizon changes in the logarithm of the spot exchange rate are predictable. Specifically, he explored to which extent deviations of the exchange rate from a fundamental value are effective in predicting exchange rate changes over the long-horizon. Thus, the study was restricted to a mere analysis of a regression on one variable, in such a way that the predictive relation could be appropriately defined. The currencies studied are US dollar prices of the Canadian dollar, the Deutsche mark, the Swiss franc and the yen from 1973 to 1991. He performed forecasts for 1-, 4-, 8-, 12-, and 16-quarter ahead changes in the log exchange rate. After analysing the estimated slope coefficient, the R^2, and root mean square error (RMSE) ratios, the author was able to present evidence that there is an economically significant predictable component in long-term changes in the logarithm of exchange rates and that this model based on a fundamental value produce more effective predictions than the random walk model. This predictable component is contained in the Swiss franc and yen rates for all the forecasts horizons, and at the 12- and 16-quarter horizons for the Deutsche mark.

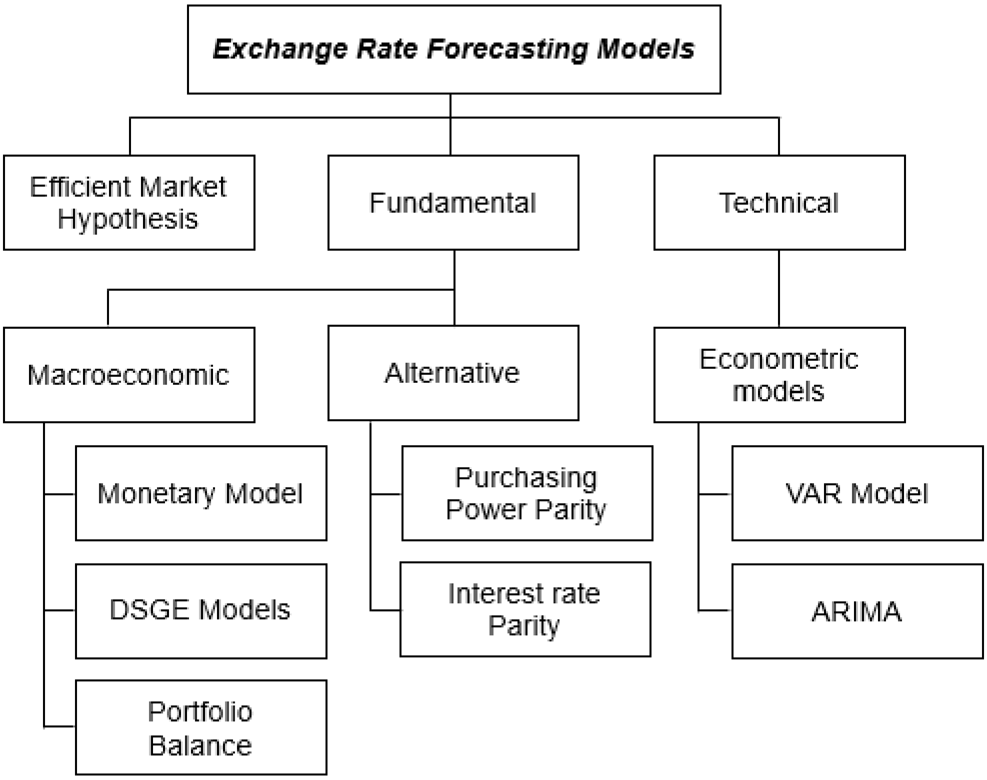
2.3 Classification of exchange rate forecasting models

There is no a generally approved classification of exchange rate forecasting models. However, all models developed by academics to reach forecast exchange rates can be gathered into three main categories:

- Efficient market hypothesis models: the main assumptions are that exchange rates move unpredictably and random walk hypothesis holds.
- Fundamental models: the principal proposition of these models is that specific macroeconomic variables (e.g. GDP, interest rate, inflation rate) impact the exchange rate.
- Technical models: according to these models, the future values of exchange rate are explained and influenced by its past value.

The figure 1 below summarizes the main models developed for each of the three categories above mentioned.

Figure 1: Classification of the main forecast models



In the following pages, studies employing these models are going to be reported and analysed, together with the results generated by each model.

2.4 The Purchasing Power Parity model

In the context of real exchange rate forecasting, it is important to point out that many researches have been addressed in evaluating the performance of the Purchasing Power Parity (PPP) theory over the random walk model, with a special focus on the long-term predictability. The interest of authors is this model has been consolidated by the panel unit root techniques, which indicate that exchange rates are better described as a stationary process rather than a random walk. This belief of stationarity and mean-reverting pattern is given for granted and authors are focusing on how to explain the slow adjustment process of exchange rates. According to Officer (1976), Cassel (1922) has been the first one who operationalized the Purchasing Power Parity and empirically tested it. His idea was that nominal exchange rates should reflect the purchasing power of one currency against another. He stated that a purchasing power exchange rate exists and can be measured as the reciprocal of one country's price level against another. Basically, he evaluated exchange rate changes needed to maintain the PPP using as a starting point the cumulative CPI inflation rates. His objective was to propound the use of PPP as an instrument to set relative gold parity.

In the literature, much attention has been devolved to the concept of Purchasing Power Parity puzzle, that is how can be attainable to reconcile the short-term volatility of real exchange rate with the slow rate at which shocks appear to be absorbed. There is an enormous consensus that estimates the rate at which PPP deviations damp to be a half-life of three to five years. According to this assumption, Ca' Zorzi et al. (2013) based their work. They analysed monthly data for nine major currencies for the period between January 1975 and March 2012. They modelled out-of-sample forecasts for horizons ranging from 1 up to sixty months ahead. Furthermore, they assume the speed of mean reversion to be between 3 and 5 years, in conformity with the PPP puzzle literature (Rogoff (1996), Murray and Papell (2002)). Thus, they built two models consistent with the duration of half-life of 3 and 5 years. The forecasting performance is then measured with the Mean Squared Forecast Errors (MSFE) method and the correlation between forecast and realized real exchange rate changes.

Analogous conclusion was reached by Lim et al. (2008), who demonstrated that in terms of exchange rate predictability, the Purchasing Power Parity (PPP), the Uncovered Interest Rate Parity (UIP), and the Sticky Prices (SP) models are in general able to outperform a random walk model as well as the historical average returns in forecasting the exchange rate movements for EUR/USD and YEN/USD, but not for GBP/USD. This result is in line with what stated by Cheung et al. (2005), who stated that a model may perform well for certain currencies but not for others.

2.5 Macroeconomic models

One of the standard workhorse in the exchange rate forecasts theoretical framework is the monetary model, according to which fundamental variables exert a great influence on exchange rates. Although it is a vintage model, the monetary model is still very important in the international economy and it provides a set of variables that influence exchange rates in the long-run. During the years, the mainly examined variables have been the Gross Domestic Product (GDP), interest rate differential and inflation rates.

The work of Dornbusch (1976) and Frankel (1979) can be considered seminal papers in this field. Both authors based their researches on the Sticky Price Monetary (SP) Model assuming that prices are sticky only in the short run and that the PPP is maintained in the long run. This assumption suggests that exchange rate can deviate from its equilibrium value only in the short run. The purpose of the first author is to study the determinants of exchange rates, both in short and long run, with a specific focus on the role of capital mobility. The baseline idea on which he grounded his work is that sticky prices in goods markets can create a difference in exchange rate between the short and long run. In particular, he states that a depreciation of the domestic currency is caused by an augmented liquidity of the domestic economy due to a decrease of the nominal interest rate relative to the expected inflation rate. According to Dornbusch, capital outflows would cause a further depreciation until the expectations of future currency appreciation will offset the low interest rate. While Dornbusch focused on the role capital mobility, Frankel pointed his attention to the role of monetary expansion. The underlying presupposition is that a monetary expansion and an increase in expected inflation cause a long-run depreciation. The explanation behind this relation is that a monetary expansion increases the supply of the currency, whereas, an increase in expected inflation decreases the demand for the currency. Notwithstanding the different assumptions underlying these two works, both authors proved the existence of a strong relationship between fundamental variables and exchange rates, especially during the short run when prices deviate from their equilibrium level.

On the base of these two seminal papers, were conducted many studies. Among the others, Dal Bianco et. al (2012) analysed the short-run forecasting performance of economic fundamentals. Their monetary model included the differential growth of money supply in two successive periods, industrial production growth, long-term-interest rate and inflation rate. Moreover, their work distinguishes from others employing the monetary model as it uses data at two different frequencies: weekly and monthly. Their results showed an in-sample goodness of fit of about 80%. Furthermore, the out-of-sample forecasting performance is proved to be more accurate than the random walk model. These results are surprisingly in contrast with the existent literature, inasmuch previous works found that at a high frequency is hard to explain exchange rate movements and even harder to forecast them. In addition, the majority of these studies were unable to beat a simple random walk model, which predicts the exchange rate to remain unchanged over the short run.

Another innovative study was carried by Ca' Zorzi et. al (2016). They structured their work on the newest consensus that real exchange rates do not move following a random walk, but tend to be mean reverting. The research is based on an Open-economy Dynamic Stochastic General Equilibrium (DSGE) model estimated using eight macroeconomic time series: the domestic GDP and nominal exchange rate, domestic and foreign change in output, inflation and short-term interest rate. Their main finding is that the DSGE model is able to provide nearly perfect estimation about how exchange rates will react to different shocks. In addition, this model has two main advantages: it shows how a wide set of variables adjust to their equilibrium and it captures the direction of change of the real exchange rate. However, the model encounters many difficulties in forecasting the nominal exchange rate.

Among the authors that investigated the exchange rates using monetary models, it is meaningful to cite Vesilind (2003). The purpose of his paper is to determine whether there is a fundamental indicator able to detect an equilibrium level of the market, and, thus, to predict future movements of exchange rate based on its deviations from the equilibrium level. As a theoretical framework, Vesilind based his research on the standard monetary model developed by Frankel and Rose (1995). The fundamental variables considered to build the model were the price of the foreign currency in domestic currency, domestic and foreign money supply, price level, real income, and nominal interest rate. Since previous researches showed that the model has little predictive power at short and medium horizons, the author used quarterly averages data in order to eliminate disturbances deriving from speculative positions in exchange rate markets and to capture the long-term effect of macroeconomic variables on exchange rates. According to the results accomplished by Vesilind, the difference between domestic and foreign price levels has not influence on exchange rates. Furthermore, only present and lagged values of fundamental variables have predictive power on next quarters' changes in exchange rates. This feature of the model is particularly appealing since it minimises the risk of erroneous predictions of those variables.

2.6 Forecast combination techniques

Among the multitude of theories emerged until now, forecast combination techniques have gathered increasing attention in the recent years. Bates and Granger (1969) have been the pioneers in highlighting the great potential benefit deriving from a combination of forecasts. Even though their study was based on two separate sets of forecasts of international airline passenger, thus not related to the topic of this thesis, it is relevant in this context in order to derive a theory on how to combine forecasts. Indeed, they presented numerous methods of combining two different sets of forecasts. One of the leading conclusion of this study is that combination of forecasts, reached by weighting different sets of forecasts based on their individual error, leads to better results than those that assign constant weight to every forecast model.

While Bates and Granger introduced the concept of combinations of forecasts, Guidolin and Na (2007) proved the broadly accepted conclusion that, in case of structural instability (e.g. non-stationary time series), single non-linear models are likely to fail in performing accurate forecasts, whereas combinations of forecast may constitute a buffer against non-stationarity.

On the ground of these academic works, Lam et al. (2008) investigated the performance of different forecasting techniques in predicting future movements of the exchange rate. More specifically, they compared forecast performance of Purchasing Power Parity model, Uncovered Interest Rate Parity model, Sticky Price Monetary model and a combine forecasts of all the above-mentioned models with benchmarks given by the random-walk and historical average return models. The combined forecast was constructed by assigning weights to each model based on their Mean Squared Forecast Error (MSE): the smaller the forecast error, the larger was the weight assigned to that model. Their findings confirmed the theoretical consensus that combined forecasts outperform the baseline models and, generally, yield better results than single models.

2.7 Theoretical framework

This section presents a theoretical explanation of the models that are going to be implemented in this study.

