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Forecasting exchange rates in the frequency domain

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by

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Resumo

Desde há muito tempo que, a previsibilidade da taxa de câmbio é um tema quente em mente para profissionais de finanças e pesquisadores. Nesta dissertação estudamos a previsibilidade da taxa de câmbio por um método que nunca foi aplicado neste ramo: o domínio de frequências. A taxa de juro, estudada por Fisher (1896), foi o preditor selecionado para esta investigação. Em vez da original série temporal aplicada em Rossi (2013), aplicamos a metodologia de Faria e Verona (2017) na estimativa de Rossi (2013). O método preditor de decomposição em frequência testado no diferencial da taxa de juro, não melhora a previsibilidade da taxa de câmbio em toda a amostra e horizonte temporal selecionado. Esta conclusão vem de uma análise de corrida de cavalos de diferentes taxas de câmbio, diferentes filtros e diferentes frequências.

Palavras-chave: taxas de câmbio, URIP, previsibilidade, domínio de frequências

Abstract

Since a long a time that the exchange predictability is a hot topic for finance practitioners and researchers. In this dissertation we study the exchange rate predictability using a method that has never been applied in the literature: the frequency domain. The uncovered interest rate parity, studied by Fisher (1896) was the model selected for this investigation. Instead of the original time series applied in Rossi (2013), we applied the Faria and Verona (2017) methodology in the Rossi (2013) framework. The frequency-decomposed predictor method tested in the interest rate differential model, does not improve the exchange rate predictability across the sample and time horizon selected. This conclusion come from a horse race analysis of different exchange rates, different filters and different frequencies.

Keywords: exchange rate, URIP, predictability, frequency domain

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Chapter 1
Introduction

The exchange rate predictability represents a vast literature in international finance. Since Meese and Rogoff (1983, 1988), it has been well known that exchange rates are very difficult to predict using economic models. Several surveys of this large literature have been provided from time to time by several authors, like Frankel and Rose (1995), Sarno et al. (2003), Evans (2002), Cheung et al. (2005), Engel et al. (2007), Corte et al. (2009), Williamson (2009) and Rossi (2013). The focus has generally been on finding models that can forecast the future spot exchange rate better than a random walk, "the Meese and Rogoff puzzle". In this investigation we will not try to find or develop a new model, but rather a different way of estimate the uncovered interest rate parity model.

In recent years, wavelet theory has developed very rapidly and has shown very wide strong applicability in several fields. This method is becoming a popular in econometric analysis and high-frequency and low-frequency asset pricing, as in Hong and Kao (2004), Galagedera and Maharaj (2008), Xue et al. (2013), Gencay and Signori, (2015), Bandi et al. (2016), Hasbrouck (2017) and Faria and Verona (2017). The latest is the methodology applied on this paper.

In this dissertation, we analyze if the wavelet decomposition can provide a better insight into exchange rates predictability. We applied the Faria and Verona (2018) methodology, defined as the frequency decomposed predictors, in the context of Rossi (2013) URIP model. This method consists of decomposing the interest rate differential time series into n time series components, each capturing the oscillates of the original variable within a specific frequency interval. We then tested if the use of the frequency domain improves the forecasting of exchange rates.

The results reported come from a horse race analysis of different exchange rates, different filters and different frequencies. Those results show that the Wavelet decomposition methods do not improve significantly the one-month ahead forecast ability of exchange rates for a large set of countries using an interest rate parity model. This contrasts with recent empirical evidence regarding forecasting equity markets (Bandi et al. (2016) and Faria and Verona (2018)) with wavelet methods.

The rest of the dissertation is structured as follows. Chapter 2 reviews the literature, which is divided in two different parts. First, the exchange rate predictability in general and then with more focus on the uncovered interest rate parity; second on the literature wavelet filtering method. Chapter 3 presents the data and methodology. Chapter 4 presents the empirical results and compares then with related literature. Chapter 5 concludes.

