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A mixed frequency approach for exchange rates predictions

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Selecting an appropriate statistical model to forecast exchange rates is still today a relevant issue for policymakers and central bankers. The so-called *Meese and Rogoff puzzle* assesses that exchange rate fluctuations are unpredictable. In the literature, a lot of studies tried to solve the puzzle finding both alternative predictors (e.g., interest rates, price levels) and statistical models based on temporal aggregation. In this paper, we propose an approach based on mixed frequency models to overcome the lack of information caused by temporal aggregation. We show the effectiveness of our approach with an application to CAD/USD exchange rate predictions.

keywords: MIDAS, linear regression, frequency alignment, forecasting

1 Introduction

According to a popular quote attributed to Alan Greenspan, the former U.S. Federal Reserve Chairman: "*implicit in any monetary policy action or inaction is an expectation of how the future will unfold, that is, a forecast*" (Carlstrom and Fuerst, 1999). Exchange rate forecasting is an essential issue for policymakers and central bankers because these predictions are used to project in the future the potential consequences of given monetary policies. Central bank policies are described by interest rate rules, where interest rates respond to forecasts of future inflation and economic activities rather than their past values only (Wieland and Wolters, 2013). Equally important, exchange rate predictions result extremely decisive for heavy importer/exporter countries' central banks.

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The so-called *Meese and Rogoff puzzle* (Meese and Rogoff, 1983, 1988) assesses that, differently from what is claimed by the economic theory, exchange rate fluctuations are challenging to predict in practice. As a main result, the simple random walk model provides more accurate forecasts than the most competing models based on classical predictors. Previous studies (e.g., Mark, 1995; Cheung et al., 2005; Molodtsova and Papell, 2009; Ferraro et al., 2015; Cheung et al., 2019) tried to solve the puzzle by finding new competing predictors and statistical models to forecast exchange rates better than the random walk model.

Several choices have to be made to forecast the exchange rates: the predictors to be used in forecasting, the sampling frequency of the observation and the statistical model. First of all, a set of significant predictors has to be defined. Economic theory (e.g., Fisher, 1896; Frenkel, 1976; Choi and Oh, 2003) provides a powerful guide. Among *classical* theoretical frameworks, it can be mentioned the interest rate differential (*uncovered interest rate parity* theory), the price levels differential (*purchaising power parity* theory) and the money supply (*monetary* theory). Concerning the choice of the variables, Meese and Rogoff (1988) tested classical predictors' forecasting accuracy against a random walk hypothesis. A similar approach was proposed by Mark (1995); Chinn and Meese (1995); Cheung et al. (2005, 2019). Molodtsova and Papell (2009) showed that Taylor rule-based variables are, to some extent, able to forecast the exchange rates. Similarly, Ferraro et al. (2015) showed that oil price fluctuations play an important role at this aim.

A subsequent but equally relevant aspect in forecasting procedures is the time-frequency. Some studies on exchange rates focused on monthly predictions (e.g., Molodtsova and Papell, 2009), whereas other studies aimed at forecasting exchange rates with quarterly predictions (e.g., Cheung et al., 2005, 2019). Time horizon is an important choice since there is an interest in obtaining either short-run and long-run forecasts. As regards this aspect, we have to highlight that the majority of exchange rate forecasting studies uses a data aggregation step, despite the fact that exchange rate data are daily available. This aggregation step, in which daily data are aggregated to monthly or quarterly data, are usually done because the latter are the ones of interest for economists. Macroeconomics literature does not consider high frequency data analysis, since it is mainly of interest for the risk management.

The Meese and Rogoff puzzle is proved to be more difficult to be solved when exchange rate data are quarterly aggregated, as well as its predictors (e.g., Cheung et al., 2005; Rossi, 2013; Cheung et al., 2019). In particular, the temporal aggregation step induces the so-called *temporal aggregation bias* (Marcellino, 1999), consisting of a considerable loss of information once data aggregation is used. Therefore, the puzzle could be potentially explained by temporal aggregation bias that rises in aggregating monthly data in quarterly data. To avoid the consequences of the bias, a statistical model incorporating all the monthly information available in the data should be preferred.

The selection of an appropriate statistical model is an important point (see Rossi, 2013). Meese and Rogoff (1988) used the classical linear regression to obtain predictions (as well as Cheung et al., 2005; Molodtsova and Papell, 2009; Ferraro et al., 2015; Cheung et al., 2019), whereas Mark (1995) proposed long-run relationships among predictors and exchange rates with *error correction models* (ECM). Nevertheless, several papers (e.g., Kilian, 1999; Groen, 1999, 2002) showed an important drawback: the single-equation models without a co-integrating relation provide better out-of-sample forecasts for exchange rates.

Overall, the puzzle is still not properly solved, and some questions remain open. Among the others, Meese and Rogoff (1988) themselves tried to explain the puzzle through sampling errors or model misspecification. By the way, it is not clear why some authors as Molodtsova and Papell (2009) and Ferraro et al. (2015) had evidence in favour of predictability with monthly data, while other authors as Cheung et al. (2005) and Cheung et al. (2019) obtained not favourable results with quarterly data.

In this paper, by considering classical predictors suggested by the economic theory and by avoiding temporal aggregation on them, we provide long-run forecasts on quarterly exchange rates (e.g., Cheung et al., 2005, 2019). The challenge is how to handle the mixture of sampling frequencies in exchange rates' predictions. For this purpose, we implement a strategy based on the so-called *Mixed Data Sampling regression* (MIDAS: Foroni et al., 2015) which allows analysing data with different time frequency. We show that the absence of temporal aggregation allows to better forecast exchange rates.

The structure of the paper is the following. In Section 2, we briefly review the predictors commonly used to forecast exchange rates by previous studies. Then, in Section 3, we describe the implemented statistical methodology. In Section 4, we provide empirical evidence of the forecasting ability of mixed frequency models, showing a case study on CAD/USD exchange rate prediction. Some remarks are reported in the conclusions.

2 Classical predictors for exchange rates

In exchange rates' forecasting, the class of theoretical models that have been tested over time against the random walk hypothesis is vast. The selected benchmark, the random walk without drift, is written as:

$$\Delta s_t = \Delta s_{t-1} + \epsilon_t \tag{1}$$

where $\Delta s_t = s_{t+1} - s_t$ is the exchange rate differential and ϵ_t the error term. In this section, we briefly examine the most relevant models used into the reference literature.