2.7.1 Purchasing Power Parity

One of the predominant theories on the exchange rate determination is the Purchasing Power Parity theory (from now on PPP), which was first developed, after World War I, by Cassel (1922). Since this moment, the model has been widely used by Central Banks as a guide to settle new par values for their currencies when the old ones were clearly in disequilibrium. The PPP postulates that the price of identical goods in different countries should be the same if expressed in a common currency. Therefore, according to this theory, the value of a currency is expressed by what it can buy.

The principal prediction of this model is that the exchange rate will adjust towards its equilibrium level by offsetting the price changes occurring due to inflation. For this reason, the PPP model is also called 'Inflation Theory of Exchange Rates'. In fact, PPP tells us that if a country has a relatively high inflation rate, then the value of its currency should decline.

During the years, two different versions of the PPP model were developed and investigated by academics: the absolute and the relative PPP theories. The main difference between these two approaches is that the absolute PPP deals with the relationship between different currencies and price of goods, whereas the relative one investigates the impact of differences in inflation rates between two countries.

2.7.1.1 Absolute Purchasing Power Parity

This theory requires very strong preconditions: the absolute PPP holds only in an integrated, competitive product market with the implicit assumptions of a risk-neutral world and non-existence of price arbitrage, in which the goods can be traded freely without trading costs, such as transportation costs, tariffs, export quotas, and so on. It follows that, if the price of a good is not identical in two separate markets, arbitrage transactions would occur; which means that goods would be transferred from the lower price market to the higher price one, and vice-versa. In this way, thanks to these arbitrage opportunities, prices would be promptly equalised.

The absolute PPP theory is based on the 'law of one price', which argues that if the price of a good denominated in the domestic currency is multiplied by the exchange rate, it will result in an equal price of the good denominated in the foreign currency. Absolute PPP states that, since prices should be the same across countries, the exchange rate between two countries should be expressed by the ratio of the prices in each country:

$$E = \ p/p^{*} \qquad [1]$$

where E is the nominal exchange rate, defined as the value in the domestic currency of one unit of foreign currency, and p and p* the domestic and foreign price level. This equation implies that a change in p requires an equivalent change in p* to keep the exchange rate stable (Wilson, 2009).

2.7.1.2 Relative Purchasing Power Parity

Despite the failure of the absolute PPP hypothesis, it cannot be denied that prices of goods play some role in the determination of exchange rates. Thus, a great deal of attention has been focused on a PPP hypothesis with slightly weaker assumptions. Unlike the absolute PPP, the relative version of the model considers only changes in inflation rates across two countries. Indeed, according to this model, the effect exerted by inflation differentials between countries on the prices of goods, will be eliminated since the PPP will adjust to equal the ratio of domestic and foreign price levels. In other words, the currency of the country with higher inflation rate will depreciate against the other country's currency by approximately the inflation differential. The acceptance of the underlying assumption of the relative PPP model that inflation differentials influence the exchange rate movements, leads to consider the Consumer Price Index (CPI) as a promising predictor of exchange rates in this thesis.

The relative version of PPP, which is widely used in academic researches, states that the exchange rate will adjust to reflect changes in the price level of two countries. Thus, the exchange rate that would re-establish the PPP relative to some base period can be defined as:

$$E_{PPP} = E\left(\frac{1+(p_t/p_t^{*})}{1+(P_{t-1}/p_{t-1}^{*})}\right) \qquad [2]$$

where E is the nominal exchange rate, defined as the value in the domestic currency of one unit of foreign currency, p and p* the domestic and foreign price level, and p_{t-1} and p^*_{t-1} are past values of domestic and foreign price levels respectively.

2.7.1.3 Advantages and drawbacks of PPP model

One of the positive side of the PPP model is that it is less complex than other models, inasmuch only prices of tradable good are needed for the calculations. Furthermore, many researchers (Haidar (2011), Simpson and Grossman (2010)) proved that the PPP holds in different time periods, but only when considering the long period.

On the other side, despite the massive amount of attention given to the PPP model, empirical studies that utilize this model are subjects to numerous data selection issues. The main drawback of the PPP is that developed and emerging countries cannot be compared since it will not provide accurate results. This was proved by Haque et al. (2013) who found that PPP does not hold between the U.S. and emerging Asian countries. This result can be explained by the fact that the elasticity of prices of the same goods in developed and emerging economies might be different. Moreover, it was largely debated on which kind of basket of goods should be considered by the model, since, to have non-biased results, the components of the basket of goods must be the same. Many researchers argued that it is hard, if not even impossible, to select identical goods across different countries. This issue is due to the fact that many products fabricated in one country do not have a perfect or comparable substitute in another country. Furthermore, even if they are conceptually similar, aggregate price indices, such as Consumer Price Index (CPI), may include different kind of goods or may be calculated diversely across countries. For these reasons, the bulk of economic literature focuses on the relative aspect, rather than on the absolute one, of the Purchasing Power Parity model.

Notwithstanding these disadvantages, the PPP model has been largely used in academic researches and it is also used as an assumption to some of the fundamental models.

2.7.2 Monetary model

The monetary models were first introduced in the second part of the 1970-ies, as a result of the failure of the Mundell-Fleming Keynesian model in predicting exchange rates in a high-inflationary environment. Notwithstanding this model was proven to allow an assessment of the influence of monetary and fiscal policies on exchange rates, the complexity of the model given by the enormous number of different variables that have to be predicted makes it less attractive. Moreover, the underlying assumption that exchange rates adjust instantaneously after a change in macroeconomic variables, induce the model to lose validity.

2.7.2.1 Flexible Prices Monetary Model

Nowadays, the broadest known version of the monetary model is the one introduced by Frankel (1979), also known as Flexible Prices Monetary model. This monetary model states that exchange rate is a ratio of the prices of currencies in two different countries, which is given by the demand and supply of each of the currencies. Moreover, it assumes that both Purchasing Power Parity and Uncovered Interest Rate Parity hold. This is shown by the following equation:

$$s = (m_a - m_b) - \alpha(y_a - y_b) + \beta(i_a - i_b) \qquad [3]$$

Where s is the spot exchange rate, m_a and m_b are money supply in country a and b, y_a and y_b represent the incomes in the two countries and i_a and i_b are the interest rates.

Frankel's results showed that the exchange rate is positively related to the money supply, negatively related to the difference between the income levels and positively related to the interest rate. This last outcome satisfies the Uncovered Interest Rate Parity (UIP) condition, for which if the interest rate in country a is higher than in country b, then the currency a depreciates against currency b.

Although the model is less complex than the Mundell-Fleming, it incurs in various drawbacks. First of all, it does not allow to assess the influence of monetary and fiscal policies on exchange rates. In addition, it assumes that both PPP and UIP hold even though there has been little empirical evidence that these parities hold in reality (Yong et al. (2000)). Moreover, exchange rate volatility cannot be entirely determined by the model, since it fluctuates more than the fundamentals used to infer its future pattern. Finally, the model asserts that exchange rates adapt immediately to changes in macroeconomic variables, despite the fact that it was corroborated that this is not happening in reality (Chinn (2007) and Wilson (2009)). These downsides of the model were the reasons for the introduction of the Sticky Price Monetary Model.

2.7.2.2 Sticky Prices Monetary Model

The Sticky Prices Monetary model has been introduced by Dornbusch in 1976 as an alternative type of monetary model. This model explains the volatility of exchange rates better than other macroeconomics models, since it assumes that prices of goods and services do not fully react to changes in fundamental variables, and therefore, the exchange rate has to adapt in order to compensate this stickiness. In other words, when a change in a monetary variable occurs, the exchange rate reacts stronger than in a flexible monetary model, and later when prices adjust to the new monetary environment, the exchange rate decreases to the new equilibrium level. The model can be defined as:

$$s = (m_a - m_b) - \alpha(y_a - y_b) + (\beta - 1/\theta)(i_a - i_b) \qquad [\,4\,]$$

where the new term θ is the coefficient of adjustment of the present exchange rate to its long-term equilibrium.

Differently from the model developed by Frenkel, it assumes that PPP and UIP hold only in the long-term horizon and that in the long run the exchange rate is influenced by relative money supply, interest rates, and income.

The main drawback of this model is also its principal advantage. In fact, what makes this model more appealing than the flexible model is that it tries to explain why exchange rates are more volatile than fundamental variables. However, the assumption that exchange rate overshoots in the short run makes academics doubting about the validity of the model. It is, indeed, unclear how long the overshooting will last, whether it is possible that is delayed, or it might be the case that there is no overshooting at all (Breedon (1998), Rogoff (2002), and Tu (2009)).

2.7.3 Vector Autoregressive (VAR) model

The Vector Autoregressive model is one of the most successful and flexible model in analysing multivariate time series. It has proven to be especially useful and reliable in describing the behavior of economic and financial time series and forecasting them. In addition, forecasts resulting from VAR models are quite flexible, since they can be based on the potential future paths of other variables in the model.

The VAR is used to capture the linear interdependencies among multiple time series. It generalize the univariate autoregressive model (AR model) by allowing for more than one evolving variable. In fact, it is a n-equation with n-variables linear model in which each variable is explained by its own lagged values, plus current and past values of the remaining n-1 variables.

The decision to make use of the Vector Autoregressive Model (VAR) model relies on the possibility to incur into an endogeneity bias since variables can be simultaneously related. In other words, it may be the case that inflation affects the exchange rates in the sense that a higher inflation leads to a depreciation of the domestic currency. But it can also be the case that a high exchange rate leads to a decrease in inflation rates. Furthermore, this model is appropriate to test time-series, since it allows the value of a variable to depend on its own lags.

2.7.4 Implications of the VAR model assumption of endogenous variables

Both models considered before, namely the PPP and monetary model, assumed that the only endogenous variable was the exchange rate, whereas all the other variables were supposed to be exogenous. However, when employing the VAR model, every variable considered in the previous models is considered as endogenous, and consequently, this exogeneity assumption is not satisfied.

Before analysing the implications of exogeneity violation, it is worth to explain what it is meant by exogeneity. In a simple OLS regression with a dependent variable Y, independent variable X, and error term e, exogeneity means that the X variable does not depend either on Y or e, rather Y depends on X and e. Thus, the OLS assumption of exogeneity is satisfied if the condition of non-correlation between independent variable and error term, expressed as $E(u|X) = 0$, is met. Whenever this condition is violated, X is said to be an endogenous variable.

The direct consequence of a violation of the exogeneity assumption is that estimated coefficients are biased and inconsistent, and this implies that the causal interpretation of the coefficients is not valid.

Despite what just said, in this analysis, each model is considered separately from the others and the scope of the study is to find a model that produces the most accurate predictions of the exchange rate. For this reason, results and assumptions of one model should not undermine the validity of the other models into consideration

2.7.5 Combination of forecasts

The idea that a combination of forecast outperforms a single forecast model has gained increasingly attention since it was firstly introduced by Bates and Granger in 1969. Their study was based on the concept that some useful information is lost when considering only the best forecast since each forecast is based on variables and/or information that other forecasts didn't examine. The combined forecasts model was built assigning a weigh *k* to the first forecast model and a weight *1-k* to the second. The weight parameter *k* was determined with the aim of minimizing the forecast errors, and, thus, the overall variance σ_c^2, which can be written as:

$$\sigma_c^2 = k^2\sigma_1^2 + (1-k)^2\sigma_2^2 + 2pk\sigma_1(1-k)\sigma_2 \qquad [\,5\,]$$

where *k* and *1-k* are the weights given to the two sets of forecasts and *p* is the correlation between the forecast errors. In order to minimize σ_c^2, they differentiated with respect to *k* and assumed a *p=0*, reaching the equation:

$$k = \sigma_2^2/(\sigma_1^2 + \sigma_2^2) \qquad [\,6\,]$$

The combined forecast C_T for the period t was calculated as:

$$C_T = k_t f_{t,1} + (1-k_t) f_{t,2} \qquad [\,7\,]$$

where $f_{t,1}$ and $f_{t,2}$ are the forecasts at time T from the first and second set of forecasts, respectively.

3. Data and descriptive statistics

This thesis is an empirical investigation in forecasting using the exchange rate between the US-dollar (USD) and Euro (EUR), Japanese Yen (JPY) and Chinese Yuan Renminbi (CNY). The sample encompasses the period from January 2000 to August 2017 and is available at weekly frequencies. All exchange rates are expressed in units of national currency per US-dollar and are obtained from the DataStream database.