Chapter 2
Literature Review

2.1. Exchange rate predictability

Exchange rates are very difficult to predict using economic models. Meese and Rogoff (1983) find that a random walk model would have predicted major-country exchange rates during the recent floating-rate period. In fact, the random walk is often known to generate better forecasts, in terms of exchange rates, than other economic models. Nowadays, the recent literature has identified new macroeconomic and financial predictors that seem to forecast well exchange rates.

According to Rossi (2013), the analysis of the predictability of exchange rates is based on a series of traditional predictors that have emerged in the literature. We used a few models to explain why they should forecast exchange rate according to the economic theory. The classic models that have been used in the literature so far are based on the traditional predictors: interest rate, prices money and output differentials.

Interest rate differential, the predictor analyzed on this dissertation, utilizes the uncovered interest rate parity (UIRP), which was first studied in the end of the 19th century by Fisher (1896). On the latest paper, an analysis is provided about how interest rate can be related to expected changes in foreign currencies. The UIRP states that the expected movement in an exchange rate is related to the difference in interest rates between two countries. According to

Rossi (2013), UIRP model states that, in a world of perfect foresight with a nominal bilateral exchange rate S_t, investors can buy $1/S_t$ unit of foreign bonds using one unit of the home currency. Meese and Rogoff (1988) to forecast real exchange rates out-of-sample using real interest rate differentials and compare its performance with the random walk, finding that the latter forecasts better. Cheung et al (2005) and Alquist and Chinn (2008) find that, although for some countries UIRP forecasts better than the random walk at long horizons, its performance is never significantly better. In-sample empirical evidence is not favorable to UIRP either. Rossi (2013) concludes that the consensus is that estimates of the equation above typically display a negative and significant slope, and a constant significantly different from zero.

The price and inflation differential (PPP) of comparable commodity baskets in two different countries has to be the same, so the price level in the home country, converted to the currency of the foreign country by the nominal exchange rate, should equal the price level of the foreign country. A unit of currency in the home country will have the same purchasing power in the foreign country. Cheung et al (2005) find that, although PPP forecasts better than the random walk at the longest horizons, its performance is never significantly better at shorter horizons as it is significantly worse than the random walk. Rogoff (1996) notes that deviations from PPP can be attributed to transitory disturbances in the presence of nominal price stickiness; thus, they should be short-lived, while in the data, half-life deviations from PPP range between three to five years. This empirical inconsistency was named by Rogoff (1996) as the PPP puzzle. A few authors like Cheung and Lai (2000), Kilian and Zha (2002), Murray and Papell (2002) concluded that possible concerns and explanations include underestimation of the uncertainty regarding point estimates and heterogeneity in disaggregate data.

The monetary model of the exchange rate determination reflects movements in countries relative money, output, interest rates and prices. The demand for real money is viewed as a function of income and the interest rate, in order to substitute relative interest rates and prices as function of exchange rates by using UIRP and PPP, obtains a relationship between exchange rates, money and output differentials. Meese and Rogoff (1983) demonstrate that the random walk forecasts exchange rates out-of-sample better than any of the monetary model. This was confirmed by Chinn and Meese (1995) for short horizon forecasts, while Cheung et al (2005) and Alquist and Chin (2008) , who find that the monetary model does not predict well even at longer horizons a finding that was also supported. Likewise, Molodtsova and Papell (2009) also discovered very limited empirical evidence in favor of the model. On the other hand, Mark (1995) finds strong and statistically significant evidence in favor of the monetary model at very long horizons. The empirical evidence on the monetary model is thus mixed, as the in-sample evidence is somewhat positive, while the out-of-sample evidence is less positive.

Regarding the productivity differentials, the relative prices are expressed as a function of productivity differentials, following Balassa (1964) and Samuelson (1964). Instead of productivity differentials can be used the real price of the non-tradable. Cheung et al (2005) measure a productivity differential by labor productivity indices, like real GDP per employee. Overall, they concluded that the model with productivity differentials does not forecast better than the random walk.

Traditional portfolio balance models include a measure of stock balances. Several measures of balances have been used in the literature as broad proxies: cumulated trade balance differentials, cumulated current account balance differentials, and government debt. Meese and Rogoff (1983) find that even after augmenting the monetary model by a measure of trade balance differentials, the model still does not forecast better than the random walk, a finding confirmed by Cheug et al (2005).

