Exchange Rate Uncertainty and the Interest Rate Parity*

Julián Fernández-Mejía†

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Abstract

This paper studies the effect of exchange rate uncertainty on the deviations Covered Interest Rate parity for benchmark bank rates and government yields. I develop a method for estimating the daily uncertainty from an endogenous factor clustering method to determine the currency grouping and an optimal number of groups and general factors explaining the data. I find that there are defined clusters of exchange rates that remain even after a structural change in the financial crisis and follow geographical characteristics. The deviations from the bank rates differ in form and dependency on the government, where factors such as interest rates and fluctuations in the value of dollar exchange rates. I show that the exchange rate uncertainty increases the deviations of parity and the convenience yield of the US bond and treasury yields, and that effect is economically significant.

Keywords: Uncertainty, Exchange Rate, Factor Clustering, Covered Interest Rate Parity
JEL Codes: C38, C55, E58, F31, F44

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†Copenhagen Business School, Copenhagen, Denmark, e-mail: jfm.eco@cbs.dk

Introduction

Opportunities for arbitrage in the foreign exchange market are supposed to occur rarely and under small time windows. Since the financial crisis, however, they have persisted longer than expected in the foreign exchange markets. Recent empirical evidence by Du and Schreger (2016), Du et al. (2018b), and Jiang et al. (2021) showed that there had been persistent deviations from the interest rate parity. The deviation implies that an investor can make a risk-free profit from borrowing from a low-interest rate country and invest in a safe asset from the high interest of the other, with or without hedging for risk. Under no friction and rational expectations, the exchange rate should adjust and eliminate any opportunity for profit. The persistence of such deviations reflects uncertainty in the market, which generates mispricing of the currencies and persistent volatility. The fluctuations affect the gross capital inflows and outflows, which determine the behavior of the stock market, prices, and the Fiscal (through the Balance Sheet Effect) and the Monetary Policy (Gourinchas and Rey, 2014).

In this paper, I analyze the effect that uncertainty in the fluctuations of the exchange rates generates on the deviations of the Covered Interest Rate Parity (CIP). The create an estimate of this relationship, I propose a new high-frequency measure of exchange rate uncertainty that reflects the fluctuations and the state of the foreign exchange market and provide information on the existence of arbitrage opportunities. Previous models use generalized volatility measures such as realized volatility, the Implied Volatility of the futures of the financial markets, or text mining of newspapers. Colacito et al. (2022) shows that macroeconomic factors' volatility is not completely traduced in the exchange rate volatility. By not including the behavior of the endogenous uncertainty generated from the fluctuations of exchange rates, it ignores the channel of the uncertainty coming from the microstructure of the exchange market. Then, to capture this puzzle arising from exchange rate markets, I estimate the uncertainty from the exchange rates to extract the additional information their variations entail.

One of the paper's main contributions is assessing the relationship between Exchange Rate Uncertainty and the Deviations of the Currency Interest Rate Parity for both Libor and Government bonds by providing a new measure of currency uncertainty. I find evidence that it significantly explains the deviations for most currencies and is a vital factor to the inclusion of control variables, such as the dollar factor, which Avdjiev et al. (2019) and Cerutti et al. (2021) prove capture most of its variability. After an increase in uncertainty, the CIP increases on average by 28 basis points and the convenience yields of US government bonds by 82 basis points. Additionally, the model provides better goodness of fit to other measures, such as the CBOE's Volatility indices like the VIX and VXO, which are traditionally used in the literature.

The Exchange Rate Uncertainty captures the effect of international and currency-related events, such as currency crises, which differ from other broad measures in the literature. As a byproduct of the estimation, I obtain that a single common factor and different groups represent the exchange rate fluctuations, contrary to traditional ad-hoc clustering by commodity production, regional proximity, or interest rate spread. The fact that a common factor affects all the exchange rates goes in line with the literature on the global financial cycle hypothesis of Rey (2015), and the role of the USD as dominant currency (Gopinath et al., 2020; Boz et al., 2022). Furthermore, I use Barigozzi et al. (2018) methodology and find the existence of a structural change in July of 2007, in which the number of clusters is reduced, which goes in accordance with the Exchange Rate Reconnect evidence from Lilley et al. (2022). I use the break to divide the sample and show that the exchange rates became more homogeneous after the crisis, passing from four groups to three groups.

With the models of Menkhoff et al. (2012a) and Ismailov and Rossi (2018), my modeling strategy is one of the first approximations to estimate an exchange rate uncertainty, rather than more broad definitions such as macroeconomic or economic policy. The model differs from the other two since I define uncertainty as the conditional volatility of an unforecastable disturbance for economic agents (Jurado et al., 2015; Ludvigson et al., 2021). I use the methodology of Ando and Bai (2017) that estimates common factors for a set of exchange rates and group-specific ones that target a cluster that shares a characteristic behavior. Brunnermeier et al. (2008), Lustig et al. (2011), Verdelhan (2018), Chuliá et al. (2018), and Aloosh and Bekaert (2022) proved that the exchange rates tend to have comovements, so there is a significant amount of information that a group of exchange rates can provide to estimate the other. An additional byproduct of the estimation is the endogenously determined exchange rate groups, which may affect economic policy coordination.

The uncertainty measure has the advantage over other methodologies as factor models have higher accuracy over traditional models predicting the exchange rate, as highlighted in the recent survey of Kavtaradze and Mokhtari (2018). Several alternative methodologies use forecasts to define the model, such as Ismailov and Rossi (2018). They use the method of Rossi and Sekhposyan (2016) that builds the models from the distribution of survey expectations of the exchange rate for only five currency pairs of industrialized countries. Nevertheless, it presents some shortcomings related to the identification, such as low frequency, survey representation, and expectations' reliability. First, Expectation data typically have monthly periodicity, while Nakamura and Steinsson (2018) mentions the advantages of using high-frequency data, as they capture the effects of "news" that may have been short-lived and adequately identify the timing of the shocks. Another shortcoming can be related to the survey itself; as noted by Coibion and Gorodnichenko (2012), Patton and Timmermann (2010), and Scotti (2016), a forecast may reflect divergence between the forecasters rather than the uncertainty itself. Finally, the reliability of the surveys for emerging countries diminishes as they have higher inattention to less liquid markets. The number of forecasters surveyed is reduced[1]. Daily data factors contain the information inherently, as the prices reflect the conditions of the moment and the general expectations.