2.1 Uncovered Interest Rate Parity

According to the *uncovered interest rate parity* (UIRP) theory (Fisher, 1896), the interest rate differentials between two countries should explain fluctuations in the exchange rates. However, many previous studies showed that more accurate forecasts can be obtained by using the random walk. Several authors found good results using monthly frequency data (Clark and West, 2006; Molodtsova and Papell, 2009). The UIRP model is specified by estimating the following equation:

$$\Delta s_t = \alpha + \beta(i_t - i_t^*) + \epsilon_t \tag{2}$$

where α is the intercept term of the model, i_t is the domestic short-term interest rate, i_t^* the foreign short-term interest rate, β is the relation between the interest rate differentials and the exchange rate fluctuations and ϵ_t is the error term. A positive value of β produces a forecast of the interest rate depreciation.

In the model, the intercept could be restricted to be zero or not (Rossi, 2013). The intercept represents the level of the exchange rates' fluctuations when the predictors are zero. Most of previous studies (e.g., Meese and Rogoff, 1983, 1988; Mark, 1995; Cheung et al., 2005; Ferraro et al., 2015)) leaved it unrestricted while some others (e.g., Molodtsova and Papell, 2009)) considered both approaches. In our paper, following Molodtsova and Papell (2009), we consider both models with and without a restriction on the α constant term.

2.2 Purchasing Power Parity

Another classical predictor is find in the *purchasing power parity* theory (PPP) considering the price level differentials of two countries. In particular, to test the validity of the PPP theory for exchange rate forecasting, the following equation is estimated:

$$\Delta s_t = \alpha + \beta(p_t - p_t^*) + \epsilon_t \tag{3}$$

where p_t is the domestic price level, p_t^* the foreign price level, α and β the parameters to be estimated and ϵ_t the error term. Previous studies showed that the out-of-sample performances are not good for the PPP model. In particular, Cheung et al. (2005) found that predictors based on PPP produce more accurate forecasts than random walk within a long timescale but their performance are never significantly better. Molodtsova and Papell (2009) showed instead that the PPP model is significantly worse than a random walk in shorter time horizons. Similar results can be found in Cheung et al. (2019).

2.3 Monetary models

The monetary models (e.g., Frenkel, 1976) assess that the exchange rates are determined by the movements in countries' relative money supply, outputs, interest rates and prices. Assuming that UIRP and PPP hold, the following equation is estimated:

$$\Delta s_t = \alpha + \beta_1(i_t - i_t^*) + \beta_2(y_t - y_t^*) + \beta_3(m_t - m_t^*) + \epsilon_t \tag{4}$$

where y_t and m_t are the output and the money supply, respectively. The β_3 coefficient on money differentials is usually restricted to 1, whereas β_2 is assumed to be negative since $(y_t - y_t^*) < 0$ implies a domestic currency depreciation with an increasing (*ceteris paribus*) foreign country output. The specification in Eq. 4 has been defined *flexible price version of the monetary model* by Meese and Rogoff (1988).

Another monetary model is the so called *sticky price*, where it is supposed that the PPP holds only in the long run. The main difference with respect to Eq. 4 is that the functional relation is enriched by the price levels' differentials:

$$\Delta s_t = \alpha + \beta_1(i_t - i_t^*) + \beta_2(y_t - y_t^*) + \beta_3(m_t - m_t^*) + \beta_4(p_t - p_t^*) + \epsilon_t \tag{5}$$

Even if Mark (1995) found strong and statistically significant evidence in favour of these predictors in a very long time horizon (three to four years), these results have been later questioned by several scholars (e.g., Chinn and Meese, 1995; Cheung et al., 2005; Molodtsova and Papell, 2009; Cheung et al., 2019). Meese and Rogoff (1983) demonstrated that the random walk is better than any monetary models in forecasting exchange rates. These findings have been confirmed by Chinn and Meese (1995) for a short timescale, by Cheung et al. (2005) for very long horizon time (five years) and by Molodtsova and Papell (2009), which found good evidence just for few countries.

2.4 Taylor rule fundamentals

Some authors proposed to use predictors based on the *Taylor rule* of monetary policy (Taylor, 1993) to forecast the exchange rates. Taylor theorised that monetary authorities set the real interest rate as a function of how inflation differs from a given target. According to this claim, the central banks' response function is expressed as:

$$\hat{i}_t = \pi_t + \phi(\pi_t - \bar{\pi}) + \gamma y_t^{gap} + \bar{r} \tag{6}$$

where $\hat{i}_t$ is the target short-term interest rate, π_t is the inflation rate at current time, $(\pi_t - \bar{\pi})$ is the deviation of the current inflation rate from its target level $\bar{\pi}$, y_t^{gap} is the output gap and $\bar{r}$ is the equilibrium level of real interest rate. The parameters ϕ and γ define how the inflation rate and the output gap affect the target interest rate. Following Molodtsova and Papell (2009), we can combine π_t and $\bar{r}$ into a constant term such that:

$$\hat{i}_t = \mu_t + \phi\pi_t + \gamma y_t^{gap} \tag{7}$$

where $\mu_t = \bar{r} - \phi\bar{\pi}$. The same relation hold for a foreign central bank:

$$\hat{i}_t^* = \mu_t^* + \phi\pi_t^* + \gamma y_t^{*gap} \tag{8}$$

Assuming that the interest rate i_t immediately reaches the target $\hat{i}_t$, and that both central banks set the interest rates according to a Taylor rule, if the UIRP holds we get:

$$\Delta s_t = \alpha + \beta_1(\pi_t - \pi_t^*) + \beta_2(y_t^{gap} - y_t^{*gap}) + \epsilon_t \tag{9}$$

The above specification is known as *instantaneous* Taylor rule. However, we can suppose that the interest rate i_t slowly adjusts to the target. An example of this adjustment process is found in Molodtsova and Papell (2009), where:

$$i_t = (1-\rho)\hat{i}_t + \rho i_{t-1} + \epsilon_t \tag{10}$$

Supposing that the Eq. 10 is applied to the data of a foreign country, we estimate:

$$\Delta s_t = \alpha + \beta_1(\pi_t - \pi_t^*) + \beta_2(y_t^{gap} - y_t^{*gap}) + \beta_3(i_{t-1} - i_{t-1}^*) + \epsilon_t \tag{11}$$

that is defined as a Taylor rule *with smoothing*. The presence of smoothing reflects the assumption made about the adjustment mechanism to the interest rate target. Using Taylor rule fundamentals as predictors, Molodtsova and Papell (2009) found that the out-of-sample exchange rates forecasts are significantly better than the random walk model for several countries. Other studies (e.g., Molodtsova et al., 2011; Giacomini and Rossi, 2010; Rossi and Inoue, 2012) found evidence in favour of Taylor rule fundamentals. On the other hand, Rogoff and Stavrakeva (2008) found that the empirical evidence in favour of this fundamentals is not robust, assessing that the Taylor rule framework is a good description of monetary policies only for the past three decades. Nowadays, after the financial crises, monetary policies changed. It is interesting to highlight that Rogoff and Stavrakeva (2008) analysed quarterly data instead of monthly data, as well as Molodtsova and Papell (2009), Molodtsova et al. (2011) and Rossi and Inoue (2012).