While the out-of- sample forecasting ability of some economic models occasionally outperforms that of a random walk in some studies for some countries/time periods, it definitely does not systematically do so. More importantly, with a few exceptions, their predictive ability is not significantly better than that of a random walk at short horizons. The main exception is the work by Clark and West (2006) regarding the out-of-sample predictive ability of UIRP. At the same time, some predictors show significant in-sample fit, although with coefficient signs that are inconsistent with economic theory.

2.1.1. The uncovered interest rate parity

As we mentioned above, the predictor model, UIRP, is one of the three most used economic models in the fields of international finance and macroeconomics. The UIRP states that the expected movement in an exchange rate is related to the difference in interest rates between two countries. If the uncovered interest rate parity holds true, it will be indifferent for investors to invest in an interest rate in two countries whether the position is covered or uncovered as the exchange rate adjusted return will be the same. The future exchange rate should depreciate by exactly the interest-rate differential. If covered and uncovered interest rate parity both hold, this implies the forward rate is an unbiased predictor of the future spot rate. In the case of covered interest rate parity, the domestic interest rate, r_t is represented as:

$$r_t = r_t^* + f_t - s_t$$

where r_t^* is the foreign interest rate, f_t is the forward rate and s_t is the current spot rate. As the expectation of future exchange rate it´s not observable, so it makes the URIP more difficult to test contrary of the covered interest parity with an available forward rate. Accordingly, UIRP assumes that the current forward rate will equal the expected exchange rate plus a forecast error defined as:

$$f_t = E(s_{t+1}) + \varepsilon_{t+1}$$

Therefore, the equation of the domestic interest rate can be rewritten as:

$$r_t = r_t^* + s_{t+1} - s_t + \varepsilon_{t+1}$$

or adjusted as:

$$s_{t+1} - s_t = r_t - r_t^* + \varepsilon_{t+1}$$

Economists assess the validity of the UIRP condition by empirically estimating the parameter values of α and β in the form:

$$s_{t+1} - s_t = \alpha_0 + \beta_1(r_t - r_t^*) + \varepsilon_{t+1}$$

where α_0 should equal to zero, whereas rational expectations in exchange markets and risk neutrality among investors; the β_1 should equal to one, under the assumption of a constant risk premium. In turn, this implies a perfect depreciating relationship according to UIRP.

Interest rate parity imposes that as the interest-rate differential increases, the exchange rate should equally depreciate. For example, if the foreign interest rate is one percent higher than the domestic interest rate (for a one-year sovereign bond) than the foreign currency is expected to depreciate by one percent after one year.

2.2. Wavelet filtering method

Many people in fields such as physics, geophysics, engineering, medicine and biomedical engineering have long been using the wavelets method.

According to Faria and Verona (2017), wavelets allow overcoming some weaknesses of traditional frequency domain tools, as they provide a better time-frequency decomposition of the original time series. Wavelets are based on Fourier analyses as in Mallat (1999). However, in contrast to the Fourier analysis, wavelets are defined over a finite window in the time domain, which is automatically and optimally allocated according to the frequency of interest.

Varying the time of the window, it is possible to capture at the same time both time-varying and frequency-varying of the time series. This is especially useful with non-stationary time-series, as well as when time-series have structural breaks or jumps. Moreover, as wavelets allow frequency decomposition in the time domain, they are well suited to finance applications.

The decomposition of a time series into different frequency bands can be done by the Wavelet filtering method. In order to obtain the decomposition, an appropriate cascade of wavelet filters is applied. This is essentially equivalent to filtering by a set of band-pass filters so as to capture the fluctuations of the time series in different frequency bands.

The most popular filtering method, used by Baxter and King (1999) and Christiano and Fitzegerald (2003), known as the band-pass filter permits isolation of fluctuations in different frequency based. This methodology is a combination of a Fourier decomposition in the frequency domain with a moving average in the time domain, and it is optimized by minimizing the distance between the Fourier transform and an ideal filter. Guay and St-Amant (2005) however observe that the band-pass filter is not an ideal filter, as it is a finite representation of an infinite moving-average filter, and it performs well at business-cycle frequency but not at low and high frequencies. Furthermore, Murray (2003) points out that the band-filter may introduce spurious dynamic properties.