Covered Libor and Government Interest Rate Parity Deviations

The Covered Interest Rate Parity (CIP) measures the Parity relating to the investment returns between two countries and the exchange rate returns. It states that under rational expectations and no transaction costs, the differences between riskless investments of different countries should be equivalent once defined in the same currency. Following Du and Schreger (2022), we can define the CIP condition as,

$$(1 + y_{t,t+n})^n = (1 + y^*_{t,t+n})^n \frac{S_t}{F_{t,t+n}} \tag{1}$$

where $y_{t,t+n}$ is the n-period risk-less interest rate in the domestic currency, $y^*_{t,t+n}$ is the n-period risk-less interest rate of the foreign currency, S_t is the spot rate between the domestic currency and the foreign currency, and $F_{t,t+n}$ is the n-period forward exchange rate of domestic currency relative to foreign for time $t + n$ negotiated at time t. If we transform in logarithms and rearrange, we obtain the following identity:

$$\begin{aligned} \lambda_{t,t+n} =& y_{t,t+n} - (y^*_{t,t+n} - \rho_{t,t+n}) \\ \rho_{t,t+n} =& \frac{log(F_{t,t+n}) - log(S_t)}{n} \end{aligned} \tag{2}$$

where $\rho_{t,t+n}$ is the annualized forward premium and $\lambda_{t,t+n}$ is the CIP deviation, also called the n-period Cross-currency basis or Libor Cross-currency Basis, because we use each countries' Libor rates as the risk-less interest rates. If the CIP holds such that there are no opportunities for arbitrage, the basis value should be zero. So the equation measures the difference between the domestic rate and the synthetic domestic rate. Hence, if the Basis is negative, it implies that the synthetic rate is higher than the domestic rate, or the inverse if it is positive. Any deviation from the zero value means an opportunity for arbitrage to any

[1] In the appendix A.2 of Kalemli-Ozcan and Varela (2021), they show the difference between the number of forecasters assigned between developed and emerging markets, where the average number is 55 and 17, respectively. The maximum and minimum average number of forecasters by country are 107 and 4 for Germany and Ukraine.

market participant.

We can extend the CIP model from risk-free rates in the market to government bonds. Following the notation in Du and Schreger (2022), we can refer to the Government cross-currency basis as

$$\lambda_{t,t+n}^{Gov} = (y_{t,t+n}^{Gov*} - \rho_{t,t+n}) - y_{t,t+n}^{gov} \tag{3}$$

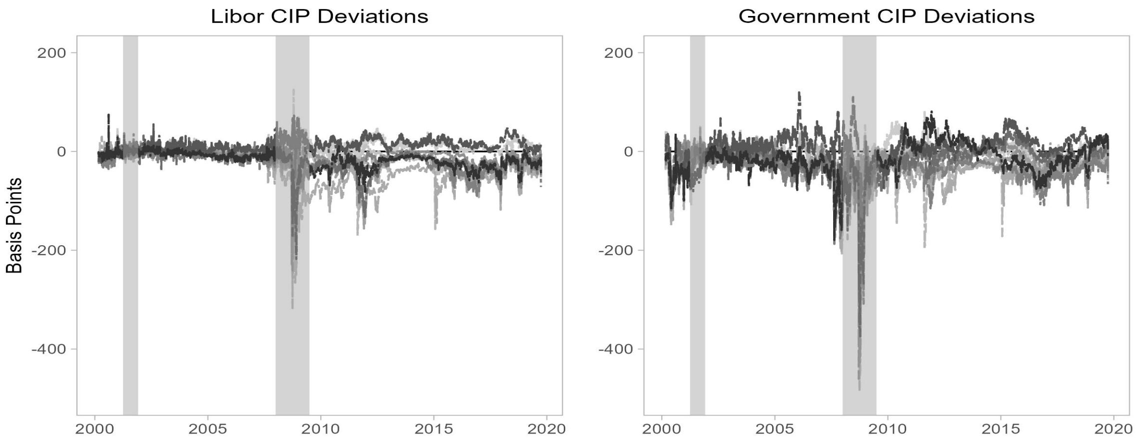
where $\lambda_{t,t+n}^{Gov}$ is the n-period Government Cross-currency basis, $y_{t,t+n}^{Gov*}$ is the n-period government interest rate in the foreign currency, and $y_{t,t+n}^{Gov}$. We can notice that the Equations 2 and 3 are different, in the sense that the Government Cross-currency basis is the negative specification of the Libor Cross-currency Basis. As the authors mention, the definition binds the Cross-currency basis with the concept of the Convenience Yield defined explicitly by Feldhütter and Lando (2008) and Krishnamurthy and Vissing-Jorgensen (2012) and further developed in Du and Schreger (2016), Du et al. (2018a), and Jiang et al. (2021). Convenience Yield refers to the benefits of the liquidity and safety that the government treasury bonds of the domestic economies confer related to the foreign. The high valuation of these assets maintains the yield lower than other safe-asset with the same maturity, creating a spread that gives the issuer/holder a premium.

In Figure 1, I present the calculated Libor and Government Cross-Currency Basis using Equations 2 and 3[2]. As we can see, the basis points, although expected to be closely related, are different, being the Government CIP deviations the highest. One clear pattern we can see is the behavior of both Basis before and after the Financial Crisis of 2007; this change will be reflected in the behavior of the forward premium. As the size of the currency basis increases afterward, especially after the crisis, we can suppose that the higher uncertainty level affects the level of deviations, as higher uncertainty raises the demand for safe foreign assets, especially the USD debt.