For the purpose of this thesis, the variables considered to predict exchange rate movements are Consumer Price index (CPI), long-term interest rates (10-years government bond), money supply M1 and Industrial Production real growth (IP). These fundamental variables were obtained from OECD Main Economic Indicator. To compute the Industrial Production growth for the euro area, Germany's data are used. This choice resides in the fact that Germany is Europe's largest economy, accounting for almost a third of the economic output in the eurozone.

The reason behind the choice of the CPI as an indicator of inflation relies mainly on the accuracy of this measure. In fact, it has been strongly argued, also among central banks, that CPI is the most accurate measure, primarily because it is calculated as a geometric average. This implies that the CPI allows for a shift in consumers preferences for quantities of goods and services they buy whenever the relative prices of these goods and services change. Moreover, it is less volatile than other inflation indicators, such as the Retail Price Index (RPI).

Another fundamental that is taken into consideration for the model construction is the 10-years government bond as a measure of long-term interest rate. This choice was driven by the findings of Lace et. al (2015), who found that the 10-years government bond yields were the major determinant of exchange rate movements. In addition, in the model, I consider M1 as a fundamental that exerts an influence on exchange rate behavior. The motivation is that, since M1 includes only the most liquid portion of the money in circulation, such as currency held by consumers, deposits, savings and, loans, it is the most useful indicator for monitoring central banks' monetary policy and, thus, for predicting the future effects of monetary policy on exchange rates.

Finally, I include an estimation of Japanese Yen/Dollar exchange rate because, alongside with US and Germany, Japan is a large important global economy.

Furthermore, I analyse the Chinese Yuan/Dollar exchange rate because I want to test the predictive power of each of the forecasting models when comparing a developed and an emerging country.

3.1 Data transformation process

Before proceeding with the construction of the models, I performed some analysis and transformations to the raw data. In this section, I will describe this process.

Firstly, I constructed the variables as they are needed by the models. In particular, I calculated the inflation rate (Inf), interest differential (IntDiff), business cycle (BC), and money aggregate differential (MD). The formulas used to calculate these variables are shown below:

$$Inf = \frac{CPI_{Eur-Jap-Chi}}{CPI_{U.S.}} \quad [8]$$

$$IntDiff = Int_{U.S} - Int_{Eur-Jap-Chi} \quad [9]$$

$$BC = \frac{IP_{U.S.}}{IP_{Eur-Jap-Chi}} \quad [10]$$

$$MD = \frac{M1_{U.S.}}{M1_{Eur-Jap-Chi}} \quad [11]$$

After having generated the variables needed for the regressions, I proceeded with the Dickey-Fuller test for unit root to investigate if the variables analysed are stationary or not. This test investigates the null hypothesis of whether a unit root is present in an autoregressive model. This means that, if the null hypothesis is accepted, the time series is not stationary.

Table 1 below presents results of the Dickey-Fuller test for each variable used to construct the models. The values connotated by an asterisk represent the variable for which the null hypothesis of non-stationarity is rejected. In order to reject the null hypothesis, the test statistic value generated by the test has to be in absolute terms higher than the 1%, 5%, and 10% critical values. Whenever the null hypothesis cannot be rejected at a first glance, I calculated the first difference and I run again the test. These variables are denoted by the prefix D_. Each of them resulted stationary at their first difference at 1%, 5%, and 10% confidence level.

Table1: Interpolated Dickey-Fuller Test for unit roots

Variable	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
BC_EUR	-10.744*	-3.430	-2.860	-2.570
Inf_EUR	-1.348	-3.430	-2.860	-2.570
D_Inf_EUR	-21.319*	-3.430	-2.860	-2.570
IntDiff_EUR	-1.492	-3.430	-2.860	-2.570
D_IntDiff_EUR	-21.319*	-3.430	-2.860	-2.570
MD_EUR	-2.001	-3.430	-2.860	-2.570
D_MD_EUR	-21.369*	-3.430	-2.860	-2.570
BC_JAP	-10.052*	-3.430	-2.860	-2.570
Inf_JAP	-1.429	-3.430	-2.860	-2.570
D_Inf_JAP	-21.384*	-3.430	-2.860	-2.570
IntDiff_JAP	-2.913	-3.430	-2.860	-2.570
D_IntDiff_JAP	-21.351*	-3.430	-2.860	-2.570
MD_JAP	0.9454	-3.430	-2.860	-2.570
D_MD_JAP	-21.392*	-3.430	-2.860	-2.570
BC_CHI	-9.625*	-3.430	-2.860	-2.570
Inf_CHI	-0.705	-3.430	-2.860	-2.570
D_Inf_CHI	-21.399*	-3.430	-2.860	-2.570
IntDiff_CHI	-1.991	-3.430	-2.860	-2.570
D_IntDiff_CHI	-20.365*	-3.430	-2.860	-2.570
MD_CHI	-6.442*	-3.430	-2.860	-2.570

3.2 Descriptive statistics

With the intention to keep the structure of this paper simple, I include graphs of exchange rates as well as of all variables used for the modelling section, together with some descriptive statistics. The fundamental variables that I am going to use in order to model the forecast experiment are available for all countries analysed and are indicated by the subscript:

Inf_Country: level of inflation calculated as the ratio between CPI of the Euro area, Japan, and China, and the one in the United States.

BC_Country: Business cycle given by the ratio of growth rate of US real Industrial Production and the one of each country under scrutiny.

Int_Diff_Country: interest differential calculated as the difference between interest rate in US and the one in Europe, Japan, and China.

MD_Country: Money supply M1 given by the level of M1 in US divided by the level of M1 in Europe, Japan, and China.

The weekly fluctuations of euro/dollar, jpy/dollar and yuan/dollar for the considered period are drawn in figures 2a, 2b, and 2c. As we can see, all these exchange rates fluctuate considerably over time, with exception for the yuan/dollar, which in the period between 2000 and 2005 was steady at a level around 8.27.

Figure 2a: Line graph of the EURUSD exchange rate

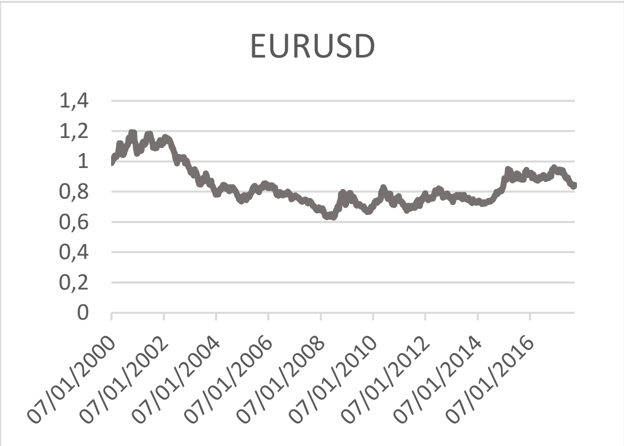


Figure 2b: Line graph of the JPYUSD exchange rate

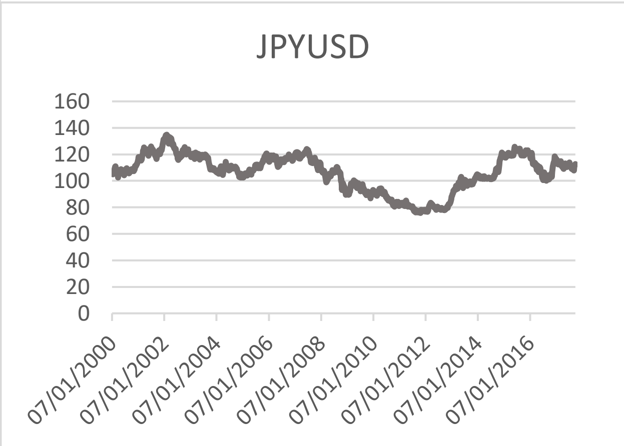
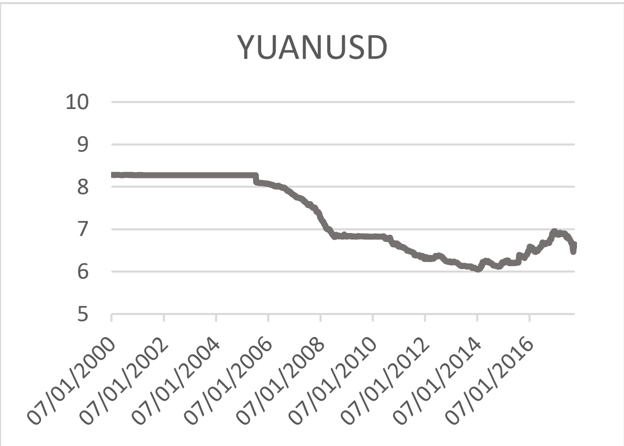


Figure 2c: Line graph of the YUANUSD exchange rate



Some descriptive statistic reporting the key measures of all variables are exposed in table 2.

Table 2: Descriptive statistics for all variable

Variable	N° of observations	Mean	Std. Deviation	Variance	Skewness	Kurtosis
EURUSD	915	0.0841	0.1342	0.0180	0.9245	2.9526
JPYUSD	915	106.1158	14.0263	196.7377	-0.5365	2.3851
YUANUSD	915	7.2640	0.8508	0.7238	0.6962	1.3078
Inf_EUR	915	0.9232	0.1150	0.0132	-0.3748	2.0781
Inf_JAP	915	0.8794	0.1271	0.0161	-0.2649	2.2391
Inf_CHI	915	0.9441	0.1528	0.0233	0.1698	1.4983
BC_EUR	907	0.8030	4.0536	16.4320	-1.4838	27.4987
BC_JAP	907	0.4042	2.2376	5.0069	-2.4988	38.8910
BC_CHI	911	0.2568	2.0085	4.0334	1.6212	14.9268
IntDiff_EUR	915	-0.0272	0.8136	0.6619	-0.5096	2.6555
IntDiff_JAP	915	2.4801	0.8668	0.7514	0.2692	2.7866
IntDiff_CHI	834	0.4152	2.2003	4.8412	-0.4645	1.9685
MD_EUR	915	1.2103	0.1562	0.0244	-0.2204	1.8245
MD_JAP	915	1.0483	0.2188	0.4788	0.3974	1.6373
MD_CHI	915	1.6390	0.6938	0.4814	0.9438	2.5657

In the table, I included also values relative to Skewness and Kurtosis which are useful to understand whether a series is normally distributed or not. Specifically, a series is normally distributed when its Skewness is equal to zero and Kurtosis is equal to 3. As we can see from the table above, the majority of the variables are normally distributed, assuming values close to zero and three. In cases in which variables exhibited a significant Skewness and Kurtosis, as for Business Cycle, I calculated the natural logarithm to normalize the data set.

4. Methodology and model construction

In this section, I provide a description of the methodology followed to produce predictions of EURUSD, JPYUSD, and YUANUSD exchange rates. Before analysing the models in detail, a small section in which are illustrated the assumptions underlying this work is provided.

4.1 Assumptions and specifications

The first assumption on which this research is based, is related to the findings of Engels et al. (2007), according to which standard models presuppose near-random walk behavior in exchange rates. Assuming this implies that their power to beat the random walk in out-of-sample forecasts is low. For this reason, in this context, I will produce and test in-sample predictions of exchange rate movements.

The second conjecture is to assume that the levels of exchange rates are related to those of explanatory variables, over the long-term. In this way, I suppose that exchange rates incorporate news about realized values of fundamentals. Following this assumption, I give the exchange rate models an advantage over the random walk model: predictions will be made using realized values of the independent variables rather than their own forecasts. This technique was used by Meese and Rogoff (1983) in their seminal paper.

Furthermore, I assume the growth rate of exchange rate to be dependent on the growth rates of fundamental variables.

Lastly, since fundamental data are expressed at a monthly frequency and knowing that weekly data are needed to build the models, monthly data are assumed to be constant throughout the month: in other words, to each week is assigned its respective monthly value.