On the other hand, the wavelet filtering provides better resolution in the time domain as the wavelet basis functions are both time-localized and frequency-localized.

Since Ramsey (1999), the predictive power of wavelet based methods were applied to time series. Wong et al. (2003) provided an innovative application to exchange rates, as well as, Conejo et al. (2005) for forecasted electricity prices and more recently, Berger (2016) separated short-run noise from long-run trends and assessed the relevance of each frequency for volatility forecasting. Rua (2011) proposed a wavelet based multiscale principal component analysis to forecast GDP growth and inflation and found that significant predictive short-run improvements can be obtained with wavelet decomposition in combination with factor-augmented models.

Chapter 3
Data Description and Methodology

In this section, we focus on the data used and the methodology applied in our investigation. The methodology adopted is the same as in Faria and Verona (2017) in the context of Rossi (2013) URIP estimation. We tested if the use of the frequency domain improved the forecasting of exchange rates. In the first subsection, we present the data and the source, and in the second subsection we present the methodology adopted.

3.1. Data Description

Rogoff and Stavrakeva (2009) state that the predictive ability of fundamentals-based exchange rate models is often dependent of the sample. The data used in this thesis is taken from Rossi (2013). However, I have data on exchange rates, relative to the Unites States, for several countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, New Zealand, Spain, Sweden, Switzerland and United Kingdom. The monthly data was collected for all countries on overnight interest rates and exchange rates relative to the USD. The aforementioned data come from the IMF database via DataStream, as well as Philip Lane's website (http://www.philiplane.org/EWN.html). Since the countries' geographical definitions have changed over time (for example, after the introduction of the euro currency), the sample size differs across countries. Initially Rossi (2013), series did not account for seasonal adjustments, and so seasonal adjustment was achieved by using one-sided moving average with backward, equal weights.[1]

3.2. Methodology

3.2.1. Wavelet decomposition

Percival and Walden (2000) showed that the decomposition of a time series could be achieved through the discrete wavelet transform (DWT) multiresolution analysis (MRA), so that the time series is turned into its constituent multiresolution components.

Two types of wavelets can be: father wavelets (ϕ), which capture the smooth and low-frequency part of the series, and mother wavelets (ψ), which capture the high frequency components of the series, where $\int \phi\,(t)dt = 1$ and $\int \psi\,(t)dt = 0$

Given a time series $\mathrm{y}(t)$ with N representing the number of observations, the decomposition with wavelet can be obtained through:

$$\mathrm{y}(t) = \sum_k s_{j,k}\,\phi_{j,k}(t) + \sum_k d_{j,k}\,\psi_{j,k}(t) + \sum_k d_{j-1,k}\,\psi_{j-1,k}(t) + \sum_k d_{1,k}\,\psi_{1,k}(t)$$

where J represents the number of multiresolution levels, or scales, k ranges from one to the number of coefficients in the corresponding component, $\phi_{j,k}(t)$ and $\psi_{j,k}(t)$ are the wavelet functions generated from ϕ and ψ through scaling and translation. The coefficients $s_{j,k}$, $d_{j,k}$, $d_{j-1,k}$, . . . , $d_{1,k}$ are the wavelet transform coefficients.

The wavelet functions are generated from the father and mother wavelets through scaling and are translated as follows

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[1] For monthly data the filter is (1/12)+(1/12)L+ ... + (1/12)L^{11}. Empircal results based on seasonally unadjusted data are quantatively similar.

$$\phi_{j,k}(t) = 2^{-\frac{J}{2}}\phi\,(2^{-J}t - k)$$

$$\psi_{j,k}(t) = 2^{-\frac{J}{2}}\psi\,(2^{-J}t - k)\,,$$

while the wavelet transform coefficients are given by

$$s_{j,k} = \int y_t\,\phi_{j,k}\,(t)\,dt$$

$$d_{j,k} = \int y_t\,\psi_{j,k}\,(t)\,dt$$

where $j = 1, 2, \ldots, J$.