Literature Review. Before the Financial Crisis of 2007, lasting arbitrage opportunities following the CIP deviations were deemed costly, and short-lived Akram et al. (2008); Burnside et al. (2007, 2011b). Nevertheless, later evidence showed that this condition became persistent, as early empirical evidence from Jurek (2014) showed that by taking into account Uncovered Interest Rate Parity (UIP) strategies, currencies could deliver annual positive Sharpe ratios. Ivashina et al. (2015) argue that in the European crisis of 2011, the lack of market liquidity did not allow to sustain the Parity concerning the dollar market.

[2]The calculation of the Basis required me to annualize the forward premium of the currencies and interest rates. I follow the measures of Du and Schreger (2022) presented in Appendix A of the paper to replicate their results. I match the days of the maturity of the forward with the interest rates to guarantee that there are no specification or bias problems, as mentioned by Bekaert and Hodrick (1993)

Figure 1: Libor and Government CIP Deviations for the G10 Currencies



Note: The graph plot the Libor and Government Cross-currency basis for the G10 currencies. I graph the inverse of $\lambda_{t,t+n}^{Gov}$ for comparison to $\lambda_{t,t+n}$, but in the rest of the paper, I will use it in terms of convenient yield. The shaded region corresponds to *Sources:* Bloomberg and author's calculations.

Recent empirical evidence in measures of the Libor and Government Bonds in Du and Schreger (2016), Du et al. (2018a), Du et al. (2018b), and Jiang et al. (2021) demonstrated the existence of persistence of such deviations in the Covered Interest Rate Parity. Du and Schreger (2022) resume the causes for the presence of such opportunities to Supply and Demand Reasons. For the first case, leveraged constraints in the intermediary markets due to financial regulations which limited the supply of hedging instruments (Cenedese et al., 2021; Fang and Liu, 2021; Du et al., 2022) and for the second, the demand of the safe assets from the US bond and treasury markets has increased the spread between foreign and domestic markets interest rates, as mentioned in Krishnamurthy and Vissing-Jorgensen (2012), Gourinchas and Rey (2014), and Gourinchas and Rey (2022). Recent papers like Avdjiev et al. (2019) and Cerutti et al. (2021) have tried to explain the factors that generate such deviations. They focus on the role of the dollar fluctuations and other macroeconomic variables, such as the interest rates, the VIX to measure overall volatility and risk aversion, and the intermediary leverage. This paper tries to complement this result by proposing an uncertainty measure that provides additional information on the sources of both Libor and Government basis deviations, which I show is complementary to the other variables in the previous literature.

I follow the hypothesis of Berg and Mark (2018b), Husted et al. (2018), Ismailov and Rossi (2018), Kalemli-Ozcan and Varela (2021), and Della Corte and Krecetovs (2022) of the effect of uncertainty in the UIP and extend it to the CIP and include my measure of exchange rate uncertainty rather than the macroeconomic ones they used. The argument for having it as an explanatory variable for the deviation comes from its effect on generation fluctuations in the expectations. Uncertainty generates that individuals cannot efficiently price the future exchange rate and adequately reflect its expected value. Although measuring delay seems straightforward by just following the definition, there is an increasing amount of different methodologies in the literature trying to determine the predictable variability of the series. The whole model structure depends on forecast, so it requires considering the recent developments in econometric modeling. Optimal models will guarantee that we can filter the most amount of possible information that can be used by economic agents and isolate unforecastable movements.

The base of my model is the one presented in Jurado et al. (2015), and Ludvigson et al. (2021), which use the Factor Augmented Vector Autoregressive (FAVAR) model of Bernanke et al. (2005) to estimate the forecast by incorporating multiple macroeconomic and financial variables for the US economy. Scotti (2016) takes the difference between the realized value of macroeconomic variables and their forecasts and then aggregates them using a Dynamic Factor Model (DFM). Carriero et al. (2018) propose using a Large Vector Autoregressive Model with stochastic volatility to incorporate the errors and the volatility straight in the model.

Other widely used measures of uncertainty follow methodologies different from those based on forecasting predictions. One of them is the one proposed by Bloom et al. (2007) and Bloom (2009), which take Firm data to construct the uncertainty index. Gilchrist et al. (2014) and Chuliá et al. (2017) use stock market returns of a high number of non-financial firms that trade in the US market to construct a financial uncertainty index based on factor models. Baker et al. (2016) complete the Economic Policy Uncertainty Index based on the news coverage frequency by taking the number of times policy-related words appear in newspapers. Finally, the measure of Rossi and Sekhposyan (2016) construct an uncertainty index based on the historical forecast error distribution built by using professional surveys, and then analyzing if it is the upside and downside uncertainty[3].

The exchange rate uncertainty has, in comparison, a lower amount of literature behind it. In contrast to the previously mentioned work of Ismailov and Rossi (2018), which uses the Survey of Forecasters density forecast, Menkhoff et al. (2012a) uses a proxy for global FX using weighted absolute returns of different exchange rates, and the Kalemli-Ozcan and Varela (2021) which construct an Economic Policy Uncertainty (EPU) type of measure based on newspaper keywords as Baker et al. (2016). Most of the rest of the models that focus on measuring uncertainty use different variations of a Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model, such as the case of the VAR-GARCH model of Caporale

[3]Bloom (2014), Ferrara et al. (2018), and Castelnuovo (2019) present further literature on the topics

et al. (2015).

1 Econometric Model

I estimate the uncertainty measures for Exchange Rates based on the model of Jurado et al. (2015) and Ludvigson et al. (2021) and combine it with the model of Ando and Bai (2017). The procedure has two benefits; the first is the possibility to endogenously determine clusters of exchange rates that share the same approximate behavior and uncover potential hidden structures of the market. The second is to estimate the model with targeted factors, which offer an improved forecasting performance than standard factor models (Bai and Ng, 2008). Furthermore, I filter the model with other variables commonly used in the literature to forecast exchange rates. Finally, I estimated the conditional volatility of the factors by calculating the model's unforecastable errors following a stochastic volatility model.