3 Statistical methodology

Traditional literature of exchange rate forecasting implements standard statistical models that incorporate economic predictors (Meese and Rogoff, 1983, 1988). These statistical models are mainly based on single equations within a linear regression framework, where the estimation of the relationships showed in Section 2 are done by *ordinary least squares* (OLS). This approach has been followed, for example, by Cheung et al. (2005), Bacchetta et al. (2009) and Ferraro et al. (2015). Alternatively, some authors proposed to include some lags, fitting a *distributed lag model* (e.g., Wright, 2008; Molodtsova and Papell, 2009; Molodtsova et al., 2011). Moreover, in the class of single-equation models, another widely used alternative is the *error correction model* (ECM), which assumes a long-run relationship between exchange rate levels and predictor levels.

The co-integration vector parameter can be either calibrated (e.g., Mark, 1995; Chinn and Meese, 1995; Abhyankar et al., 2005; Berkowitz and Giorgianni, 2001; Kilian, 1999) or estimated (e.g., Alquist and Chinn, 2008; Chinn, 2012; Cheung et al., 2005, 2019). Positive evidence favouring the ECM model within a long time horizon has been found by Mark (1995), whereas most of the other authors find no predictive ability. More interestingly − using exactly the same ECM specification of Mark (1995) − Kilian (1999), Groen (1999) and Groen (2002) find no predictive ability for monetary models. In other words, single-equation models without a co-integrating relation provide better out-of-sample forecasts for exchange rates. For this reason, in the following, we focud on single-equation models involving mixed-frequencies (Ghysels et al., 2004, 2007).

In the class of single-equation models, the *mixed data sampling* (MIDAS: Foroni et al., 2015) regression is very promising in facing this kind of problems. The MIDAS shares some features with distributed lag models, and from several point of views they are very similar. The basic single equation with high-frequency regressor and low frequency dependent variable is:

$$y_t = \beta_0 + \beta_1 B(L^{1/m};\theta)x_t^{(m)} + \epsilon_t^{(m)} \tag{12}$$

where $(L^{1/m};\theta) = \sum_{k=0}^{K} B(k;\theta)L^{k/m}$ and $L^{1/m}$ is a lag operator such that $L^{1/m}x_t^{(m)} = x_{\frac{t-1}{m}}^{(m)}$ (for $t = 1, ..., T$). We suppose that y_t is observed at low frequency (e.g., quarterly) and $x_t^{(m)}$ is observed m times in the same period. It is clear that we are projecting y_t onto a history of lagged observation of the high-frequency variable $x_{t-k}^{(m)}$. The parameterisation of the lagged coefficients of $B(k;\theta)$ in a parsimonious way is one of the MIDAS key features that avoid parameter proliferation. Various are the choices for $B(k;\theta)$ with the exponential Almon lag and Beta function as most common (Ghysels et al., 2007).

Foroni et al. (2015) introduced also the so-called *unrestricted* MIDAS (U-MIDAS) which has very appealing features. As the authors showed in their study, when the difference in sampling frequencies between the dependent variable and the regressors is not so large (as often happen with macroeconomic applications), it might not be necessary to employ distributed lag functions $B(k;\theta)$. The essential operation made in estimating equations within the MIDAS framework is the so-called *temporal alignment*. The frequency alignment is used to transform an high-frequency vector $\mathbf{x}$ with mT elements into a low-frequency matrix $\mathbf{X}$ with T rows and m columns known as *stacked vectors*:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ \vdots \\ x_{(mT)} \end{bmatrix} \rightarrow \begin{bmatrix} x_m & x_{m-1} & \cdots & x_1 \\ \vdots & \vdots & \vdots & \vdots \\ x_{(mT)} & x_{(mT-1)} & \cdots & x_{(mT-(m-1))} \end{bmatrix} = \mathbf{X} \tag{13}$$

The MIDAS mapping follows a simple time-ordering aggregation scheme. Suppose that y_t is observed quarterly and the aim is to explain its relationship with the monthly-observed variable x_t. Stated that each quarter has three months, a value of $m = 3$ has to be used. Let consider that only the monthly data in the current quarter have explanatory power (i.e., we are estimating a single equation without lags). Assuming that the exchange rates are quarterly observed, it is possible to transform a high-frequency predictor $\mathbf{x}$ in a low-frequency matrix $\mathbf{X}$ with $m = 3$ stacked vectors:

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \vdots \\ x_{(3T)} \end{bmatrix} \rightarrow \begin{bmatrix} x_3 & x_2 & x_1 \\ x_6 & x_5 & x_4 \\ \vdots & \vdots & \vdots \\ x_{(3T)} & x_{(3T-1)} & x_{(3T-2)} \end{bmatrix} = \mathbf{X} \tag{14}$$

The previous formalisation indicates that for the quarter t we want to model y_t as a linear combination of the monthly predictors observed within each quarter t. Alternatively, we can write:

$$y_t = \alpha + \beta_1 x_{3t} + \beta_2 x_{3t-1} + \beta_3 x_{3t-2} + \epsilon_t \tag{15}$$

The frequency alignment procedure turns a MIDAS regression into a classical time series regression where all the variables are observed at the same frequency. Moreover, this operation makes the single equation model to be estimated by OLS. An important advantage is that with MIDAS techniques we use all the available information for predicting the subsequent quarter. Moreover, MIDAS regression is very promising in explaining the role of temporal aggregation bias in exchange rate predictions. Therefore, we propose the mixed-frequency extensions of the models presented in the Section 2. For example, we estimate the mixed frequency UIRP model as in the following:

$$\Delta s_t = \alpha + \beta_1(i_{3t} - i^*_{3t}) + \beta_2(i_{3t-1} - i^*_{3t-1}) + \beta_3(i_{3t-2} - i^*_{3t-2}) + \epsilon_t \tag{16}$$

where $(i_{3t} - i^*_{3t})$, $(i_{3t-1} - i^*_{3t-1})$ and $(i_{3t-2} - i^*_{3t-2})$ are the inter-quarterly interest rates differences. In a similar way, we extend the PPP model using mixed frequencies:

$$\Delta s_t = \alpha + \beta_1(p_{3t} - p^*_{3t}) + \beta_2(p_{3t-1} - p^*_{3t-1}) + \beta_3(p_{3t-2} - p^*_{3t-2}) + \epsilon_t \tag{17}$$

where $(p_{3t} - p^*_{3t})$, $(p_{3t-1} - p^*_{3t-1})$ and $(p_{3t-2} - p^*_{3t-2})$ are the inter-quarterly price levels' differences. The same specification for the monetary models (4) and (5) produces:

$$\begin{aligned} \Delta s_t = {} & \alpha + \beta_1(i_{3t} - i^*_{3t}) + \beta_2(i_{3t-1} - i^*_{3t-1}) + \beta_3(i_{3t-2} - i^*_{3t-2}) + \\ & + \beta_4(y_{3t} - y^*_{3t}) + \beta_5(y_{3t-1} - y^*_{3t-1}) + \beta_6(y_{3t-2} - y^*_{3t-2}) + \\ & + \beta_7(m_{3t} - m^*_{3t}) + \beta_8(m_{3t-1} - m^*_{3t-1}) + \beta_9(m_{3t-2} - m^*_{3t-2}) + \epsilon_t \end{aligned} \tag{18}$$

$$\begin{aligned} \Delta s_t = {} & \alpha + \beta_1(i_{3t} - i^*_{3t}) + \beta_2(i_{3t-1} - i^*_{3t-1}) + \beta_3(i_{3t-2} - i^*_{3t-2}) + \\ & + \beta_4(y_{3t} - y^*_{3t}) + \beta_5(y_{3t-1} - y^*_{3t-1}) + \beta_6(y_{3t-2} - y^*_{3t-2}) + \\ & + \beta_7(m_{3t} - m^*_{3t}) + \beta_8(m_{3t-1} - m^*_{3t-1}) + \beta_9(m_{3t-2} - m^*_{3t-2}) + \\ & + \beta_{10}(p_{3t} - p^*_{3t}) + \beta_{11}(p_{3t-1} - p^*_{3t-1}) + \beta_{12}(p_{3t-2} -^*_{3t-2}) + \epsilon_t \end{aligned} \tag{19}$$

In the case of *instantaneous Taylor rule*, it easily follows that:

$$\Delta s_t = \alpha + \beta_1(\pi_{3t} - \pi^*_{3t}) + \beta_2(\pi_{3t-1} - \pi^*_{3t-1}) + \beta_3(\pi_{3t-2} - \pi^*_{3t-2}) + \beta_4(y^{gap}_t - y^{*gap}_t) + \epsilon_t \tag{20}$$

An inter-quarterly adjustment mechanism for the interest rate is supposed to be:

$$i_{3t} = (1 - \rho_1 - \rho_2 - \rho_3)\hat{i}_t + \rho_1 i_{3t} + \rho_2 i_{3t-1} + \rho_3 i_{3t-2} + \epsilon_t \tag{21}$$

where $\hat{i}_t$ is the quarterly target level of the interest rate, i_{3t} is the interest rate in the end of the quarter, i_{3t-2} the second month of the quarter and i_{3t-1} the first one. To test the validity of the *Taylor rule with inter-quarterly smoothing* mechanism of the interest rate, we finally estimate the following relation:

$$\begin{aligned} \Delta s_t = \alpha + \beta_1(\pi_{3t} - \pi^*_{3t}) + \beta_2(\pi_{3t-1} - \pi^*_{3t-1}) + \beta_3(\pi_{3t-2} - \pi^*_{3t-2}) + \\ + \beta_4(y^{gap}_{3t} - y^{*gap}_t) + \beta_5(i_{3t} - i^*_{3t}) + \beta_6(i_{3t-1} - i^*_{3t-1}) + \beta_7(i_{3t-2} - i^*_{3t-2}) + \epsilon_t \end{aligned} \tag{22}$$

4 An application to CAD/USD exchange rate

To show the forecasting ability of the proposed approach, we consider the quarterly data of the Canadian Dollar (CAD) / U.S. Dollar (USD) exchange rate. We collect the data from FRED database[1] and compute the logarithm of the nominal monthly CAD/USD exchange rate from 01/01/1985 to 01/01/2019. More recent data about 2020 is not considered because of the COVID-19 pandemic. We aggregate the monthly data into quarterly data and calculate the returns of exchange rates (Fig. 1).

To empirically test the performances of the UIRP-based model, we use the data related to the short-term interest rate collected by the OECD database[2] as in Molodtsova and Papell (2009). The price levels, necessary to make forecasts with PPP-based predictors, is captured by the monthly logarithmic Consumer Price Index (CPI). For monetary models, we download the data of money supply index from the OECD database according to M3 monetary stock definition and compute the logarithm of this variable. As output variable, we consider the quarterly GDP measured in logarithmic levels. All the variables (showed in Fig. 2) are expressed as differences between the domestic (Canada) and foreign (U.S.) countries' values. Moreover, we need the output gap for the implementation of Taylor rule-based models. Following the literature, we compute the output gap as the GDP deviation from its long-run trend, obtained by applying the Hodrick and Prescott (1997) filter. The country's inflation rate are compute as the first difference of the price levels logarithm (the predictors are shown in Fig. 3).

[1] `https://fred.stlouisfed.org/tags/series`
[2] `https://data.oecd.org/`

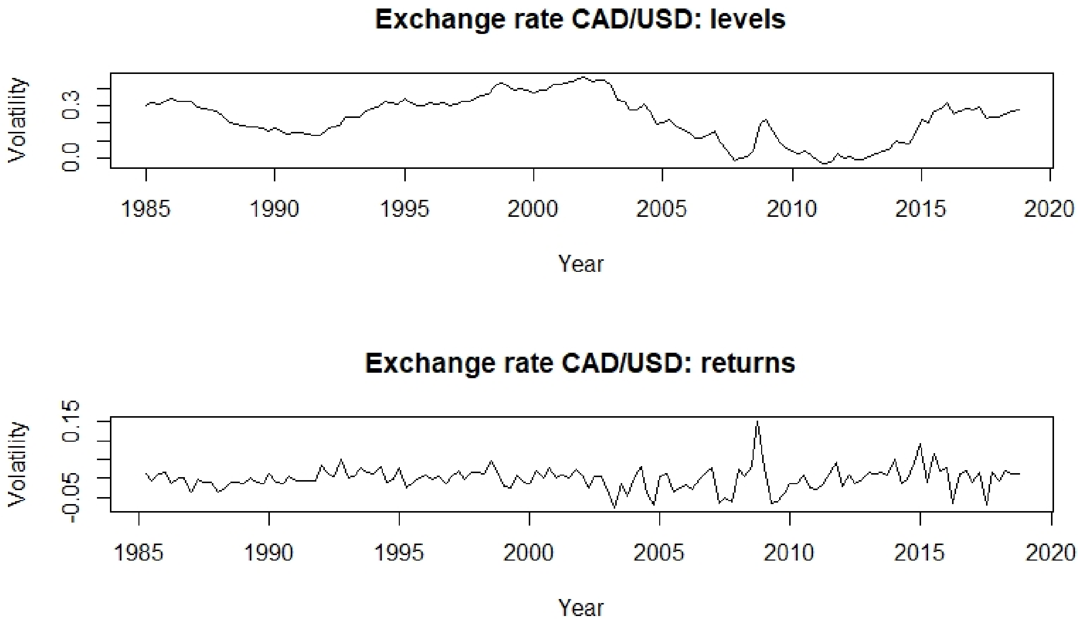

Figure 1: CAD/USD exchange rate fluctuations (top) and logarithmic returns (bottom)