4.2 Purchasing Power Parity

As stated in the theoretical framework section, due to several shortcomings of the absolute PPP, for the purpose of this thesis, I am going to predict future exchange rates using the relative version of PPP, which is given by equation 2:

$$E_{PPP} = E\left(\frac{1+(p_t/p_t^*)}{1+(P_{t-1}/p_{t-1}^*)}\right) \qquad [\,2\,]$$

Where E is the realized exchange rate and p, p*, p_{t-1} and p^*_{t-1} are present and past values of the domestic and foreign CPI. In the table below are reported some calculations that show how the PPP between Euro/Dollar exchange rate was computed, followed by some preliminary results of these calculations.

Some calculations for 2000w9:

$$E_{PPP} = 1.01482 * \left(\frac{1 + (91.81993/113.9636)}{1 + (93.35256/112.3854)}\right) = 1.000988152$$

Table 3: preliminary results for Euro/Dollar PPP calculation

Date	CPI EUR	CPI US	Actual E_EURUSD (E)	In-sample PPP (E_PPP)	Error ε=E-E_PPP
2000w1	93.35256	112.3854	-	-	-
2000w5	91.81993	113.9636	1.01482	-	-
2000w9	90.37327	114.7326	1.03681	1.00098	0.0358
2000w14	88.83984	115.2498	1.04592	1.02647	0.0194
2000w18	87.38805	117.7737	1.1029	1.03607	0.0668
2000w22	90.47439	117.0927	1.05152	1.08434	-0.03348
2000w27	89.82564	117.04006	1.06701	1.07003	-0.0030

The same procedure was followed in order to calculate the PPP between JPY/USD and YUAN/USD.

Once the PPP is calculated, the exchange rate is regressed on the PPP in the form of an OLS regression given by the formula:

$$y = \alpha + \beta PPP + \mu \qquad [\,12\,]$$

Where μ is the noise disturbance term (residuals) which is assumed to be normally distributed, with mean zero and variance 1.

4.3 Monetary model

Considering the numerous drawbacks of the two main monetary models, to carry out my analysis, I am going to make use of the monetary model used by Ghalayini (2013). According to this model, the exchange rate is explained by four macroeconomic variables, namely: inflation rate differential, interest rate differential, business cycles differential and money aggregate differential. This relationship can be written as a simple OLS regression in the form of:

$$E = \alpha + \beta_1 Inf + \beta_2\left(Int_{US} - Int_{EUR,JAP,CHI}\right) + \beta_3 BC + \beta_4 MD + \mu \qquad [13]$$

Where μ is the noise disturbance term at time t with mean zero and constant variance.

The inflation rate is calculated as the ratio between Consumer Price Index of the Euro area, Japan, and China, and the one in the United States. The variable Business Cycle is computed by dividing the growth rate of US real Industrial Production by the one of each country under scrutiny. Finally, the money aggregate differential, MD, is given by the level of M1 in US divided by the level of M1 in Europe, Japan, and China, where M1 represents the most liquid portion of money supply which includes currency and assets that can be quickly converted into cash.

Before analysing the parameter estimation and their meanings, it is important to point out the main underlying assumptions of the model. Firstly, and most importantly, it assumes that the money market is in continuous equilibrium. In other words, it assumes that the demand of money equals, over time, the supply of money. A theoretical explanation of this relation can be found in Appendix A. The second assumption is that both nominal interest rates and money supply are exogenous. Finally, it assumes that only price levels, and not also interest rates, move to clear the market in case of disequilibrium.

The OLS regression in equation 13 indicates that exchange rate is determined by inflation rate, and consequently level of prices, nominal interest rates, money supply, and business cycle differential. Supposing the validity of money market equilibrium assumption, an increase in the domestic prices would cause an increase in the demand of money and, thus, an appreciation of the domestic currency. Consequently, the coefficient β_1 is expected to be negative. A similar relation exists between Business Cycle and exchange rate; hence I presume also the coefficient β_3 to be negative. On the contrary, a direct relationship is supposed to be present between both interest rate and money aggregate differential and exchange rate. The first relation relies on the Interest Rate Parity (IRP) theory, for which an increase in the US interest rate over the European, Japanese or Chinese ones, would imply a decrease in the dollar value and thus an increase in the exchange rate. Likewise, an increase in the US money supply would comport an increase in national prices and, therefore, a decrease in the dollar value against the other basket of currencies.

To summarise, I expect the coefficients β_2 and β_4 to be positive, whilst the expectation for inflation and business cycle is to generate negative coefficients β_1 and β_3.

4.4 Vector Autoregressive (VAR) model

The VAR is a stochastic process model which captures the linear interdependence among several time-series. In particular, it fits a multivariate time-series regression of each dependent variable on lags of itself and on lags of all the other independent variables. One of the key features of the VAR is that it does not require much knowledge about the dependent variable and forces affecting it, since it only require a set of variables which can be reasonably hypnotized to influence each other.

The main difference between a simple Autoregressive (AR) model and the VAR is that the former allows the dependent variable to be determined only by its past values, whereas, as stated above, according to the VAR model its future values are based on its past values and those of each independent variable included in the model. The most simplified version of an Autoregressive model is the AR(1) model, which is a first order autoregression in which the dependent variable is affected only by its last observation. It can be expressed as:

$$y_t = \theta y_{t-1} + \varepsilon_t \qquad [\,14\,]$$

Where the error term ε_t is uncorrelated with the past levels of y_t and represents every innovation that comes from the external environment (e.g. each variable that influences y_t but is not included in the model). A generalization of the AR(1) model is the AR(p) model, in which y_t is affected not only by its most recent observations but also by previous ones. This relation is showed by the following formula:

$$y_t = \theta_1 y_{t-1} + \theta_2 y_{y-2} + \cdots + \theta_p y_{t-p} + \varepsilon_t \qquad [\,15\,]$$

As stated above, in this thesis, I am going to conduct my analysis employing the VAR model which, as stated by Del Negro and Schorfheide (2011), appears to be a straightforward multivariate generalization of univariate autoregressive models.

The first step while computing the VAR model is to formulate a system of VAR model that represent each potential outcome given the number of variables taken into account and p lags. The general formulation of a p-lags VAR is expressed by formula 13 below:

$$y_t = G_0 + G_1 y_{t-1} + G_2 y_{t-2} \dots + G_p y_{t-1} + \varepsilon_t \qquad [\ 16\ ]$$

Where:

G_0 is a nx1 vector of constants

G_p represents a nxn matrix of coefficients

ε_t is a vector of white noise innovation

In my case, the vector of endogenous variables takes the form of y_t = (exchange rate, inflation, interest rate differential, business cycle, money aggregate differential). To every equation is assigned the same numbers of lags of all endogenous variables, which makes the VAR model unrestricted.

The matrix notation of this model is reported in Appendix B.

4.4.1 Lag Length Selection

One of the most important steps while computing the VAR motes it to establish the right number of lags to base the model on. In fact, if the number of lags is too low, the model might be poorly specified. Whereas, in the opposite scenario, if the number of lags is too high, the model loses too many degreed of freedom. In general, the optimal number of lags should be sufficient for residuals to form white noises. The lag length for the VAR(p) model can be determined using model selection criteria such as Final Predictor Error (FPE), Akaike (AIC), Schwarz-Bayesian (BIC) and Hanna-Quinn (HQ).

Even though the FPE cannot be considered a mere information criterion, it is included in this analysis since the scope of lag selection tests is to minimize the number of lags and the prediction error. However, the SBIC and the HQIC have a theoretical advantage over the AIC and the FPE. As Lutkepohl (2005) demonstrated that choosing p to minimize the SBIC or the HQIC provides consistent estimates of the true lag order, p. In contrast, minimizing the AIC or the FPE will overestimate the true lag order with positive probability, even with an infinite sample size. For this reason, when n lags are chosen by AIC and FPE test and n lags are selected by SBIC and HQIC, the number of lags which resulted optimal for the last pair of tests will be adopted.

4.4.2 Test for Granger causality

Since the VAR model relies on the assumption that all variables in the model are endogenous, before starting building the model, testing whether this assumption is verified or not is necessary.

The Granger causality doesn't allow to test directly for endogeneity, but if a variable is endogenous, it should Granger-cause the other, and vice-versa. Thus, the model aims to answer whether changes in one variable cause changes in another. A time series X is said to Granger-cause Y if its values provide statistically significant information about the future trend of Y. However, since Granger causality is nothing but a mere correlation between the past values of a variable and the present value of another, we cannot strictly say that changes of one variable cause changes of the other. For this reason, many econometricians assert that the Granger test finds only "predictive causality".

In this context, I am going to test whether the exchange rate is Granger caused by the endogenous variables considered in the model, namely inflation, interest rate differential, business cycle and money supply. In particular, I am going to singularly test the effect that each of the variables considered in the model exert on the exchange rates.

4.5 Forecast Procedure

In this section, I am going to describe the procedure followed to compute the predictions for each model illustrated above. In general, the scope of this thesis is to predict the exchange rate based on a number of fundamental variables. Since the rationale behind the forecast imputation is the same for each model, I am going to base my example on the forecast of Euro/Dollar exchange rate produced with the monetary model. The purpose of this model is to predict the future patterns of Euro/Dollar as a function of inflation, interest differential, business cycle, and money aggregate differential. This relationship is described by equation 13 mentioned above.

It is important to point out that since I am making predictions, it doesn't have to be necessarily true that movements of the exchange rate are caused by these fundamental variables.

The first step is to regress the dependent variable on the independent variables. This generates estimated coefficients β_1, β_2, β_3, and β_4, together with the standard error in each estimation. An important value that has to be considered is the R^2 value of the regression, which indicates in which portion the fundamentals can predict the variation in Euro/Dollar exchange rate.

To obtain a point estimation of Euro/Dollar rate for each fundamental, in equation 13, we can replace the coefficients β_1, β_2, β_3, and β_4 with the estimated coefficients given by the model. However, performing this calculation for each observation is time consuming and error-prone. Therefore, I make use of the post-estimation tool of stata “predict” which performs all these calculations and returns estimations for each observation.

4.6 Combination of forecasts

Notwithstanding the combination of forecasts exposed in section 2.7.4 obtained surprisingly positive results, to carry my analysis I am going to build a combined forecast model using a weighting scheme similar to the one applied by Stock and Watson (1998) and Lam et al. (2008). What makes this model more attractive than the one introduced by Bates and Granger is that weights are assigned based on the relative Mean Squared Forecast Error (MSE) of each forecasting model. Thus, accordingly to this weighting scheme, the smaller the MSE of a model is, the higher is the weight assigned to that model. The MSE at time *t* for each model, *i=1, ……, n*, will be calculated as:

$$MSE_{T,i} = \frac{\sum_{t=1}^{T}(e_t - \hat{e}_{t,i})^2}{N} \qquad [\,17\,]$$

where e_t is the realised exchange rate, $\hat{e}_{t,1}$ is the forecasted exchange rate by the model *i*, and N is the number of observations. The weight that has to be assigned to each of the models is then computed according to the expression:

$$w_{T+1,i} = \frac{1/MSE_{N,i}}{\sum_{j=1}^{n}(1/MSE_{N,j})} \qquad [\,18\,]$$

Finally, the combined forecast is constructed as:

$$ln\hat{e}_{t+1,e} = \sum_{i=1}^{n} w_{T+1,i}\,\hat{e}_{t+1,i} \qquad [\,19\,]$$

4.7 Validation tests

For the purpose of comparison and assessment of the performance of the three above-mentioned models, the driftless random walk model is used as a benchmark. This benchmark was first introduced by Meese and Rogoff (1983), who found that no estimations derived from other theoretical models were able to outperform the random walk model. The driftless random walk model can be specified as:

$$e_{t+n} = e_t + \varepsilon_t \qquad [\,20\,]$$

Where ε_t is the error term which is assumed to be independent and identically distributed. The intuition behind the random walk model is that future values of exchange rates can only be explained and predicted by its past values and by the error term ε_t. This is used as a benchmark since there's not economic intuition underlying its construction and, thus, is a good reference point to test the validity of more elaborated models.