1.1 Clustering the Exchange Rates

I follow the methodology of Ando and Bai (2017) to determine the clusters of exchange rates endogenously, which is based on Ando and Li (2014) and Ando and Bai (2015, 2016). In this case, the membership of each group and the number of variables are unknown. The previous ones either assume that the clusters are known, or the explanatory variables are assumed to be fixed. They estimate the following model,

$$y_{i,t} = X'_{i,t}\beta_i + F'_{g_i,t}\lambda_{g_i,t} + F'_{a,t}\lambda_{a,t} + \varepsilon_{i,t} \tag{4}$$

where X_t are the observable factors that affect the exchange rates, $F_{a,t}$ are the unobservable factors that have an aggregate effect, $F_{g_i,t}$ are the factors that are characteristic to group g_i, $t = 1, 2, ..., T$ is the time index, $i = 1, 2, ..., N$ is the index of the variable of interest, and N is the total number of data points. The groups g_i are such that there is a set of underlying groups $G = \{g_1, g_2, ..., g_S\}$, where S is the number of exchange rate groups such that the number of variables in the group $N_S \in N$. The factor loading's $\lambda_{g_i,t}$ are the coefficients (sensitivity) of the variable to the group' g_i factor, and $\lambda_{a,t}$ are the loadings that that effect, in general, the exchange rates. $\varepsilon_{i,t}$ is an i.i.d. error that is assumed to be uncorrelated with the regressors[4].

[4]In section 2.3 of Ando and Bai (2017), they give further assumptions made in the model.

1.2 Estimation of the Model

The model described by Equation (4) requires estimating the factors in each of the groups r_j, the general factors r, and the number of the groups g_i. The estimator of (4) is given by the minimizer,

$$L\big(\beta_1, \beta_2, ..., \beta_N, G, F_a, F_{g_1}, F_{g_2}, ...F_{g_S}, \lambda_a, \lambda_{g_1}, \lambda_{g_2}, ...\lambda_{g_S}\big) = \\ \sum_{i=1}^{N} \|y_{i,t} - X'_{i,t}\beta_i - F'_{g_i,t}\lambda_{g_i,t} - F'_{a,t}\lambda_{a,t}\|^2 + T\sum_{i=1}^{N} \varrho_i\big(\beta_i\big) \tag{5}$$

Where the first part of the right-hand side corresponds to the squared error of the model (ε^2) and the second part to the penalty function $\varrho_i\big(\beta_i\big)$. The penalty function corresponds to the Smoothly Clipped Absolute Deviation (SCAD) of Fan and Li (2001). The penalty function is such that,

$$\varrho_i\big(\beta_i\big) = \begin{cases} \kappa_i|\beta_{i,j}| & |\beta_{i,j}| \leq \kappa_i \\ \frac{\gamma\kappa_i|\beta_{i,j}| - 0.5(\beta_{i,j}^2 + \kappa_i^2)}{\gamma - 1} & \kappa_i \leq |\beta_{i,j}| \leq \gamma\kappa_i \\ \frac{\kappa_i^2\big(\gamma^2 - 1\big)}{2\big(\gamma - 1\big)} & \gamma\kappa_i < |\beta_{i,j}| \end{cases} \tag{6}$$

where $\kappa_i > 0$ and $\gamma > 2$, where Ando and Bai (2017) uses $\gamma = 3.7$ that minimizes the BIC as used by Fan and Li (2001). The model does not assume a particular value for the regularization parameter κ_i, but it is determined endogenously by the model. The model follows an algorithm that follows an iterative scheme to determine the value of each one of the parameters to estimate.

The algorithm requires that first, the values of $\kappa_1^0, \kappa_2^0, ...\kappa_N^0, r^0, r_1^0, r_2^0, ..., r_S^0$, and S be fixed. The model's β_i^0's are first estimated by regressing the variables against the endogenous, assuming that the factor loadings have zero value. In this case, the K-means Algorithm of Forgy (1965) determines the initial group membership. It determines multiple clusters and the membership of each variable bounded by a predetermined maximum of groups. The given values of both β_i^0 and the clusters G^0 are then used to estimate the values of the common factors F_a^0 and later, the group factors $F_{g_i}^0$.

Given the previously estimated coefficients, then the optimal value of g_i is updated following,

$$\tilde{g}_i = argmin_j \, \|y_{i,t} - X'_{i,t}\beta_i - F'_{g_i,t}\lambda_{g_i,t} - F'_{a,t}\lambda_{a,t}\|^2 \tag{7}$$

where $\tilde{g}_i$ is the minimizer of the squared error of the model. This optimal membership of the groups and the estimated factors are used to re-estimate the $\tilde{\beta}_i$. Furthermore, this can be used to obtain the common and grouped factors' new factors and their respective loadings. Hence, the procedure is repeated continuously until convergence is achieved[5].

Finally, the optimal model is selected following a modification of the Hallin and Liška (2007) criteria defined as,

$$\begin{aligned} PIC^c = & \frac{1}{NT}\sum_{j=1}^{S}\sum_{g_i=j} \|y_{i,t} - X'_{i,t}\tilde{\beta}_i - \tilde{F}'_{g_i,t}\tilde{\lambda}_{g_i,t} - \tilde{F}'_{a,t}\tilde{\lambda}_{a,t}\|^2 \\ & + C\frac{1}{N}\sum_{i=1}^{N}\tilde{\sigma}^2 log\big(T\big)\tilde{p}_i + Ck\tilde{\sigma}^2\left(\frac{T+N}{TN}\right)log\big(TN\big)\tilde{p}_i \\ & + \sum_{j=1}^{G} Ck_j\tilde{\sigma}^2\left(\frac{T+N_j}{TN_j}\right)log\big(TN_j\big) \end{aligned} \tag{8}$$

where $\tilde{p}_i$ are the non-zero elements of $\tilde{\beta}_i$, $\tilde{\sigma}^2$ is the estimated variance of the errors of equation (4), and C is some constant. The parameter $\tilde{p}_i$ reflects the number of variables selected by the model, and so, the effect of parameters κ and κ_i. Minimizing the PIC criteria will give the optimal quantity of groups $(G\big(S\big))$, common factors(k), group-specific factors(k_i), and the parameters $\kappa, \kappa_1, \kappa_2, ..., \kappa_N$.