We evaluate the performances of the standard models as well as of the proposed mixed frequency approach. Following Ramzan et al. (2012) and Chung and Zhang (2017), we compare the model performances with an out-of-sample analysis. We consider both a recursive approach, where the sample has an increasing size, and a rolling-window approach with a fixed sample size. To evaluate the forecasting accuracy, we use the Mean Square Forecast Error (MSFE) defined as:

$$\text{MSFE} = \sum_{n} (\widehat{\Delta s_t} - \Delta s_t)^2 / n \tag{23}$$

where, in general, the quantity $\widehat{\Delta s_t} - \Delta s_t$ represents the forecast error. The model with the lowest value of the associated loss function is the best one.

Since assessing the accuracy's improvement is not enough, it is necessary to test that the forecasts obtained with alternative models are statistically different. There are several possible approaches for this purpose. The primary predictive accuracy test in the forecasting literature is the Diebold-Mariano test (Diebold and Mariano, 2002). Given two alternative forecasting models i and j, and considering a generic loss function $g(\epsilon_{i,t})$, the loss difference is computed as in the following:

$$d_{ij,t} = g(\epsilon_{i,t}) - g(\epsilon_{j,t}) \tag{24}$$

The null hypothesis of the test is:

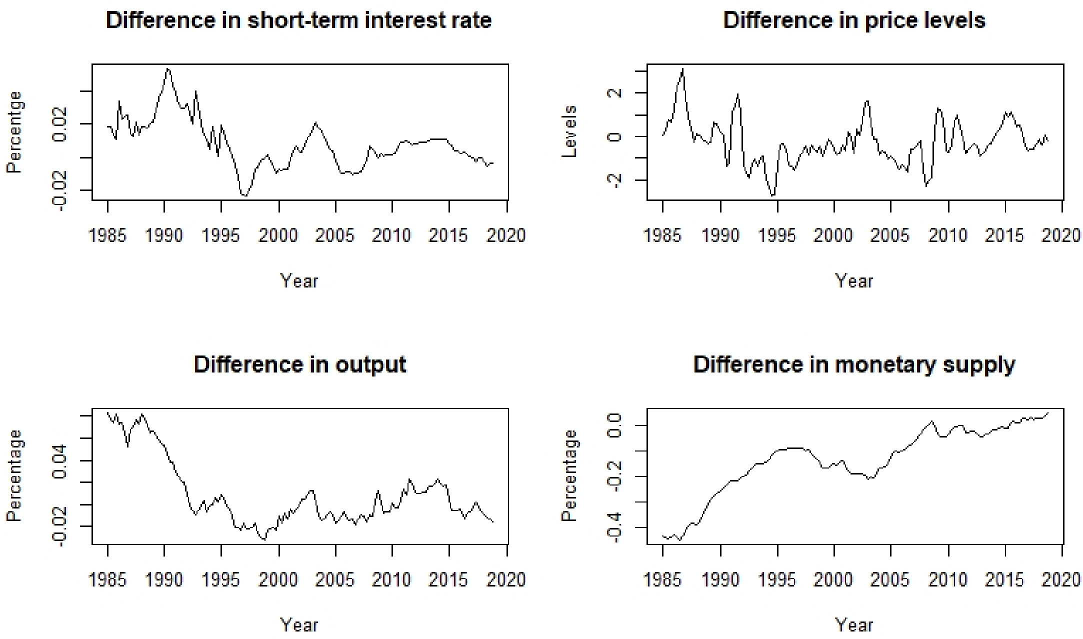

Figure 2: Classical predictors for exchange rates suggested by the economic theory: differentials between domestic and foreign country of short-term interest rates, price levels, GDP output and monetary supply

$$H_0 : E(d_{ij,t}) = 0$$

where $d_{ij,t}$ follows a $N(0, 1)$ distribution. However, the main drawback of this approach − as pointed out by Diebold (2015) − is that the test compares forecasts but does not compare models. Therefore, following the exchange rate forecasting literature, we also implement the Clark and West (2006) test to compare the performances of the proposed complex models.

5 Empirical results and discussion

According to the unit root tests of Said and Dickey (1984) (ADF) and Kwiatkowski et al. (1992) (KPSS), we obtain evidence of stationarity for all the considered variables (see Table 1). For the ADF test, we consider the null hypothesis of not stationarity, while for KPSS we consider the null hypothesis of stationarity. To get consistent estimates, stationarity of all the involved variables is required. The integration order represents the number of differentiations that the time series need in order to be covariance-stationarity according to both tests.

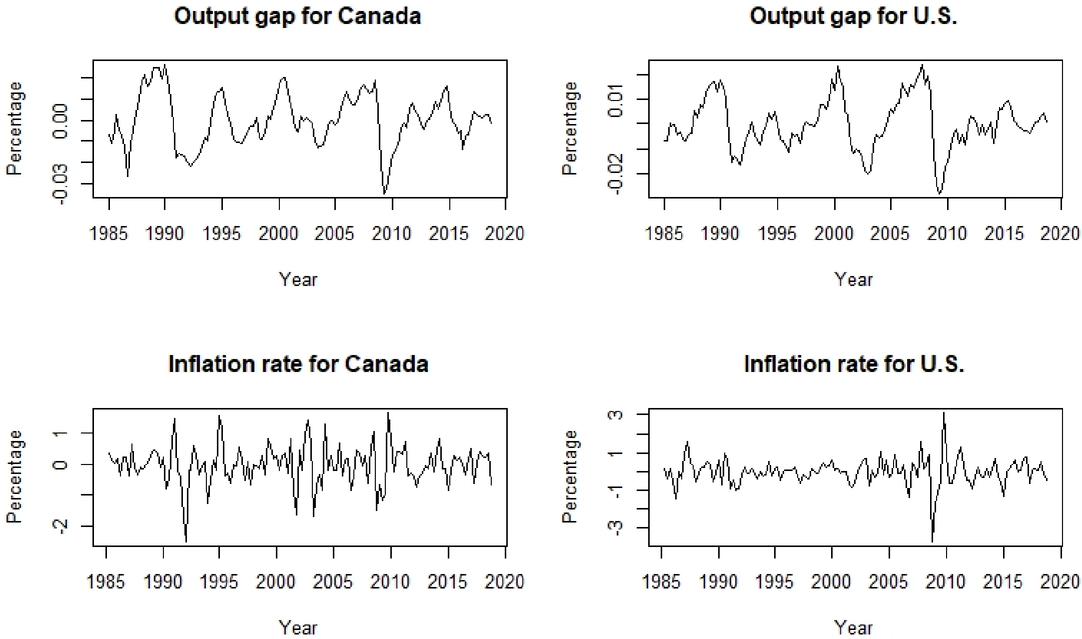

Figure 3: Interest rate differentials and output gap (obtained by applying the Hodrick-Prescott filter) are other suggested variables to predict the exchange rates