To evaluate the forecasting accuracy of each model, three measures are used. The ratio between the Mean Squared Forecast error (MSE) of each model and the random walk is the first measure used. The rationale behind this measure is that if the ratio is inferior than one, the model has more predictive power than the benchmark. And vice-versa, a ratio higher than one denotes a higher error in the forecasts of the model. In other words, the smaller is the ratio, the better is the forecast. The MSE can be expressed as equation 17 aforementioned:

$$MSE_{T,i} = \frac{\sum_{t=1}^{T}(e_t - \hat{e}_{t,i})^2}{T} \qquad [\,217\,]$$

Where e_t is the actual value, $\hat{e}_t$ corresponds to the forecast value and *T* is the number of observations.

The second measure employed to evaluate the predictive power of each model is Direction of Change (DoC) criterion. In order to calculate the DoC, for each ex-post forecasting period a one is assigned if the model predicts correctly the direction of the exchange movements and a zero in the opposite circumstance. The DoC is given by the proportion of 'ones' among all forecasting periods. If the ratio is greater than 0.5, the forecasts generated by the model are more accurate. The higher the ratio, the better the forecast.

The last measure is a quantitative measure that counts for the number of forecast errors that are lower than the ones produced by the benchmark. A one is assigned to all the periods that have a lower forecast error and a zero otherwise. Once assigned all values, the Forecast Error ratio is calculated. This latter is given by the proportion of smaller forecast errors among all ex-post forecast horizons. As for the DoC ratio, the higher the FE ratio is, the more accurate is the model.

5. Empirical Results

This section presents the empirical findings of my study. The chapter is divided into three parts: in the first I am going to expose the results of my regression analysis, whereas in the second fraction of the chapter, results from the forecast comparison will be exposed; finally, in the last section, results of the robustness tests are reported.

5.1 Regression Analysis

To further investigate the effect of fundamentals on exchange rate movements, I am going to undertake regression analysis. As stated in the forecast procedure section, in order to compute the prediction, were run some regressions for each of the three models considered. These are expressed by equations 12, 13, and 16 mentioned in the text above.

In the following subsections, the output of regressions of each model will be analysed separately.

5.1.1 Purchasing Power Parity model: regressions analysis

In table 4 below are displayed the results from the regressions of Euro/Dollar, Japanese Yen/Dollar, and Chinese Yuan/Dollar exchange rates. In the table, model 1 refers to the PPP model of Euro/Dollar exchange rate, model 2 to the one of Japanese Yen/Dollar and, finally, model 3 reports the estimated results of the PPP model referring to the Chinese Yuan/Dollar exchange rate.

What appears immediately clear from this table is the high correlation existing between the PPP and Euro/Dollar exchange rate. This can be deduced from the high value of R-squared, which, with a value of 0.9902, indicates that PPP is able to predict 99.2% of the movements of Euro/Dollar. Same results were found for both Japanese Yen/Dollar and Chinese Yuan/Dollar exchange rates. In both regressions, R-squared assumer a high value, of 0.9841 and 0.9992, respectively.

Furthermore, it can be noticed a direct relationship between the dependent and independent variables. In fact, the positive sign of the coefficient indicates that a unit increase in the PPP would cause an increase of 0.995, 0.992, and 0.999 in Euro/Dollar, Japanese Yen/Dollar, and Chinese Yuan/Dollar respectively.

Table 4: Regressions estimations of the PPP model

	(1)	(2)	(3)
VARIABLES	EURUSD	JPYUSD	YUANUSD
PPP_EURUSD	0.995***		
	(0.0033)		
PPP_JPYUSD		0.992***	
		(0.0042)	
PPP_YUANUSD			0.999***
			(0.001)
Constant	0.004	0.899**	0.006
	(0.0028)	(0.4469)	(0.007)
N. Observations	913	913	913
R-squared	0.9902	0.9841	0.9992

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5.1.2 Monetary Model: regression analysis

This subsection investigates the relationship between exchange rates and fundamentals as resulting from regressions under the monetary model. These results can be found in table 5. Each model (1, 2, and 3) represents separately outcomes for every exchange rate investigated.

In the methodology section I made some prediction about the sign of the coefficients corresponding to the independent variables used in the regression. Specifically, I expected the coefficient of inflation and business cycle to be negative, while the coefficient of interest differential and money aggregate differential was expected to be positive. As can be seen in the table above, these conjectures were partially correct. In fact, as per Euro/Dollar, it exists an inverse relationship between the dependent variable and inflation, whereas, contrary to what predicted, there is a positive sign for the coefficient of business cycle. In the same way, we can see a direct relationship with money aggregate differential, whilst a negative coefficient is associated with the interest differential variable.

More similar results to what assumed in an earlier stage, are related to the Japanese Yen/Dollar exchange rate. In effect, as we can see in table 5, an inverse relationship is present for both inflation and business cycle. However, the sign of the coefficient corresponding to MD, which was expected to be positive, is negative. Finally, as predicted, it persists a direct relation between interest rates differential and exchange rate.

As far as Chinese Yuan/Dollar exchange rate is concerned, I obtained similar results as with the Euro/Dollar. In fact, also in this case, results show a direct relationship between the dependent variable and both business cycle and money aggregate differentials, whereas an inverse relationship persists when we look at inflation and interest rate differentials.

Table 5: Regression output monetary model: EURUSD exchange rate

	(1)	(2)	(3)
VARIABLES	EURUSD	JPYUSD	YUANUSD
inf_EUR	-1.117***		
	(0.016)		
IntDiff_EUR	-0.014***		
	(0.0016)		
BC_EUR	0.0002		
	(0.0003)		
MD_EUR	0.053***		
	(0.0107)		
Inf_JAP		-82.995***	
		(1.3457)	
IntDiff_JAP		9.967***	
		(0.2105)	
BC_JAP		-0.049	
		(0.0698)	
MD_JAP		-13.941***	
		(0.9067)	
Inf_CHI			-4.951***
			(0.0499)
IntDiff_CHI			-0.034***
			(0.0032)
BC_CHI			0.002
			(0.0016)
MD_CHI			0.276***
			(0.0076)
Constant	1.808***	169.008***	11.489***
	(0.0257)	(2.068)	(0.0544)
N. Observations	907	907	830
R-squared	0.9372	0.8944	0.9889
Standard errors in parentheses			
*** p<0.01, ** p<0.05, * p<0.1			

What is also interesting to point out is that in all regressions, coefficients insignificantly different from zero are found for the variable business cycle. These results in contrast with the monetary theory can be caused by the parameter instability of this model. This has been found in many studies. For example, Mulligan and Sala-i-Martin (2000) evinced that money demand and interest rate elasticity varies depending on the level of interest rate. Moreover, according to Wilson (1979), the dynamics of exchange rate are different whether the changes on monetary policy were anticipated or not.

5.1.3 Vector Autoregressive Model: regressions analysis

The first step when computing the VAR model is to calculate the optimal number of lags on which to base the model. Tables 6a, 6b, and 6c exhibit the results of Final Predictor Error (FPE), Akaike (AIC), Schwarz-Bayesian (BIC) and Hanna-Quinn (HQ) test for EURUSD, JPYUSD, and YUANUSD respectively. The values denoted by an asterisk are those selected by each criterion employed to calculate the best number of lag. In other words, the asterisk is assigned to the number of lags that generates the lowest values when the test is run.

Table 6a: Lag length selection Euro/Dollar

lags	p	FPE	AIC	HQIC	SBIC
0		0.01772	-1.194	-1.184	-1.168
1	0.000	0.00012	-6.117	-6.104*	-6.085*
2	0.540	0.00012	-6.115	-6.100	-6.077
3	0.033	0.00012*	-6.118*	-6.101	-6.075
4	0.447	0.00012	-6.116	-6.098	-6.068
5	0.202	0.00012	-6.116	-6.095	-6.062
6	0.960	0.00013	-6.113	-6.091	-6.055
7	0.387	0.00013	-6.112	-6.088	-6.048
8	0.971	0.00013	-6.110	-6.083	-6.041
9	0.818	0.00013	-6.109	-6.079	-6.033
10	0.102	0.00013	-6.108	-6.078	-6.028

Table 6b: Lag length selection Japanese Yen/Dollar

lag	p	FPE	AIC	HQIC	SBIC
0		0.19801	1.218	1.229	1.240
1	0.000	0.00020	-5.668	-5.655*	-5.634*
2	0.237	0.00020	-5.667	-5.652	-5.627
3	0.607	0.00020	-5.665	-5.647	-5.619
4	0.077	0.00020	-5.666	-5.647	-5.615
5	0.225	0.00020	-5.666	-5.644	-5.609
6	0.028	0.00020	-5.669	-5.645	-5.606
7	0.298	0.00020	-5.668	-5.642	-5.599
8	0.399	0.00020	-5.667	-5.638	-5.592
9	0.009	0.0002*	-5.672*	-5.642	-5.592
10	0.282	0.00020	-5.671	-5.639	-5.586

Table 6c: Lag length selection Yuan/Dollar

lag	p	FPE	AIC	HQIC	SBIC
0		191.3710	8.092	8.102	8.118
1	0.000	2.2277	3.638	3.651	3.67*
2	0.028	2.2207*	3.635*	3.649*	3.673
3	0.350	2.2235	3.637	3.653	3.679
4	0.440	2.2269	3.638	3.656	3.686
5	0.749	2.2316	3.640	3.661	3.693
6	0.785	2.2364	3.643	3.665	3.701
7	0.118	2.2353	3.642	3.666	3.706
8	0.519	2.2393	3.644	3.670	3.713
9	0.010	2.2279	3.638	3.667	3.713
10	0.703	2.2325	3.641	3.671	3.721

According to the results showed above, the optimal lag length for EURUSD and JPYUSD is one since it was selected by both HQIC and SBIC, whereas for YUANUSD corresponds to two. In this case, the lag length of two was chosen by three tests, namely FPE, AIC, and HQIC.

Tables reporting results of the VAR model can be found in the Appendix B. In general, an output table of VAR model is rather long since a VAR with *n* variables and *p* lags will have $n^2 * p$ coefficients. In my model with 5 variables and two lags, there are nearly 50 coefficients. Moreover, it is not immediately informative to look individually at the coefficients of covariates. For this reason, I am going to report only post-estimation statistics that are used to assess the VAR output: namely the Granger Causality test. These results are represented in tables 7a, 7b, and 7c.

What can be deduced from these results is that there is a Granger causality relationship between the Euro/Dollar exchange rate and inflation rate, whereas there's no Granger causality with the other variables considered in the model, namely interest differential, money supply and business cycle.

Table 7a: Granger causality test results for Euro/Dollar exchange rate

Equation	Excluded	F	df	df_r	Prob > F
EURUSD	Inf_EUR	23.341	1	899	0.0000
EURUSD	IntDiff_EUR	0.00756	1	899	0.9307
EURUSD	MD_EUR	0.65528	1	899	0.4184
EURUSD	BC_EUR	0.9432	1	899	0.3317
EURUSD	ALL	6.5085	4	899	0.0000

As far as Japanese Yen/Dollar exchange rate is concerned, as shown in the table below, it appears to exist a Granger causality relationship between this former and inflation and money supply. Both results are significant at a 5% confidence level. Analogously to what resulted for the Euro/Dollar, both interest differential and business cycle do not Granger cause the Japanese Yen/Dollar exchange rate.

Table 7b: Granger causality test results for Japanese Yen/Dollar exchange rate

Equation	Excluded	F	df	df_r	Prob > F
JPYUSD	Inf_JAP	43.833	2	892	0.0000
JPYUSD	IntDiff_JAP	1.1193	2	892	0.3270
JPYUSD	D_MD_JAP	3.2451	2	892	0.0394
JPYUSD	BC_JAP	0.8932	2	892	0.9146
JPYUSD	ALL	12.587	8	892	0.0000

Finally, while considering the Chinese Yuan/Dollar exchange rate, it emerges that it is Granger caused by money supply and business cycle but not by interest differential and inflation. Moreover, the relationship between business cycles is weaker than the one with money supply since the former is only significant at a 10% confidence level whilst the latter is significant at a confidence level of 1%.