The Equation (8) is the one that, combined with the algorithm defined previously, determines the unknown parameters in the model. The penalization of the model depends on the value of C; depending on its values, the common and group factors will reduce considerably. The approximation to the optimal value will be related to the characteristic function of the empirical variance given by the following,

$$\begin{aligned} V_C^2 = & \frac{1}{A}\sum_{a=1}^{A}\left(r^C\Big(N^a, T^a\big) - A^{-1}\sum_{b=1}^{A} r^C\Big(N^b, T^b\big)\right)^2 \\ & + \sum_{j=1}^{S_{max}}\left[\frac{1}{A}\sum_{a=1}^{A}\left(r^C\Big(N^a, T^a\big) - A^{-1}\sum_{b=1}^{A} r^C\Big(N^b, T^b\big)\right)^2\right] \end{aligned} \tag{9}$$

The equation (9) measures the variability of the common and the group-specific factors. From here, we can derive the final algorithm to determine the model's optimal coefficients, as detailed by Ando and Bai. The optimal 8-step model algorithm is then given by

1. Choose the initial optimal values of the number of common and specific-group factors

[5]As noted by Ando and Bai (2017), this procedure can be seen as equivalent to the one used by Bai and Ng (2002) to estimate the factor structure.

$(r, r_1, r_2, ..., r_S)$, the regularization parameter $(\kappa_1, \kappa_2, ..., \kappa_N)$, and the number of groups S (estimated through the K-means).

2. Fix the number of groups S and, based on them, determine the number of common and group-specific factors.

3. Given the current values of the parameters S, k, and $k_1, k_2, ..., k_S$, optimize the regularization parameters κ_i using the criteria defined in equation (8).

4. Using the previously estimated parameters, re-optimize the value of the common factors k using equation (8).

5. with the previous parameters and the estimated k in step 4, estimate the group-specific factors k_g using equation (8).

6. Repeat the previous steps until the model achieves convergence.

7. Change the value of the number of groups and repeat the previous steps until achieving convergence

8. compare the results of each group and select based on the minimizer of the Information Criteria, PIC.

Based on the estimated initial values and the algorithm of Ando and Bai (2017) detailed previously, we can obtain the optimal number of factors for common and group-specific factors. The importance of β_i expresses the significant exogenous variables.

Once estimated, from the model, we can obtain the information that data cannot explain and get the unforecastable fluctuations of the exchange rates[6]. We can obtain this by

$$\varepsilon_{i,t} = y_{i,t} - X'_{i,t}\beta_i - F'_{g_i,t}\lambda_{g_i,t} - F'_{a,t}\lambda_{a,t} \tag{10}$$

Following Jurado et al. (2015) and Ludvigson et al. (2021), I estimate the conditional volatility using the stochastic volatility of Kastner and Fruhwirth-Schnatter (2014) for each exchange rate.

1.3 Stochastic Volatility Model

The stochastic volatility model described by Kastner and Fruhwirth-Schnatter (2014) estimates the conditional volatility based on filtered series in equation (10) by assuming the form for each i as

[6]Bai and Ng (2006) and Jurado et al. (2015) mention that for samples of data big enough, we can treat the estimated Factors as the forecasts of the variables in the next period

$$
\begin{aligned}
\varepsilon_t =& e^{\frac{h_t}{2}} \epsilon_t \\
h_t =& \mu + \phi\big(h_{t-1} - \mu\big) + \sigma \upsilon_t
\end{aligned} \tag{11}
$$

and also,

$$
\begin{aligned}
\varepsilon_t \sim& N\big(0, \omega e^{\sigma h_t}\big) \\
h_t =& \phi h_{t-1} + \sigma \upsilon_t
\end{aligned} \tag{12}
$$

where ϵ_t and υ_t correspond to i.i.d. errors that distribute standard normal, h_t is the unobserved latent time-varying volatility process such that it follows a stationary distribution $h_0|\mu, \phi, \sigma \sim N\big(\mu, \frac{\sigma}{1-\phi^2}\big)$. The model described by equation (11) defines a "Centered Model" and the one in equation (12) as "Non-Centered." As suggested by Kastner and Fruhwirth-Schnatter (2014), the estimation of the model defined by the two equations involves interweaving between the two in the algorithm called the Ancillary-Sufficiency Interweaving Strategy (ASIS). As the likelihood of both equations is not observable, it is approximated to the data using the Markov Chain Monte Carlo (MCMC) method. The uncertainty of the exchange rate is defined as the conditional volatilities u of i; $\hat{U}_{i,t}(h_t)$.

1.4 Uncertainty Measure

The uncertainty measure can be determined by either aggregating the total uncertainties of the exchange rates or using the particular exchange rate uncertainties estimated in the previous model. I calculate the wide measure of uncertainty as,

$$
\hat{U}_t = \sum_{i=1}^{N} W_i \hat{U}_{i,t}\big(h_t\big) \tag{13}
$$

where W_i is the weight of the exchange rate in the economy. In Jurado et al. (2015) and Chuliá et al. (2017), they use equal weights ($W_i = \frac{1}{N_i}$) in each one of the variables, so they determine the factors as a simple average of the whole uncertainties. A possible weight that can be applied is the percentage of the market turnover of the exchange rate, so uncertainties of the fewer trade currencies have less weight than the most traded and relevant ones. Nevertheless, that will downplay the effect of currency shocks coming from them, which will be the case of the Asian crisis.