Table 1: Unit root test: results

	ADF	KPSS	Integration order
CAD/US exchange rate	-4.2404***	0.1205	$I(0)$
Interest rate differential	-2.4043	0.9066***	$I(1)$
Price level differential	-3.1993*	0.2240	$I(0)$
Money supply differential	-2.8085	2.1546***	$I(1)$
Output differentials	-2.0744	1.1409***	$I(1)$
Canada output gap	-4.7458***	0.0337	$I(0)$
U.S. output gap	-4.1525***	0.0362	$I(0)$
Canada inflation rate	-5.5314***	0.0324	$I(0)$
U.S. inflation rate	-5.2739***	0.0221	$I(0)$

*** significance at 1%, ** at 5% and * at 10%

To make the out-of-sample analysis, the first step is to split the sample into a training set and a testing set. We obtain the forecasts according to both a recursive and a rolling window schemes. As training set we select the period from 1985 to 1994, while as testing set we choose the time window between 1995 and 2019. Table 2 contains the list of the estimated models in our empirical analysis.

The results of the forecasting accuracy obtained by the recursive scheme and the associated predictive accuracy are in Table 3. The majority of the forecasting models (the only exception is the MM_2 model) provides more accurate forecasts than the benchmark in Eq. 1. We consider the random walk model without drift. Forecasts are one step ahead ($h = 1$). In the DM column are reported the values associated with the Diebold and Mariano (2002) test, computed assuming MSFE loss function. In the CW column, instead, are reported the values associated to the Clark and West (2006) tests.

We observe a better performance of the Taylor rule-based models. In particular, we achieve the most accurate forecasts with the instantaneous Taylor rule model ($TYLR_1$), whereas the Taylor rule model with smoothing ($TYLR_2$) performed poorer. The worst model seems to be the sticky price version of the monetary model (MM_2). The Taylor rule with inter-quarterly adjustment (MF-$TYLR_2$), proposed in this paper, provides the most accurate forecasts within the class of mixed frequency models.

Table 2: Estimated models: classical models and their mixed frequency extensions

Acronym	**Model description**
UIRP	Uncovered Interest Rate Parity estimated by the equation (2)
PPP	Purchasing Power Parity estimated by the equation (3)
MM_1	Flexible price monetary model estimated by the equation (4)
MM_2	Sticky price monetary model estimated by the equation (5)
$TYLR_1$	Instantaneous Taylor rule estimated by the equation (9)
$TYLR_2$	Taylor rule with smoothing estimated by the equation (11)
MF-UIRP	Mixed frequency version of (2) estimated by (16)
MF-PPP	Mixed frequency version of (3) estimated by (17)
MF-MM_1	Mixed frequency version of (4) estimated by (18)
MF-MM_2	Mixed frequency version of (5) estimated by (19)
MF-$TLYR_1$	Mixed frequency version of (9) estimated by (20)
MF-$TYLR_2$	Mixed frequency version of (11) estimated by (22)

In conclusion, with a recursive approach, the mixed frequency based extensions improve the forecasting accuracy in comparison with the classical models. In particular, the MF-UIRP is the 2.3% more accurate than UIRP, the MF-PPP is the 8.2% more accurate than PPP, and the MF-$TYLR_2$ is the 18% more accurate than $TYLR_2$. The highest benefit of considering a mixed frequency model is reached, in terms of accuracy, with the mixed frequency sticky price version of the monetary model (MF-MM_2), that is the 53.6% more accurate than the classical MM_2 model.

In a similar way, we evaluate the forecasting accuracy of the proposed models according to a rolling window scheme (see Table 4).

Table 3: Out-of-sample analysis: recursive approach with unconstrained intercept

	MSFE	DM	CW
Random Walk	0.001984	-	-
UIRP	0.001649	7.7800***	$1.53e^{-18}$***
PPP	0.001776	6.6951***	$5.87e^{-13}$***
MM_1	0.001500	7.3806***	$8.98e^{-19}$***
MM_2	0.003241	-7.6012***	$1.01e^{-16}$***
$TYLR_1$	0.001155	3.2853***	$9.71e^{-17}$***
$TYLR_2$	0.001547	7.3827***	$1.12e^{-18}$***
MF-UIRP	0.001612	7.7164***	$8.21e^{-19}$***
MF-PPP	0.001630	7.5522***	$3.28e^{-16}$***
MF-MM_1	0.001439	6.9542***	$3.15e^{-18}$***
MF-MM_2	0.001504	7.1243***	$5.87e^{-18}$***
MF-$TYLR_1$	0.001318	6.0342***	$3.39e^{-16}$***
MF-$TYLR_2$	0.001358	5.8580***	$1.40e^{-18}$***

*** significance at 1%, ** at 5% and * at 10%

Table 4: Out-of-sample analysis: rolling w. approach with unconstrained intercept

	MSFE	DM	CW
Random Walk	0.001984	-	-
UIRP	0.002137	-1.2658	0.1498
PPP	0.001596	7.1651***	$2.73e^{-15}$***
MM_1	0.002355	-2.0977***	0.1238
MM_2	0.005823	-7.1600***	0.9999
$TYLR_1$	0.001189	4.2468***	$1.25e^{-17}$***
$TYLR_2$	0.001550	5.2236***	$8.15e^{-11}$***
MF-UIRP	0.001923	0.5376	0.0013***
MF-PPP	0.001482	7.1987***	$9.84e^{-18}$***
MF-MM_1	0.005702	-3.2726***	0.0810*
MF-MM_2	0.007596	-3.5049***	0.1251
MF-$TYLR_1$	0.001447	6.6033***	$4.21e^{-18}$***
MF-$TYLR_2$	0.001854	2.9112***	$1.43e^{-04}$***

*** significance at 1%, ** at 5% and * at 10%

The results are completely different from the ones reported in Table 3. First of all, the presence of the Meese and Rogoff (1983) puzzle is here more evident. For example, the classical UIRP model is not able to predict the exchange rate, as well as the monetary models. This result is confirmed by both the Diebold and Mariano (2002) and the Clark and West (2006) tests. As in Molodtsova and Papell (2009) and Molodtsova et al. (2011), the Taylor rule-based forecasts provide good results, because both the instantaneous rule ($TYLR_1$) and the smoothing rule ($TYLR_2$) provide better forecasts than the benchmark.