Table 7c: Granger causality test results for Yuan/Dollar exchange rate

Equation	Excluded	F	df	df_r	Prob > F
YUANUSD	Inf_CHI	0.32311	1	823	0.5699
YUANUSD	IntDiff_CHI	0.11625	1	823	0.7332
YUANUSD	D_MD_CHI	24.069	1	823	0.0000
YUANUSD	BC_CHI	3.0184	1	823	0.0827
YUANUSD	ALL	7.4421	4	823	0.0000

5.1.4 Test for homoscedasticity and autocorrelation of residuals

As stated in the methodology and model construction section, I assumed independent and identically distributed (i.i.d.) residuals with mean zero and constant variance. However, it might be the case that these residuals are autocorrelated, in the sense that the residual for period a is correlated with the one for a subsequent period b, or are not identically distributed and, thus, we are in presence of heteroskedasticity. To test whether the assumption of i.i.d residuals is met, I run three tests: Shapiro-Wilk test, White's test, and Durbin Watson Test. The first two are used to test for heteroskedasticity, while the third is employed to test for autocorrelation. Moreover, since the results of the first two test can be biased by the assumption for the residuals, I combine these results with a graphical analysis in which I compare the distribution of residuals with the normal distribution.

In the tables and figures below are showed the results of these tests. The first residuals that I am going to consider are those resulting from the PPP model. Figures 3a, 3b, and 3c are report the plotted distributions of these residual together with the normal distribution curve. It appears immediately clear that only residuals of the PPP model for Euro/Dollar are normally distributed, while those relative to Japanese Yen/Dollar and Chinese Yuan/Dollar present clear signs of heteroskedasticity.

Figure 3a: Plotted residuals distribution PPP eur/usd

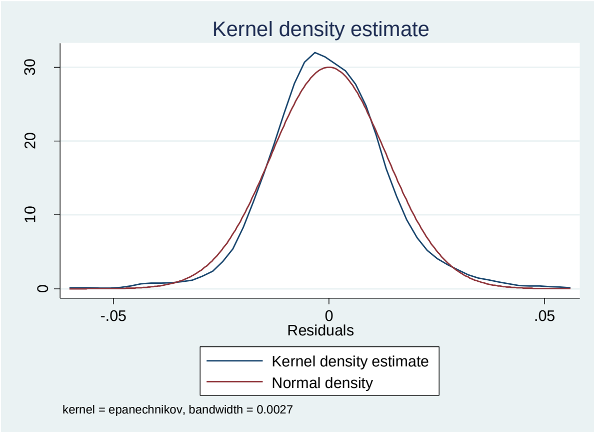


Figure 3b: Plotted residuals distribution PPP jpy/usd

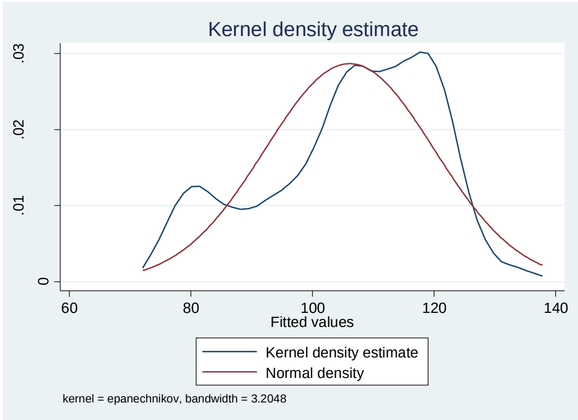
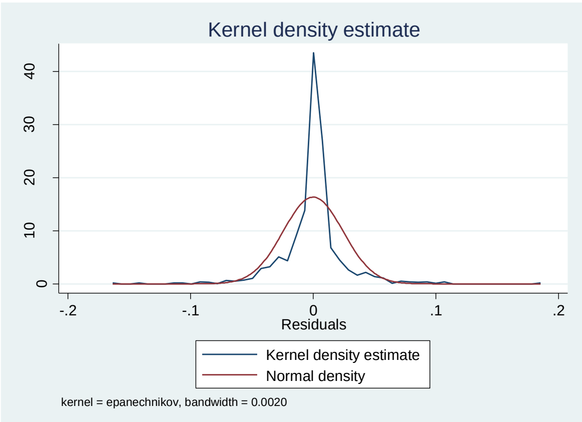


Figure 3c: Plotted residuals distribution PPP yuan/usd



These results are confirmed by those of Shapiro-Wilk and White's tests displayed in table 9 below. As far as Shapiro-Wilk test is concerned, W and V are specific test parameters, the former represents the test statistics while the latter is the measure that is taken into account to test for normality. In general, a V-value equal or close to one corresponds to a normal population. As we can see, none of the residuals are normally distributed. The same conclusion can be extrapolated from the White's test. The intuition behind this test is straightforward: it tests for the null hypothesis of homoscedasticity. So, whenever the p-value is higher than 0.5, we would have to accept the null hypothesis and reject the alternative one of heteroskedasticity.

Table 8: Shapiro-Wilk and White's test for PPP model

	Shapiro-Wilk test		
Variable	W	V	p>z
r_EUR	0.987	7.427	0.00
r_JPY	0.946	31.037	0.00
r_YUAN	0.824	102.296	0.00
	White's test		
Variable	chi2	df	p
r_EUR	42.85	2	0.00
r_JPY	10.84	2	0.004
r_YUAN	7.19	2	0.027

According to both tests, residuals are not normally distributed. However, as said before, since these tests might be biased by the model's assumptions, in case of Euro/Dollar model residuals are considered to be identically distributed.

If we look at the distribution of the residuals relative to the monetary model, we can see that they appear more normally distributed than those produced by the PPP model. In fact, if we look at the graphs 4a, 4b, and 4c showing the plotted distribution of residuals compared with the normal distribution curve, it can be concluded that, apart from residuals deriving from the Japanese Yen/Dollar monetary model which exhibit a negative kurtosis, residuals from this model follow a normal distribution.

Figure 4a: Plotted residuals distribution MM eur/usd

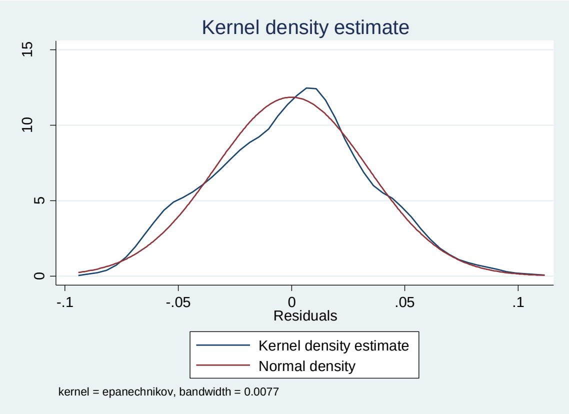


Figure 4b: Plotted residuals distribution MM jpy/usd

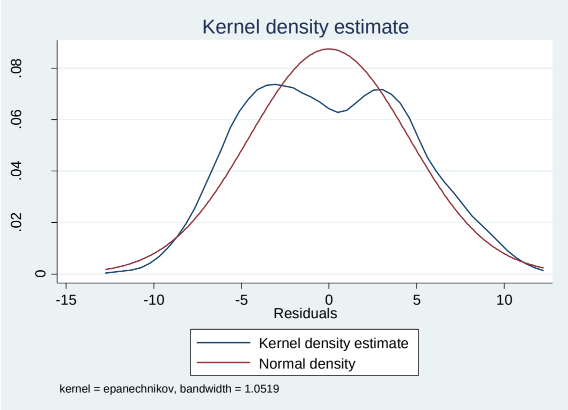
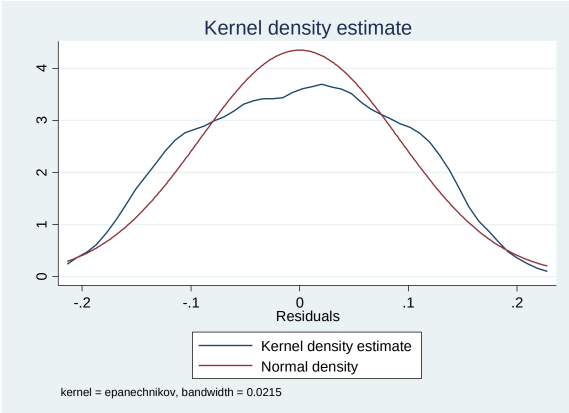


Figure 4c: Plotted residuals distribution MM yuan/usd



However, if we look at the results from the Shapiro-Wilk and White's tests, we achieve a different conclusion. In fact, as shown in table 9, according to both model we have to reject the null hypothesis of homoscedasticity and accept the alternative one of heteroskedastic residuals.

Table 9 Shapiro-Wilk and White's test for MM model

	Shapiro-Wilk test		
Variable	W	V	p>z
r_EUR	0.994	3.15	0.002
r_JPY	0.986	8.234	0.00
r_YUAN	0.983	8.906	0.000
	White's test		
Variable	chi2	df	p
r_EUR	454.7	14	0.00
r_JPY	225.96	14	0.00
r_YUAN	160.33	14	0.00

The last model's residuals that remain to analyse are those generated by the VAR model. The plotted distributions of residual are displayed in figures 5a, 5b, and 5c. According to these figures, residuals relative to the Euro/Dollar VAR model follow a normal distribution, while VAR built with other two pairs of currencies manifest high kurtosis in its residuals. Specifically, those of Japanese Yen/Dollar present a negative kurtosis, while residuals deriving from the VAR model of Chinese Yuan/Dollar have a highly positive kurtosis.

Figure 5a: Plotted residuals distribution VAR eur/usd

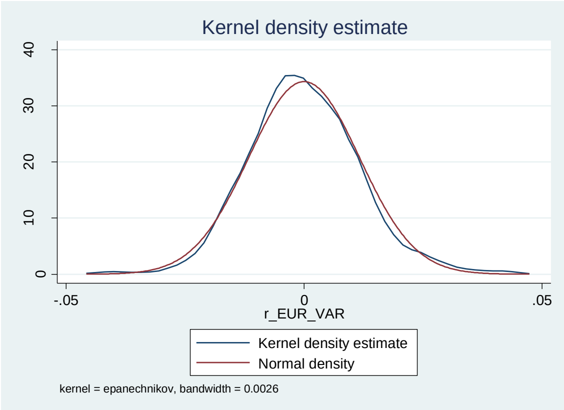


Figure 5b: Plotted residuals distribution VAR jpy/usd

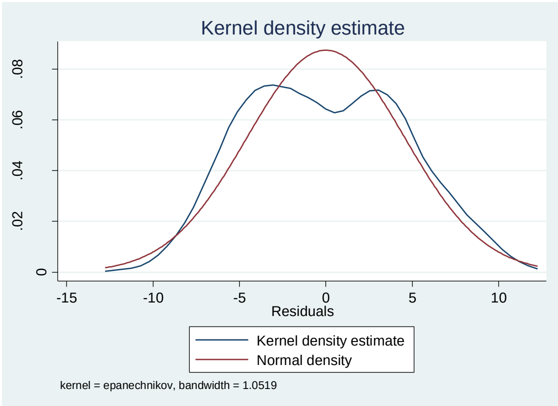
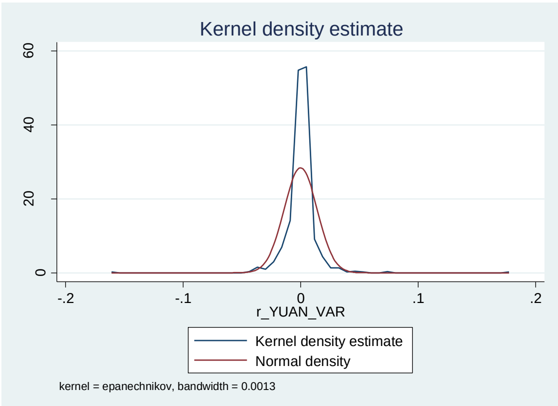


Figure 5c: Plotted residuals distribution VAR yuan/usd



Also looking at the result of Shapiro-Wilk test reported in table 10, it is understandable that these residuals are not normally distributed. For the VAR model, I used only the Shapiro-Wilk test since it is not possible to run the White's test with this model.

Table 10: Shapiro-Wilk test for VAR model

	Shapiro-Wilk test		
Variable	W	V	p>z
r_EUR	0.991	5.407	0.002
r_JPY	0.99	5.981	0.00
r_YUAN	0.701	158.9	0.000

All in all, heteroskedasticity implies biased standard errors. In order to deal with heteroskedasticity, I included in the regression Heteroskedasticity-consistent standard errors (also known as Huber-White standard errors), which relax the assumption of independent and identically distributed residuals. This does not change the estimated coefficient of the regressions but produces more accurate p-values.