2 Data

I use daily data of 31 exchange rates from July 1993 to December 2019, a total of 6906 days. I focus on the most traded exchange rates on the market that have both fluctuations in the exchange rates and available data. Table **??** presents the exchange rates used with their respective country, turnover[7], the "Coarse" Classification of Exchange Rate Arrangements (ERA) of Ilzetzki et al. (2019), and the Monetary Policy Framework classification of the International Monetary Fund (2020). These exchange rates corresponded to the last price of the domestic currency against the US dollar (USD). They were downloaded from the Bloomberg database[8].

Furthermore, I use thirteen variables as additional predictors and fundamentals of the model selected based on the literature on exchange rate prediction. The data used in the models is the one presented in Cheung et al. (2005), Chen et al. (2010), Rossi (2013), Kavtaradze and Mokhtari (2018), Cheung et al. (2019), and Lilley et al. (2022). The chosen predictors of the exchange rates are the Morgan Stanley Capital International (MSCI) World Index that captures 1517 large and mid-sized stocks prices of firms in 23 developed countries, the 3-Month Treasury Constant Maturity Rate (T-Bill), the 10-Year Treasury Constant Maturity bond, the three month ahead monthly fed funds futures (FF4), the three-month ahead monthly WTI Futures (CL3), the Bloomberg Commodity index, the $S\&P500$ Index, the DXY Dollar Spot Index, the West Texas Intermediate (WTI) price of Oil, the Chicago Board Options Exchange (CBOE)'s volatility index (VIX), and the Shadow Short Rates (SSR) of USA, Japan, UK, and Euro-area calculated by Krippner (2013a, 2015). The previous variables come mostly from Bloomberg, but the SSR series are from LJK Limited webpage. The period is chosen based on the availability of the data and to further include episodes of high exchange rate uncertainty and volatility, as in the last half of the 1990s, the next period of the GFC and euro debt crisis.

For the Covered Interest Rate Parity model, I follow the data used in Du and Schreger (2016), Du et al. (2018a), Du et al. (2018b), and Du and Schreger (2022) daily data for the exchange rate spot price against the USD, the three-month Forward exchange rates, and the 3-month Libor inter-bank benchmark and Government rates for the countries from Bloomberg. I follow their data to replicate their cross-currency basis and compare the results to theirs. Additionally, I will center the CIP analysis on the G10 currencies; The Australian Dollar (AUD), Canadian Dollar (CAD), Swiss Franc (CHF), Danish Krone (DKK), Euro

[7] The BIS calculates the turnover in the Triennial Central Bank Survey of Foreign Exchange and Over-the-counter (OTC) Derivatives Markets in 2019. It takes data from the Central Banks' surveys of banks and dealers on their FX transactions.

[8] Appendix A.1 present some descriptive statistics of the series.

Table 1: Exchange Rates by Country and Turnover

Currency	Country	Mnemonic	BIS Turnover	ERA	MPF
Euro	European Union	EUR	2	1	Other
Japanese Yen	Japan	JPY	3	4	IT
Pound Sterling	Great Britain	GBP	4	4	IT
Australian dollar	Australia	AUD	5	4	IT
Canadian dollar	Canada	CAD	6	4	IT
Swiss franc	Switzerland	CHF	7	3	Other
Chinese Yuan (Renminbi)	China	CNY	8	2	Comp.
Hong Kong dollar	China	HKD	9	1	CB-USD
New Zealand dollar	New Zealand	NZD	10	3	IT
Swedish krona	Sweden	SEK	11	3	IT
Korean won	Korea	KRW	12	3	IT
Singapore dollar	Singapore	SGD	13	3	Cr-Comp.
Norwegian krone	Norway	NOK	14	3	IT
Mexican peso	Mexico	MXN	15	3	IT
Indian rupee	India	INR	16	2	IT
Russian ruble	Russia	RUB	17	3	IT
South African rand	South Africa	ZAR	18	4	IT
Turkish lira	Turkey	TRY	19	3	IT
Brazilian real	Brazil	BRL	20	3	IT
Taiwanese Dollar	Taiwan	TWD	21		
Danish krone	Denmark	DKK	22	1	Peg-Euro
Polish zloty	Poland	PLN	23	3	IT
Indonesian rupiah	Indonesia	IDR	25	3	IT
Hungarian forint	Hungary	HUF	26	2	IT
Czech kruna	Czech Republic	CZK	27	3	IT
Israeli new shekel	Israel	ILS	28	3	IT
Chilean peso	Chile	CLP	29	3	IT
Colombian peso	Colombia	COP	32	3	IT
Malaysian ringgit	Malaysia	MYR	34	3	Other
Argentine peso	Argentina	ARS	-	5	Mon. Aggr.
Peruvian sol	Peru	PEN	-	2	IT

Notes: There are 31 exchange rates in the model from different countries. The table presents the currency, the country, their Mnemonic, BIS's Turnover from the Triennial Central Bank Survey of Foreign Exchange and Over-the-counter (OTC) Derivatives Markets in 2019, the Exchange Rate Arrangements (ERA) of Ilzetzki et al. (2019), and the Monetary Policy Framework of the International Monetary Funds' Exchange Rate Arrangement from the Annual Report on Exchange Arrangements and Exchange Restrictions. The last presents two types of classification, Fine and Coarse, which ranges from 1-13 and 1-6. They go from low flexibility being a currency union to high flexibility being a Free floater. The coarse is classified as: 1-Peg or Currency Board, 2-Crawling Peg, 3- Crawling Band and Managed Floating, 4-Free Floating, 5- Free-Falling, 6- Dual Market with parallel data missing. Free Falling refers to an economy with free-floating ER and high Inflation. *Sources:* Bloomberg, Bank of International Settlements, IMF, and Ilzetzki et al. (2019).

(EUR), British Pound (GBP), Japanese Yen (JPY), Norwegian Krone (NOK), New Zealand Dollar (NZD), and Swedish Krone (SEK). I ware "emerging markets" to avoid cases of possible Peso problems, as described in Burnside et al. (2011a) and Engel (2014), that may distort the results.