As in the recursive approach, with the mixed frequency extensions we obtain better results than the classical models for the majority of the cases. The MF-UIRP model provides better results than the benchmark in terms of MSFE (the classical UIRP specification based on temporal aggregation provided less accurate forecasts). The gain in accuracy of the MF-UIRP with respect the classical UIRP is exactly equal to 10%. While the classical UIRP provides the same forecasts of the random walk without drift, with the MF-UIRP specification we obtain a statistically significant over performance. In other words, the unpredictability of UIRP model is explained by temporal aggregation. Similar conclusions can be drawn for the MF-PPP model, since it provides more accurate forecasts than the classical PPP model with an accuracy gain close to 7.2%.

Another important point is to test if the predictions, obtained with the mixed frequency extensions, statistically differ from the classical models ones. With this respect, the Table 5 shows the results of the Diebold and Mariano (2002) test applied to classical and mixed frequency models.

Table 5: Predictive accuracy tests: classical vs mixed frequency models with unconstrained intercept

	DM-recursive	DM-rolling w.
UIRP vs MF-UIRP	5.9832***	6.0685***
PPP vs MF-PPP	5.8982***	4.6052***
MM_1 vs MF-MM_1	3.6657***	-3.2809***
MM_2 vs MF-MM_2	7.9290***	7.0872***
$TYLR_1$ vs MF-$TYLR_1$	-1.2483	-1.8250*
$TYLR_2$ vs MF-$TYLR_2$	2.6353**	-4.8321***

*** significance at 1%, ** at 5% and * at 10%.

The first column of the Table 5 shows the results obtained by using a recursive forecasting scheme. The most of the implemented statistical models provides statistically significant different forecasts. Therefore we can argue that the over-performances obtained by the mixed frequency specifications of the UIRP, the PPP and both the monetary models are statistically significant. On the other side, the mixed frequency extension of the instantaneous Taylor rule (MF-$TYLR_1$) has the same predictive ability of the one based on temporal aggregation ($TYLR_1$). Moreover, the mixed frequency extension of the Taylor-rule with smoothing (MF-$TYLR_2$) provides more accurate forecasts than the classical specification ones ($TYLR_2$).

The second column of the Table 5 shows, instead, the results obtained by a rolling-window approach. According to the predictive accuracy test, the results reported in the second column are very similar to those in the first one. For example, the UIRP and the PPP models achieve better forecasts if their mixed frequency extensions are considered.

We also consider models with restrictions on the constant term. We assume $\alpha = 0$ and test that no other factors can explain the exchange rate fluctuations rather than those considered in the model (e.g., Molodtsova and Papell, 2009).

The out-of-sample analysis is conducted by a recursive forecasting scheme (see Table 6) and by a rolling-window one (see Table 7).

Table 6: Out-of-sample analysis: recursive approach with constrained intercept

	MSFE	DM	CW
Random Walk	0.001984	-	-
UIRP	0.001288	5.6315***	$2.89e^{-16}$***
PPP	0.001375	6.0796***	$3.51e^{-16}$***
MM_1	0.001233	5.5709***	$2.32e^{-17}$***
MM_2	0.002106	-2.2300**	0.9365
$TYLR_1$	0.001151	4.2104***	$2.51e^{-16}$***
$TYLR_2$	0.001312	5.6915***	$6.51e^{-16}$***
MF-UIRP	0.001278	5.5947***	$2.42e^{-16}$***
MF-PPP	0.001315	5.6679***	$6.90e^{-16}$***
MF-MM_1	0.001206	5.8857***	$7.84e^{-16}$***
MF-MM_2	0.001199	5.3172***	$1.95e^{-17}$***
MF-$TYLR_1$	0.001222	4.9146	$1.33e^{-16}$***
MF-$TYLR_2$	0.001334	5.8594	$6.82e^{-08}$***

*** significance at 1%, ** at 5% and * at 10%

For the recursive scheme, the results are better than the ones in Table 3. With the intercept restriction we also obtain an accuracy gain by specifying the mixed frequency extensions in the case of UIRP and PPP models. However, differently from the previous ones, the reduction of the loss function is also obtained in the monetary models (MM_1 and MM_2). For the rolling window scheme, we also highlight similar conclusions to the ones in Table 4.

In the end, similarly to Table 5, we show the comparisons among the classical models and the mixed frequency extensions according to the Diebold and Mariano (2002) test (see Table 8). The conclusions in the case of constrained intercept are the same of the ones in Table 5.

Therefore, the overall evidence of the presented study suggests different findings with respect to other recent studies (e.g., Cheung et al., 2019), in which the evidence was

Table 7: Out-of-sample analysis: rolling w. approach with constrained intercept

	MSFE	DM	CW
Random Walk	0.001984	-	-
UIRP	0.001255	5.7223***	1.64e^{-06}***
PPP	0.002572	-3.0343	0.9089
MM_1	0.001382	5.2489***	7.84e^{-16}***
MM_2	0.005273	-5.0877***	0.9940
$TYLR_1$	0.001176	4.1394***	2.45e^{-17}***
$TYLR_2$	0.001237	3.9466***	9.58e^{-13}***
MF-UIRP	0.001200	5.4211***	1.62e^{-17}***
MF-PPP	0.002261	-1.8027*	0.6218
MF-MM_1	0.001294	6.3602***	7.80e^{-23}***
MF-MM_2	0.001367	5.6075***	1.95e^{-17}***
MF-$TYLR_1$	0.001236	4.1529***	4.09e^{-16}***
MF-$TYLR_2$	0.001321	2.8723***	0.0050***

*** significance at 1%, ** at 5% and * at 10%

Table 8: Predictive accuracy tests: classical vs mixed frequency models with constrained intercept

	DM-recursive	DM-rolling w.
UIRP vs MF-UIRP	3.5159***	2.0891**
PPP vs MF-PPP	3.9213***	6.4927***
MM_1 vs MF-MM_1	-0.7775	2.1976***
MM_2 vs MF-MM_2	4.9132***	5.0948***
$TYLR_1$ vs MF-$TYLR_1$	-1.3561	-1.8715*
$TYLR_2$ vs MF-$TYLR_2$	-2.2004**	-1.3400

*** significance at 1%, ** at 5% and * at 10%.

against predictability for the CAD/USD exchange rate using quarterly data. An important result is that by incorporating mixed frequency we were able to improve forecasting accuracy. Moreover, we can also conclude that our results are not affected by the kind of restrictions we put on the intercept term in the statistical model.