Considering the Durbin Watson Test, the interpretation of the results is driven by the value assumed by DW. In particular, a DW equal or close to 2 indicates no serial correlation. If it is smaller than 1.60 there's a positive serial correlation, whereas if it is bigger than 2.40 there's a negative autocorrelation. Results of this test are shown in table 11.

Table 11: Durbin Watson Test results

Model	Variable	DW
PPP Model	r_EUR	1.652
	r_JPY	1.693
	r_YUAN	1.828
Monetary Model	r_EUR	1.688
	r_JPY	1.827
	r_YUAN	0.086
VAR Model	r_EUR	2.059
	r_JPY	2.065
	r_YUAN	2.039

As can be seen from this table, for all residual, except those relative to the monetary model of Chinese Yuan/Dollar, the null hypothesis of absence of derail correlation can be accepted. Contrarily, for the residuals generated by the monetary model that analyses the Chinese Yuan/Dollar exchange rate, the null hypothesis is rejected and the alternative one of autocorrelation is accepted.

5.2 Forecast comparison

As already announced before, in this section I am going to undertake the last step of my analysis consisting on the forecast comparison, which is intended to be an indicator of model quality. To evaluate the forecast performance of the three models employed in this study, I am going to make use of three different models: mean squared forecast error (MSE), direction of change (Doc), and forecast error ratio (FE). Tables 12a, 12b, and 12c display the results of my in-sample forecasting exercise using the basic model described in section 4 and compare them with those of a simple driftless random walk model. In addition to MSE, DoC, and FE ratio, in the last two rows of the tables are reported two other measures: the MSE ratio and the DoC ratio which are the ratio between the MSE/DoC produced by the basic models and those produced by the benchmark. For the first ratio, a value smaller than one indicates a better forecast performance of the basic model. Whereas, for the second ratio, a value higher that one denotes a failure of the benchmark to outperform the basic models. Moreover, an asterisk is assigned to the model that, according to the validation tests, produces the best forecasts.

Table 12a: in-sample prediction of EURUSD evaluations

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	COMB	RW
MSE	0.000176	0.000139*	0.001127	0.000139*	0.000168	0.000139*	0.000267	0.000139*
DoC	0.510405	0.51917*	0.65165*	0.51917	0.510451	0.51917*	0.52352*	0.51917
FE ratio	0.451366	-	0.20176	-	0.506037*	-	0.47802	-
Ratio MSE	1.2645		8.0854		1.20665		1.91711	
Ratio DoC	0.9831		1.2552*		0.98321		1.00839*	

The table above shows that, as far as Euro/Dollar exchange rate is concerned, none of the models built are able to outperform the driftless random walk model. In fact, according to all tests, the PPP model is outperformed by the random walk model. Similar results are found for the monetary model and VAR model which were accepted only by the DoC measure and the FE ratio respectively. Also the combination of forecasts does not deliver more accurate prediction than the random walk model.

Below are displayed the results of the forecast validation tests concerning the Japanese Yen/Dollar exchange rate. Also in this case, the PPP is found to be outperformed by the random walk model. This result is the same for all validation tests. Same results are found for the combination of forecasts model which, according to all validation tests, delivers worse prediction than the benchmark. The VAR model is the one that produces the best results, inasmuch for both DoC measure and FE ratio it generates better results than the benchmark. Lastly, the monetary model is found to be accepted only by the DoC measure, while, in accordance with the MSE measure and the FE ratio, the random walk model has a better forecast accuracy.

Table 12b: in-sample prediction of JPYUSD evaluations

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	COMB	RW
MSE	3.1233	2.2943*	20.7052	2.2943	20.6798	2.2943*	2.7817	2.2943*
DoC	0.4611	0.4797*	0.5549*	0.4797	0.4901*	0.4797	0.4657	0.4797*
FE ratio	0.4361	-	0.0143	-	0.5270*	-	0.4703	-
Ratio MSE	1.3613		9.0246		9.0135		1.2124	
Ratio DoC	0.9612		1.1568*		1.0216*		0.9708	

The last results that I am going to analyse are those referring to the Chinese Yuan/Dollar exchange rate. In the same manner as the results analysed above, also concerning the Chinese Yuan/Dollar nor the PPP, the monetary model or the VAR model is able to produce more accurate prediction than the random walk model. These results are attested by the fact that there's not a model unanimously accepted by all validation tests. However, surprisingly good results are found for the combination of forecasts model. In fact, it outperformed the random walk model according to all validation tests except the FE ratio.

Table 12c: in-sample prediction of YUANUSD evaluations

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	COMB	RW
MSE	0.000595	0.000255*	0.008406	0.000255*	0.0002005*	0.000255	0.000246*	0.000255
DoC	0.4808	0.50493*	0.5657*	0.50493	0.48251	0.50493*	0.5235*	0.50493
FE ratio	0.2973	-	0.04699	-	0.33735	-	0.3313	-
Ratio MSE	2.33725		33.0075		0.7874		0.9662*	
Ratio DoC	0.95228		1.12044*		0.9556		1.0368*	

5.3 Robustness test

Since the assumption underlying this work of constant value throughout the month to consider the monthly data as weekly might imply biased results, I decided to run a robustness check to test the validity of my results. This has been accomplished by constructing the same models using data at a monthly frequency. In the tables below, are shown the results of this robustness test.

Table 13a: Robustness test EURUSD

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	Comb	RW
MSE	0.00105	0.00042*	0.00105	0.00042*	0.00038*	0.00042	0.00031*	0.00042
DoC	0.5433	0.622*	0.9139*	0.622	0.6205	0.622*	0.6731*	0.622
FE Ratio	0.244	-	0.3524	-	0.5741	-	0.6029*	-
Ratio MSE	2.5024		2.5		0.9019*		0.7416*	
Ratio Doc	0.8734		1.4692*		0.9971		1.0821*	

Table 13b: Robustness test JPYUSD

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	Comb	RW
MSE	16.515	6.3043*	19.127	6.3043*	6.0867*	6.3043	5.6459*	6.3043
DoC	0.5	0.5502*	0.8086*	0.5502	0.5577*	0.5502	0.5913*	0.5502
FE Ratio	0.2727	-	0.0785	-	0.5072*	-	0.5359*	-
Ratio MSE	2.6196		3.0340		0.9655*		0.8956*	
Ratio Doc	0.9088		1.4696*		1.0136*		1.0747*	

Table 13c: Robustness test YUANUSD

	Model							
Measure	PPP	RW	Monetary model	RW	VAR	RW	Comb	RW
MSE	0.0083	0.0011*	0.009	0.0011*	0.0005*	0.0011	0.0005*	0.0011
DoC	0.4904	0.612*	0.6158*	0.612	0.61290*	0.612	0.5625	0.612
FE Ratio	0.1150	-	0.0780	-	0.39040	-	0.3924	-
Ratio MSE	7.5455		8.1818		0.4364*		0.4182*	
Ratio Doc	0.8013		1.0062*		1.0015*		0.9191	

These results are in line with what found before. In fact, as we can see from tables 13a, 13b, and 13c there is not a model, with exception of the monetary model relative to the Japanese Yen/Dollar exchange rate, that significantly outperformed the benchmark constituted by the driftless random walk model. however, differently from the results of the models constructed with weekly data, surprisingly positive results are found for the combination of forecasts model. In fact, according to all validation tests, it outperformed the random walk model predictions for both Euro/Dollar and Japanese Yen/Dollar exchange rates. What can be deduced from this robustness check is that, even though the assumption of constant data throughout the month may constitute a limitation, running the models with monthly data does not deliver completely different results.

Conclusion and Discussion

Since the collapse of Bretton Wood system of fixed exchange rate, many authors have focused on founding a model able to forecast future movements of exchange rates. For most of these studies, the standard for evaluating exchange rate models has been out-of-sample fit. Specifically, a model has been estimated successful or unsuccessful based on its ability to produce out-of-sample forecasts able to outperform the random walk model. However, many of the models used in these studies imply a nearly random walk pattern for exchange rates. For this reason, we should not expect the models to have a better out-of-sample forecast accuracy than a mere random walk model.

The purpose of this study was to answer the research question: is there a forecasting model able to outperform a simple random walk model in the short run?

To answer this question, I investigated the predictive power of three models belonging to the three main categories of exchange rate forecasting models: the Purchasing Power Parity, representative of the efficient market hypothesis category, the Monetary model, amenable to the fundamental models, and the Vector Autoregressive model, which belongs to the technical models category. The predictions resulting from these models were then compared to those produced by a driftless random walk model. The exchange rates analysed were Euro/Dollar, Japanese Yen/Dollar, and Chinese Yuan/Dollar, all of them expressed at a weekly frequency.

The results showed that for all currencies analysed, none of the models constructed has been capable to produce prediction on future movements of exchange rates more accurate than the benchmark, consisting in the random walk model. These results are in line with many previous researches, who found that at a short-term forecast horizon forecasts produced by a random walk outperform those generated by all other forecast models.

Limitations and suggestions for future researches

Although the use of PPP model, monetary model, and Vector autoregressive model has been a fairly common approach to forecast exchange rate, this study does not provide a complete picture of the efficacy of these models. In particular, this study incurs in many limitations that are going to be exposed in the paragraph below.

Even though it has been proved that exchange rates follow a nearly random walk pattern and thus the probability of producing reliable out-of-sample forecast is approximately zero, focusing only on a mere in-sample prediction may produce an overly optimistic picture of the forecasting ability of the model. Future researches could overcome this limitation, by creating out-of-sample prediction splitting the dataset in an in-sample period, used for the parameter estimation, and an out-of-sample period used to evaluate the forecasting performance.

Another limitation of this study is the forecast horizon adopted. In fact, the study focused only on short-term forecast horizon, in particular, it produces one week ahead forecast. Thus, it might be interesting for future researches, to analyse the forecast accuracy of these models at a longer forecast horizon.

Moreover, in this research study standard forecasting models have been used, which, already in previous researches, produced predictions of exchange rates that were as precise as those resulting from a simple random walk model. My suggestion for future researches, it to investigate the reliability in forecasting exchange rates of new models, such as Neutral Network techniques (Sermpinis, et al. 2014) or to use surveys as a measure of expectations about exchange rate movements (Engel, et al. 2007). Also, if we look at the daily movements of exchange rates, we can see that they are becoming always more disconnected from fundamentals. Indeed, in an era in which public speeches, meetings of central banks, and posts on social networks are becoming more and more important, they rather appear to be influenced by these variables. Thus, it may be interesting to look at how a tweet of Mr. Trump, or a meeting of the European Central Bank, or also a speech of Mr. Draghi, influence daily changes of exchange rates.

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Appendix A: Definition of Monetary Market Equilibrium

In the section of 'Methodology and model construction' referring to the monetary model, I implied the validity of the assumption of an enduring equilibrium of the monetary market. This appendix describes the intuition behind this assumption.

The money market equilibrium is described by the theory of liquidity preference developed by Keynes. To understand better this equilibrium, we have to analyse the two curves that establish it: namely the demand and supply of money. The demand of money depends chiefly on three motivations:

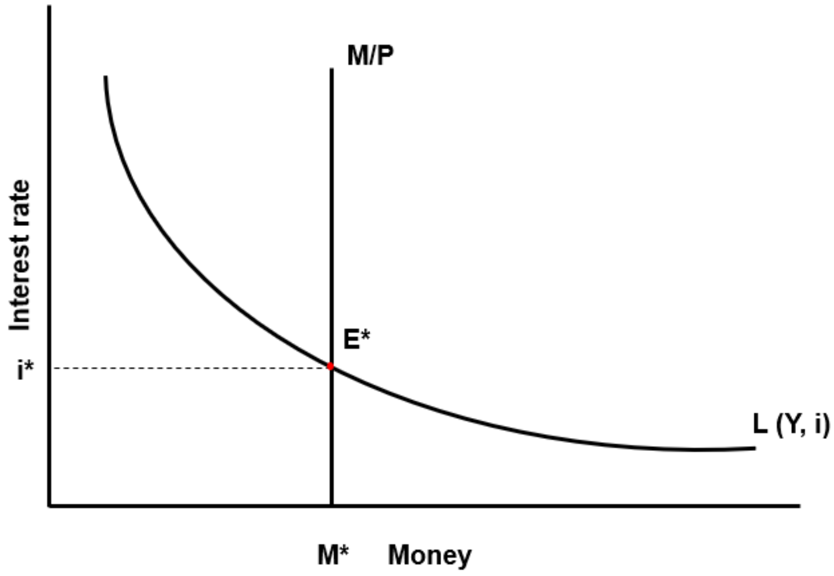
- Transactional: people prefer liquidity for their day-to-day needing. The level of liquidity depends on the relative wealth, the wealthier people are the more money they require;
- Precautional: it refers to the demand of liquidity to hedge unforeseen expenditures;
- Speculative: the level of liquidity depends on the willingness of people to take advantage from future changes in interest rates. According to Keynes, a higher interest rate would lead to a lower speculative demand of money, and vice versa.