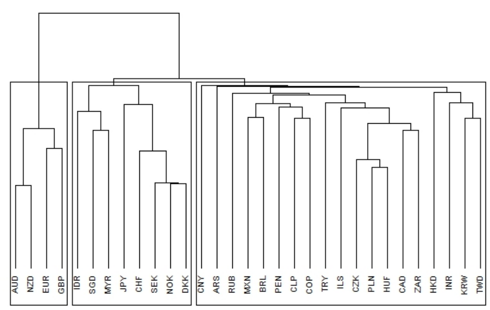
3 Empirical analysis

In this section, I will present the empirical results of the paper; First, I will give the results of the estimation of the general and specific uncertainty indices and the endogenous clusters determined by the model. Second, I will use uncertainty as a key variable to explain the variations in the Libor and Government cross-currency basis of different Developed currencies.

3.1 Measuring FX Uncertainty

As a first step to the empirical implementation of the model, I adjust the series and transform them to be approximately stationary. Then, I test them for the presence of a non-stationary process using the Augmented Dickey-Fuller test and convert them to logarithms and logarithmic returns depending on the case. I present the test results of the ADF test in Appendix A.2.

Figure 2: Dendrogram of Exchange Rate Groups with Honrarchical Clustering



Note: The figure plots the Dendrogram and estimated clusters using Hierarchical Clustering. The number of optimal groups was determined using the Gap statistic. *Sources:* Author' calculations.

One of the starting points in the model is establishing the initial clusters of the exchange rate. To this end, I estimate them using Hierarchical Clustering, an unsupervised learning methodology, as a reference and impose the existence of eight groups, each with at least four currencies. I follow Tibshirani et al. (2001) and use the Gap Statistic to determine the optimal number of groups that described the currencies, which was defined as three groups for the whole distribution[9]. Figure 2 we can see that the grouping of the Dendrogram, especially in the lower divisions, reflects a geographical relationship between currencies, where there is a cluster of Latin American, Nordic, Euro, and Asian countries. The relationship between the Australian Dollar and the New Zealand dollar is not only one of geography, but they

[9]The Gap Statistic is a goodness of fit statistic that measures the dispersion within the groups to assess the clustering fit of the model. I contrast the estimated Gap statistics of the specifications from one to eight groups. I calculated the statistic using the Euclidean Difference around the cluster means and determined the expected error through a thousand replications using bootstrapping. Further information on the Hierarchical Clustering Method can be found in Tibshirani et al. (2001) and James et al. (2013).

also reflect that are "high-interest rate" economies as described in Lustig et al. (2011), due to exposure to productivity shocks for being commodity producers as in Chen and Rogoff (2003), Ready et al. (2017a), and Ready et al. (2017b). This methodology captures the general trends of the series and is probably a consistent first approximation to understanding the relationship between them. From Chuliá et al. (2018), one aspect that we can expect but was not present is a liquidity effect on the series. They found that exchange rates tend to co-move based on their level of turnover, while my results reflect that the clusters are also based on geographical vicinity and development level. The same applies to commodity currencies; although it shows that the Australian Dollar and New Zealand Dollar are together, they are not clustered with others such as the Ruble (RUB), the Canadian Dollar (CAD), and the South African Rand (ZAR).

I estimate the model of Ando and Bai (2017) by imposing a higher number of common factors and group-specific factors of 8 for each and again restricting the number of currencies in the groups to at least four. The group structure introduced as the prior is the one that corresponds to the hierarchical group structures presented previously. The model algorithm determined that the optimal number of groups is two for the whole sample, one common factor, and a group-specific factor for each. The number is not a surprise, as a small number can capture a high level of information (Sargent and Sims, 1977; Bernanke et al., 2005; Stock and Watson, 2016). It is coherent to have that for a variable, group-specific (targeted) factors can capture a higher level of information than a general common factor that measures a more global trend.

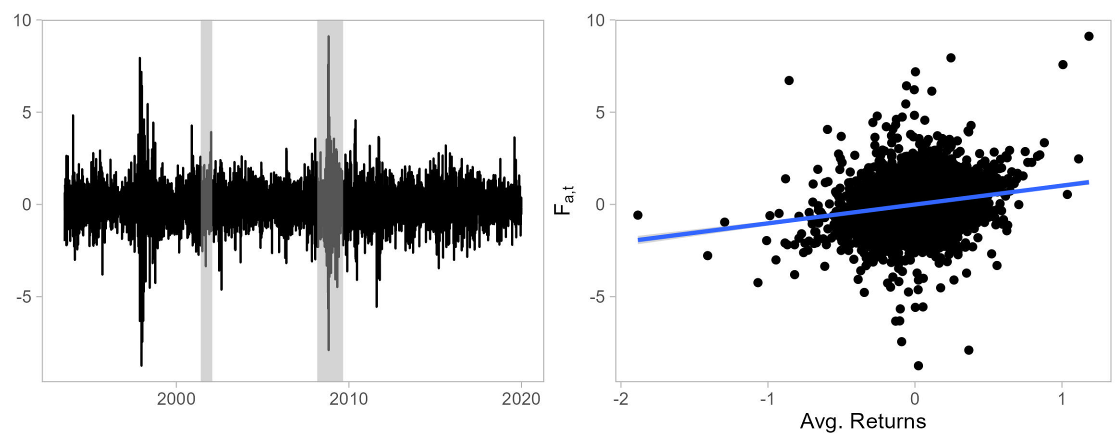
Table 2: Estimated groups following Ando and Bai (2017) endogenous clustering methodology

Group 1 (7)				Group 2 (24)			
EUR	NZD	NOK	DKK	JPY	GBP	CAD	AUD
SGD	MYR	IDR		CHF	SEK	ZAR	TRY
				PLN	CZK	HKD	KRW
				TWD	INR	MXN	BRL
				CLP	COP	ARS	PEN
				RUB	HUF	CNY	ILS

Notes: The table presents the estimated groups for each of the 31 exchange rates used in the model of Ando and Bai (2017) and assuming there are no breaks in the series. *Sources:* Author's calculations.