Using a wavelet filter, a time series y_t can be decomposed as

$$y_t = \sum_{j=1}^{J} y_t^{D_j} + y_t^{S_j}$$

where $y_t^{D_j}$, $j = 1, 2, \ldots, J$, the J wavelet detail components and $y_t^{S_j}$ is the wavelet smooth component. The original series y_t as showed by the equation above, exclusively defined in the time domain, can be decomposed in different time series components, each defined in the time domain and representing the fluctuation of the original time series in a specific frequency brand. Specifically, for small j, the j wavelet detail components represent the higher frequency characteristics of the time series, short-term behavior. As j increases, the j wavelet detail components represent lower of the series. Finally, the wavelet's smooth component captures the lowest frequency dynamics, long-term behavior.

In this thesis, we perform wavelet decomposition analysis by applying the maximal overlap discrete wavelet transform (MODWT) wavelet multiresolution analysis (MRA). This methodology i) is not restricted to a particular sample size, ii) is translation-invariant, so that it is not sensitive to the choice of starting point for the examined time series, iii) does not introduce phase shifts in the wavelet coefficients and is especially relevant for the forecasting exercise.

The wavelet multiresolution decomposition of y_t can be rewritten in a more synthetic way as:

$$y(t) = S_j(t) + D_j(t) + D_{j-1}(t) + \cdots + D_1(t)$$

where $S_j(t) = \sum_k s_{j,k}\,\phi_{j,k}\,(t)$ and $D_j(t) = \sum_k s_{j,k}\,\psi_{j,k}\,(t)$ for $j = 1, 2, \ldots, J$, are the smooth and detail components, respectively. By analyzing this equation above, we can observe that the original series $y(t)$, exclusively defined in the time domain, can be decomposed in different components, each defined in the time domain and representing the fluctuation of the original time series in a specific frequency band. More specifically, for small j, the j wavelet detail components represent the higher frequency characteristics of the time series, in other words its short-term dynamics. With the increase of, the j wavelet detail components depict lower frequency movements of the series. Lastly, the lowest frequency dynamics can be seen through the wavelet smooth component (i.e. its long-term behavior or trend).

Regarding the wavelet families used in the discrete wavelet transform, there are several alternatives in the literature, namely, Haar, Daubechies, Coiflets, Symlets, Fejer-Korovkin, among others. However, as argued by Crowley (2007) some filters are not appropriate for the study of economic variables, like Haar wavelet, due to the discontinuous nature of its waveform, but beyond this, there is any explicit choice. The best way to access the robustness of the results is to do a sensitivity analysis, with respect to the choice of the filter.

In this dissertation we perform wavelet decomposition analysis, of the predictor interest rate, by applying the MODWT MRA. In our analyses, given the availability of long data series, we apply a J=5 level MODWT MRA to the time series using coif2 wavelet filter with periodic boundary conditions[2]. The wavelet decomposition delivers six components: five wavelet details, $D_1(t)$ to $D_5(t)$, and a wavelet smooth, $S_5(t)$. Since in this dissertation we employ monthly data, the first detail component $D_1(t)$ captures oscillations between 2 and 4 months, the second detail component $D_2(t)$ captures oscillations between 4 and 8 months,

[2] We did a horse race analysis of different exchange rates, different filters, different frequencies and different boundary conditions.

while detail components, $D_3(t)$, $D_4(t)$ and $D_5(t)$ captures oscillations with a period of 8-16, 16-32 and 32-64, respectively. Finally, the smooth component $S_5(t)$, which we now rename $D_6(t)$, captures oscillations of a period exceeding 64 months.

3.2.2. Forecasting evaluation methods

To evaluate a forecast, we should make some assumptions regarding the loss function to evaluate the forecast and the test statistic to assess the significance. We have selected a few methods to measure the forecast accuracy as in Rossi (2013).