Thus, the demand of money is directly proportional to the income (Y), and inversely proportional to interest rate levels (i). This means that if there is a variation in real income, keeping the interest rate at the same level, the demand of money increases proportionally.

The supply of money can be expressed as a ratio between the quantity of money in circulation and the market interest rate. This can be expressed by the ratio M/P, where M is the money supplied and P is the market interest rate.

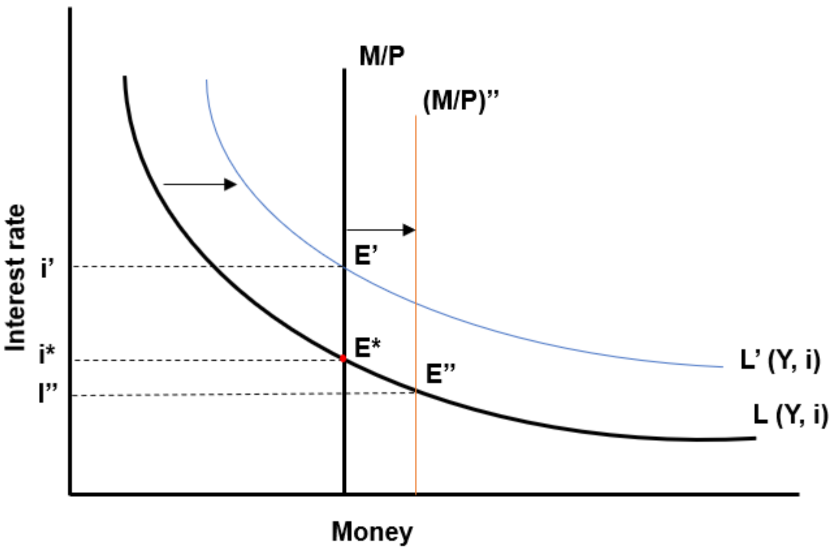
The money market equilibrium is achieved when the demand of money equals its supply. The point in which this equalization is realized, determines the equilibrium interest rate. This is showed graphically in the figure below.

Figure 6: Money market equilibrium



Assuming an ongoing equilibrium in the money market implies that to every shift in the demand of money curve corresponds a prompt adjustment in the equilibrium interest rate, so that the equilibrium is restored. Therefore, an increase in the money supply determines a decrease in the interest rate, whereas an increase in the demand of money involves an increase in the equilibrium interest rate. This relation in showed in the figure below, where i' and i'' are the restored equilibrium interest rates resulting from an increase in the demand and supply of money respectively.

Figure 7: Effect of a change in demand and supply of money on the money market equilibrium



Appendix B: System of matrix VAR model and regression results

In this appendix I am going to explain in detail the system of matrix behind the construction of the VAR model, and report the results from the regressions that have not been included in the text.

As expressed by equation 9, a p-order VAR model can be defined as:

$$y_t = G_0 + G_1 y_{t-1} + G_2 y_{t-2} \dots + G_p y_{t-1} + \varepsilon_t \qquad [\,9\,]$$

In my model I consider five variables and two lags, so equation 9 becomes:

$$y_t = G_0 + G_1 y_{t-1} + G_2 y_{t-2} + \varepsilon_t \qquad [\,19\,]$$

In matrix notation this can be indicates as

$$y_t = \begin{vmatrix} y_{1,t} \\ y_{2,t} \\ y_{3,t} \\ y_{4,t} \\ y_{5,t} \end{vmatrix}$$

$$G_o = \begin{vmatrix} G_{1,0} \\ G_{2,0} \\ G_{3,0} \\ G_{4,0} \\ G_{5,0} \end{vmatrix}$$

$$G_1 y_{t-1} = \begin{vmatrix} G_{1,1} & G_{1.2} & G_{1,3} & G_{1,4} & G_{1,5} \\ G_{2,1} & G_{2,2} & G_{2,3} & G_{2,4} & G_{2,5} \\ G_{3,1} & G_{3,2} & G_{3,3} & G_{3,4} & G_{3,5} \\ G_{4,1} & G_{4,2} & G_{4,3} & G_{4,4} & G_{4,5} \\ G_{5,1} & G_{5,2} & G_{5,3} & G_{5,4} & G_{5,5} \end{vmatrix} X \begin{vmatrix} y_{1,t-1} \\ y_{2,t-1} \\ y_{3,t-1} \\ y_{4,t-1} \\ y_{5,t-1} \end{vmatrix}$$

$$G_2 y_{t-2} = \begin{vmatrix} G_{1,1} & G_{1.2} & G_{1,3} & G_{1,4} & G_{1,5} \\ G_{2,1} & G_{2,2} & G_{2,3} & G_{2,4} & G_{2,5} \\ G_{3,1} & G_{3,2} & G_{3,3} & G_{3,4} & G_{3,5} \\ G_{4,1} & G_{4,2} & G_{4,3} & G_{4,4} & G_{4,5} \\ G_{5,1} & G_{5,2} & G_{5,3} & G_{5,4} & G_{5,5} \end{vmatrix} X \begin{vmatrix} y_{1,t-2} \\ y_{2,t-2} \\ y_{3,t-2} \\ y_{4,t-2} \\ y_{5,t-2} \end{vmatrix}$$

$$\varepsilon_t = \begin{vmatrix} \varepsilon_{1,t} \\ \varepsilon_{2,t} \\ \varepsilon_{3,t} \\ \varepsilon_{4,t} \\ \varepsilon_{5,t} \end{vmatrix}$$

Tables 14a, 14b, and 14c reported below show results of the regressions of the VAR model.

Table 14a: Regression output VAR model: EURUSD exchange rate

	(1)	(2)	(3)	(4)	(5)
VARIABLES	EURUSD	Inf_EUR	IntDiff_EURUS	D_MD_EUR	BC_EUR
L.EURUSD	0.9945***	0.0006	-0.0076	-0.0047**	-0.6127
	(0.0029)	(0.0025)	(0.0212)	(0.0019)	(0.6127)
L.D_inf_EUR	-0.1868***	0.0001	-0.0017	-0.0009	-5.974
	(0.0387)	(0.0334)	(0.2813)	(0.0246)	(8.1254)
L.D_IntDiff_EURUS	-0.0004	0.00010	0.0001	-0.0002	-2.0778**
	(0.0047)	(0.004)	(0.034)	(0.003)	(0.9826)
L.D_MD_EUR	-0.0423	0.0017	-0.0001	-0.0096	6.0931
	(0.0522)	(0.0452)	(0.3801)	(0.0332)	(10.9786)
L.BC_EUR	-0.0001	0.0000	0.0007	-0.0001	0.7940***
	(0.0001)	(0.0001)	(0.0007)	(0.0001)	(0.0202)
Constant	0.0044*	-0.0005	0.0061	0.0038**	0.6795
	(0.0025)	(0.0022)	(0.0181)	(0.0016)	(0.523)
Observations	905	905	905	905	905

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14b: Regression output VAR model: JPYUSD exchange rate

	(1)	(2)	(3)	(4)	(5)
VARIABLES	JPYUSD	Inf_JAP	IntDiff_JAP	D_MD_JAP	BC_JAP
L.JPYUSD	0.8726***	-0.0015***	0.0019	-0.0002	0.0401
	(0.0336)	(0.0002)	(0.0022)	(0.0001)	(0.03)
L2.JPYUSD	0.1238***	0.0015***	-0.0019	0.0001	-0.0372
	(0.0336)	(0.0002)	(0.0022)	(0.0001)	(0.03)
L.Inf_JAP	-40.5526***	-0.0449	0.0355	0.0012	-0.9004
	(4.8514)	(0.0358)	(0.3205)	(0.0212)	(4.3305)
L2.Inf_JAP	-22.5428***	-0.0618*	0.0557	-0.0023	3.7096
	(4.8479)	(0.0358)	(0.3203)	(0.0211)	(4.3274)
L.IntDiff_JAPUS	-0.4143	0.0006	-0.0021	-0.0002	0.0019
	(0.5477)	(0.004)	(0.0362)	(0.0024)	(0.4889)
L2.IntDiff_JAPUS	0.6966	-0.001	-0.0002	-0.0003	0.1675
	(0.5401)	(0.004)	(0.0357)	(0.0024)	(0.4821)
L.D_MD_JAP	20.1284**	0.0054	0.0284	-0.0393	-15.3917**
	(7.9912)	(0.0591)	(0.528)	(0.0349)	(7.1332)
L2.D_MD_JAP	3.714	0.0431	-0.0204	-0.0346	0.6501
	(7.9993)	(0.0591)	(0.5285)	(0.0349)	(7.1404)
L.BC_JAP	0.0006	0.0001	-0.0001	0.0001	0.9041***
	(0.0374)	(0.0003)	(0.0025)	(0.0002)	(0.0334)
L2.BC_JAP	-0.0097	0.0001	-0.0002	0.0001	-0.1070***
	(0.0374)	(0.0003)	(0.0025)	(0.0002)	(0.0334)
Constant	0.3555	-0.0025	-0.0014	0.0093***	-0.219
	(0.3815)	(0.0028)	(0.0252)	(0.0017)	(0.3405)
Observations	903	903	903	903	903

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14c: Regression output VAR model: YUANUSD exchange rate

	(1)	(2)	(3)	(4)	(5)
VARIABLES	YUANUSD	Inf_CHI	IntDiff_CHI	MD_CHI	BC_CHI
L.YUANUSD	1.0500***	-0.0492***	0.1709	-0.0042	-1.5942
	(0.035)	(0.0112)	(0.6866)	(0.0298)	(2.7544)
L2.YUANUSD	-0.0547	0.0500***	-0.182	0.002	1.5789
	(0.0348)	(0.0112)	(0.6837)	(0.0297)	(2.7425)
L.Inf_CHI	-0.0475	-0.0426	0.3323	0.037	-12.4762
	(0.1108)	(0.0355)	(2.1765)	(0.0946)	(8.7313)
L2.Inf_CHI	-0.3704***	-0.0249	0.2804	0.0255	-1.0657
	(0.1095)	(0.0351)	(2.1514)	(0.0935)	(8.6303)
L. IntDiff_CHIUS	0.0006	0.00001	-0.0002	0.0001	-0.171
	(0.0018)	(0.0006)	(0.0354)	(0.0015)	(0.1419)
L2. IntDiff_CHIUS	0.0009	0.0001	0.0002	-0.0004	-0.0571
	(0.0018)	(0.0006)	(0.035)	(0.0015)	(0.1405)
L.MD_CHI	80.0029	0.0034	-0.1443	0.9025***	0.8094
	0.0412)	(0.0132)	(0.8097)	(0.0352)	(3.2481)
L2.MD_CHI	0.0033	-0.0048	0.159	0.0961***	-0.8597
	(0.0412)	(0.0132)	(0.8093)	(0.0352)	(3.2464)
L.BC_CHI	-0.0007	0.0003	0.0023	0.00005	0.9036***
	(0.0004)	(0.0001)	(0.0088)	(0.0004)	(0.0352)
L2.BC_CHI	0.0003	0.00001	0.0022	-0.0002	-0.0861**
	(0.0004)	(0.0001)	(0.0088)	(0.0004)	(0.0352)
Constant	0.0219***	-0.0034*	0.0473	0.0152***	0.2563
	(0.0062)	(0.002)	(0.1227)	(0.0053)	(0.4921)
Observations	828	828	828	828	828

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1