6 Robustness check: alternative loss functions

In this Section, we provide some robustness checks to evaluate the performance of the proposed approach. At this aim, we consider different loss functions showing the robustness of the results. Particularly, we use the Mean Absolute Forecast Error (MAFE):

$$\text{MAFE} = \frac{\sum_n |\widehat{\Delta s_t} - \Delta s_t)|}{n} \tag{25}$$

and the Root Mean Square Forecast Error (RMSE):

$$\text{RMSFE} = \frac{\sqrt{\sum_n (\widehat{\Delta s_t} - \Delta s_t)^2}}{n} \tag{26}$$

Table 9 shows the out-of-sample forecasting accuracy by means of a recursive approach.

Table 9: Loss functions: recursive approach with unconstrained intercept

	MSFE	MAFE	RMSFE
Random Walk	0.001984	0.035015	0.044543
UIRP	0.001649	0.030116	0.040615
PPP	0.001776	0.029600	0.040221
MM_1	0.001500	0.028081	0.038733
MM_2	0.003241	0.048582	0.056927
$TYLR_1$	0.001155	0.024482	0.033972
$TYLR_2$	0.001547	0.025741	0.036427
MF-UIRP	0.001612	0.029619	0.040159
MF-PPP	0.001630	0.028757	0.039519
MF-MM_1	0.001439	0.027108	0.037945
MF-MM_2	0.001504	0.027863	0.038561
MF-$TYLR_1$	0.001318	0.024673	0.034890
MF-$TYLR_2$	0.001358	0.026013	0.036861

Models' ranking is clearly not affected by the selection of the loss function within this framework (see Table 9). Then, we compute the additional loss functions (25) and (26) in the case of a rolling window forecasting scheme. The results are reported in the Table 10. In this case the results are also robust to the loss function specification (see Table 4). The same analysis is conducted with $\alpha = 0$. The results are shown, for both recursive and rolling-window forecasting schemes, in the Tables 11 and 12. Thus, we can conclude that the mixed frequency extensions improve the predictive ability of classical models with respect to several loss functions.

Table 10: Loss functions: rolling w. approach with unconstrained intercept

	MSFE	MAFE	RMSFE
Random Walk	0.001984	0.035015	0.044543
UIRP	0.002137	0.034983	0.046231
PPP	0.001596	0.029459	0.039954
MM_1	0.002355	0.037100	0.048538
MM_2	0.005823	0.065159	0.076312
$TYLR_1$	0.001189	0.024369	0.034325
$TYLR_2$	0.001550	0.026151	0.035703
MF-UIRP	0.001923	0.032621	0.043861
MF-PPP	0.001482	0.027580	0.038499
MF-MM_1	0.005702	0.053630	0.075517
MF-MM_2	0.007596	0.028991	0.039591
MF-$TYLR_1$	0.001447	0.024676	0.035103
MF-$TYLR_2$	0.001854	0.032450	0.043050

Table 11: Alternative losses: recursive approach with constrained intercept

	MSFE	MAFE	RMSFE
Random Walk	0.001984	0.035015	0.044543
UIRP	0.0012881	0.025275	0.035891
PPP	0.0013752	0.037084	0.026365
MM_1	0.0012335	0.035121	0.024510
MM_2	0.0021062	0.036188	0.045893
$TYLR_1$	0.0011510	0.024490	0.033927
$TYLR_2$	0.0013127	0.036232	0.025521
MF-UIRP	0.0012787	0.035758	0.025155
MF-PPP	0.0013150	0.025661	0.036260
MF-MM_1	0.0012643	0.024713	0.035558
MF-MM_2	0.0011993	0.024201	0.034630
MF-$TYLR_1$	0.0012222	0.024681	0.034961
MF-$TYLR_2$	0.0013346	0.025678	0.036533

Table 12: Alternative losses: rolling w. approach with constrained intercept

	MSFE	MAFE	RMSFE
Random Walk	0.001984	0.035015	0.044543
UIRP	0.0012550	0.025778	0.035430
PPP	0.0025726	0.040111	0.050721
MM_1	0.0013823	0.027300	0.037179
MM_2	0.5273600	0.459790	0.726200
$TYLR_1$	0.0011764	0.024785	0.034299
$TYLR_2$	0.0013211	0.026099	0.036347
MF-UIRP	0.0012001	0.025049	0.034642
MF-PPP	0.0022610	0.036694	0.047550
MF-MM_1	0.0012949	0.026563	0.035985
MF-MM_2	0.0013671	0.027098	0.036974
MF-$TYLR_1$	0.0012360	0.025352	0.034961
MF-$TYLR_2$	0.0013346	0.025678	0.036533

7 Conclusions

According to the economic theory, several variables can be used to explain the exchange rate fluctuations. From an empirical viewpoint, a lot of papers shows that the variables used in the most popular frameworks forecast exchange rates worst than a random walk model. This result is called the *Meese and Rogoff puzzle*. The most shared explanation of the puzzle is that, stated the validity of the economic theory, the unpredictability should derive by the presence of sampling errors or to statistical models' misspecification.

The most common statistical approach to exchange rate forecasting is based on the classical linear regression model. Starting from the work of Mark (1995), several authors try to incorporate the long-run relationships among the predictors as additional variables but with poorer results than the standard linear regression model ones.

In this paper, we claim that a possible explanation of the Meese and Rogoff (1983) puzzle can be found in the so called *temporal aggregation bias*. This bias, caused by the information lost induced by temporal aggregation, is seen as a source of misspecification when some important (high-frequency) variables are omitted. This intuition lies on the fact that the results presented in the literature are clearly affected by the frequency at which exchange rates are sampled. Even if exchange rate data are daily available, many studies focus on monthly or quarterly frequencies because these are of interest to the economists (Rossi, 2013).

The mixed frequency regression model is a well known technique able to overcome this issue. Here, we propose to use monthly-sampled predictors to forecast the (long-run) quarterly exchange rates by means of a Mixed Data Sampling (MIDAS) regression.

The main empirical finding of the paper − on the basis of a case study concerning the CAD/USD exchange rate − is that the mixed frequency regression model improves the predictive ability in comparison with the classical models, that are instead affected by the temporal aggregation bias. Therefore, the contribution of this paper is two-fold. First of all, we show the implementation of the MIDAS regression to predict quarterly exchange rates with very promising results, offering a new applicative domain for this approach. Moreover, we provide a possible explanation of the Meese and Rogoff (1983) puzzle. These findings can be interesting for a varied audience, including both scholars and practitioners.

A future development consists in the analysis of a greater sample of countries, like the exchange rates of the domestic currencies of Australia, Switzerland, Japan versus the US dollar as in Molodtsova and Papell (2009). Another interesting point can be the inclusion of the lag polinomial function as in the usual MIDAS of Andreou et al. (2010) instead of the more simple mixed frequency regression that we consider in this paper.

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