Concerning the loss function, the literature usually evaluates the models' out-of-sample forecasting performance through the root mean square forecast error (RMSFE). As in the same as Meese and Rogoff (1983, 1988). Some researchers also used mean absolute errors (MAE) (Meese and Rogoff (1983)) and asymmetric loss functions (eq Ito (1990) and West et al (1993)). This forecast evaluation method can target: i) the direction of the prediction, it means, calculates the distribution of forecasts that correctly predict the direction of change of the exchange rate; ii) a utility-based measure, it is basically the "cost" for providing estimates of the economic model instead of the economic model; or iii) the whole predictive density or interval forecasts.

The statistical significance of superior forecast performance is typically assessed via out-of-sample predictive ability tests or in-sample Granger causality tests. The out-of-sample tests are used to evaluate if the predictors would have improved exchange rates estimations in forecasting environments that look like as closely as possible the one faced by forecasters in practice, as in Meese and Rogoff (1983). The in-sample tests where the lagged predictor has significant explanatory power for exchange rates over the entire sample, as in Andersen et al. (2003). Both cases add important insights and are used for different goals, however it is important to highlight that the out-of-sample is a much more challenging exercise than the in-sample; because the predictors that pass the in-sample test may still not have predictive ability in a truly out-of-sample forecasting exercise. Meese and Rogoff (1983) puzzle confirms that, despite of fundamentals are significant predictors of exchange rates in-sample, their predictive ability is not higher than the random walk. Instead of the traditional Granger causality tests, we use a different version of this robust test from Rossi (2005). It catches the predictive ability even if it appears only in subsample, or in the case that the predictive relationship changes overtime. This test has been used by Chen, Rogoff and Rossi (2010).

Traditional tests of out-of-sample predictive ability can be differentiated between absolute tests, which evaluate properties such as unbiasedness and uncorrelatedness and relative tests, evaluate which of the models forecast better. Among others, the test proposed by Diebold and Mariano (1995) and West (1996) and Clark and West (2006, 2007) are a relative test of forecast evaluation. While the tests for relative forecast performance developed in the literature are typically applied to MSFE differences between models, there is an important difference among them: on one hand West (1996) and Clark and West (2006, 2007) test out-of-sample whether the benchmark model is equivalent to the competing model in population, on the other hand Diebold and Mariano (1995) test whether two models‘ forecasting ability is the same. The West (1996) and Clark and West (2006, 2007) test, in a out-of-sample context, test whether the forecasts of the fundamental model and that of the random walk are equivalent, ideally we use this test when we are interested in evaluating models in population The Diebold and Mariano (1995) test whether the forecasts of the fundamental model and that of the random walk are equivalent. So, this approach might be useful when the researcher is interested in evaluating forecasts. The main difference between the approaches above is that, in nested models, the sample MSFE from the larger model is expected to be greater than that of the small model even when, in population, the two models have the same predictive ability, since the larger model introduces noise into its forecasts by estimating parameters that are useless in forecasting, as we can see in Clark and West (2006).

Emerged on the literature, we can conclude that the use of different evaluation method may explain the contradicting evidence on the empirical validity of UIRP. Typically, most of the studies that find gaps on predictability for interest rate differentials either focus on RMSFEs or on the Diebold and Mariano (1995) test. Clark and West (2006) find that, based on the Diebold and Mariano (1995) and West (1996) tests, there is little evidence that UIRP beats the random walk. Nevertheless, UIRP produces better forecasts than the random walk according to the Clark and West (2006) test. Alquist and Chinn (2008), using the CW test, could conclude that UIRP can significantly outperform the random walk at long horizons. Despite of all the evaluation method that we have used on this dissertation, we focused our analysis in the RMSFE and CW test.

Chapter 4
Empirical Results

In this section we report the results obtained in this dissertation trough the wavelet decomposition of a predictor, in this case, interest rate differential. We evaluate different exchange rates, different filters and different frequencies. In the first subsection, we present the results using a wavelet decomposition and the second subsection is the comparison between the Rossi (2013) estimation and our estimation in the frequency domain.

4.1. Results with frequency-decomposed predictors

The results are reported in table 1 for the UIRP model using a traditional time series with those using a frequency-decomposed interest rate differential. The wavelet decomposed results come from a monthly forecasting horizon, a frequency of 16 to 32 months, using a coif2 wavelet filer and a periodic boundary conditions.

The first column reports the country whose the nominal exchange rate we are forecasting (relative to the US Dollar). The second column (labeled "GC"), reports p-values of Granger causality test robust to instabilities. The next column, denoted with "RMSFE", reports the ratio of the root mean squared forecast error of the model relative to the random walk. A value smaller than unity denotes that the model forecasts better than the random walk. The column labeled DMW reports the p-values of the Diebold and Mariano (1995) and West (1996) test. The last column reports the p-values of the Clark and West (2006) test. The Newey and West´s (1987) heteroskedasticity and serial correlation robust covariance matrix is implemented in all the tests, the truncation parameter is $T^{1/4}$, where T is the available sample size.

	GC		RMSFE		DMW		CW	
	Normal	Wavelets	Normal	Wavelets	Normal	Wavelets	Normal	Wavelets
Australia	0,44	0,11	1,00	1,00	0,52	0,49	0,58	0,03
Austria	0,10	0,57	1,01	1,00	0,53	0,53	0,48	0,62
Belgium	0,26	0,71	1,01	1,01	0,54	0,61	0,56	1,00
Canada	-	0,65	1,00	1,00	0,51	0,49	0,40	0,13
Denmark	1,00	0,14	1,01	1,00	0,56	0,51	0,95	0,45
Finland	0,63	1,00	1,02	1,00	0,57	0,55	0,86	0,65
France	0,78	0,84	1,02	1,01	0,54	0,59	0,75	0,99
Germany	-	1,00	1,00	1,00	0,53	0,53	0,47	0,66
Ireland	-	0,12	1,03	1,00	0,54	0,54	0,76	0,64
Italy	0,28	0,62	1,01	1,01	0,55	0,53	0,80	0,46
Japan	0,05	1,00	1,00	1,00	0,54	0,53	0,81	0,62
N. Zeland	1,00	0,39	1,00	1,00	0,53	0,49	0,53	0,06
Spain	0,74	0,58	1,02	1,01	0,56	0,56	0,81	0,91
Sweden	-	0,05	1,04	1,00	0,53	0,47	0,88	0,02
Switzerland	0,45	0,10	1,01	0,99	0,55	0,43	0,84	0,00
UK	1,00	0,13	1,01	1,00	0,58	0,50	1,00	0,08

Table 1-The table reports the p-values of the following tests: Granger-casuality robust ("GC"), Diebold and Mariano (1995) and West (1996) ("DMW"). "RMSFE" denotes the ratio of the root mean squared forecast error of the model relative to that of the random walk without drift. For both, times series and wavelet decomposition.

As we can see from table 1, the forecast using the frequency decomposed of interest rate differential does not improve significantly the exchange rate predictability. We focus specially on the third and fifth column (RMSFE and CW, respectively). Ideally, we would like to find values lower than 1 for the RMSFE and lower than 0,10 for the CW. Actually, we could find a few countries like Austira, New Zeland, Sweeden, Switzerland and UK that satisfy those criteria. Moreover, the most predictable exchange rate, for the wavelet decomposed result, is for sure the CHF vs USD.

Comparing the time series and wavelets method, the later improve a bit the quality of the estimation but nothing significantly relevant for this time horizon, set of countries and sample period.

Chapter 5
Conclusion

In this thesis, we explore the exchange rate predictability by considering a frequency domain analysis.

To conduct our investigation, we used the wavelet filtering method proposed by Faria and Verona (2018) and replicate the Rossi (2013) estimation of the uncovered interest rate parity model. Intuitively, we propose to forecast using the frequency decomposed interest rate differential, instead of the traditional time series. We run a horse race analysis of different exchange rates, different filters and different frequencies. These results show that the wavelet decomposition methods do not improve significantly the one-month ahead forecast ability of exchange rates for the set of countries using an interest rate parity setting.

We only focus our analysis on the uncovered interest rate for a time horizon of one month and a limited set of countries. A natural extension of the research work in this dissertation is to analyze the exchange rate predictability in the frequency domain using other traditional models like PPP or monetary model, or the URIP for a different time horizon, different sample and different countries.

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