In Table 2, I present the result of the estimation of Ando and Bai (2017) model with the prior groups estimated in Figure 2. We can see that the model had different groups than the Hierarchical Clustering Model. One characteristic is that group one preserved the EUR and NZD and gained the IDR, SGD, MYR, NOK, and DKK. The changes in group two of the original clustering method remain the relationship of the Dendrogram of the southwest Asian countries and one of the two Nordic countries. Figure 3 plots the aggregate common factor estimated in the model, $F_{a,t}$, and the correlation with respect to the average returns of the G10 currencies. From the factor, we can see that it does not capture the crisis in the early 2000s, but it captures the volatility from the late 90s product of the Asian and Russian crises. If we compare the factor with respect to the average returns of the G10 countries, the correlation between the two is just 0.2, more significant than 0.02 if we include the whole sample. Reducing the model increases the correlation, meaning that the aggregate shocks come primarily from the developed economies and transfer to the rest of the world and support the hypothesis of the great financial cycle of Rey (2015).

Figure 3: First Common Factor and the USD Returns

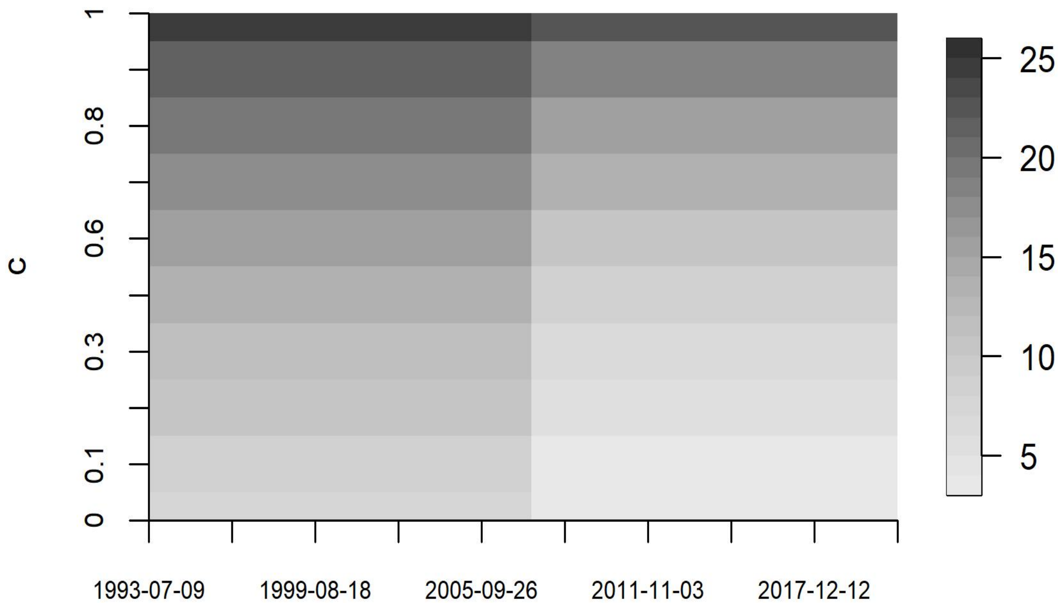


Note: The figure presents the relationship between the estimated common factor of the currencies' returns of the G10. The left panel plots the common factor's daily behavior and presents the behavior of the Calculated Common Component $F'_{a,t}$. Shaded areas correspond to the recession periods dated by the NBER. The right panel presents a Scatter plot of the factor and Average Returns of the G10 currencies, showing the correlation between the two variables. *Sources:* Bloomberg and author's calculations.

Although it is plausible that the factor structure remained consistent in time, evidence in the behavior of Libor and Government Cross-currency Basis in Du et al. (2018b) as well as the results in Bussière et al. (2022), Cheung and Wang (2022), Engel et al. (2022), and Lilley et al. (2022), suggest the existence of a structural change in the behavior of exchange rates after the Financial Crisis of 2007. That is why I applied the methodology of Barigozzi et al. (2018) that determines the existence of breaks in the general factor structure of the series, in this case, the $F'_{a,t}$ in equation 4. If the Aggregate factor changes, we can expect that the group structure will also change. For the analyzed period, there is a break in July of 2007, in the Financial Crisis, as assumed by most of the literature. The model gives us a break and the number of principal components needed to capture the information available. Hence, in

Figure 4, we can see that after the change, the amount of factors is reduced, showing that the fluctuations of the exchange rates became more homogeneous in 2007-2019.

Figure 4: Regime Change in the General Factors Structure



Note: The Model plots the estimated factor structural change in the whole 1993-2007 sample using the methodology of Barigozzi et al. (2018). I use a rolling window of years to calculate the dynamic measure in the model. The model found a break in July 2007, at the beginning of the GFC. The y-axis plots the percentage of information contained in the factors. The figure shows the number of factors needed to capture the information, where darker color means more factors. Less-heterogeneous exchange rates characterize the post-GFC, and a few factors can capture its fluctuations. *Sources:* Author' calculations.

The break found and the evidence of different structures in the factors between 1993-2007 and 2007-2019 tells us that the specification of just one model for the whole sample may not be adequate. Hence, I divide the piece into those two periods and re-estimated the model for each. In Table 3, I present the estimated groups for each period, which yield a different and higher number of groups with respect to the no-break model. Consistent with the results of 4, I find that the number of groups needed to represent the time-series relationship between the exchange rates is reduced in the last period. Figure 5 presents the transition between groups, where we can see that, in general, there are four for the first part and three groups for the second, but we notice that there are still relationships between variables that remain close in the groups. In group one remain, three out of the four variables, seven in group two, and five in group four, while five of the currencies (LATAM countries, except Argentina) in group three went to group two.

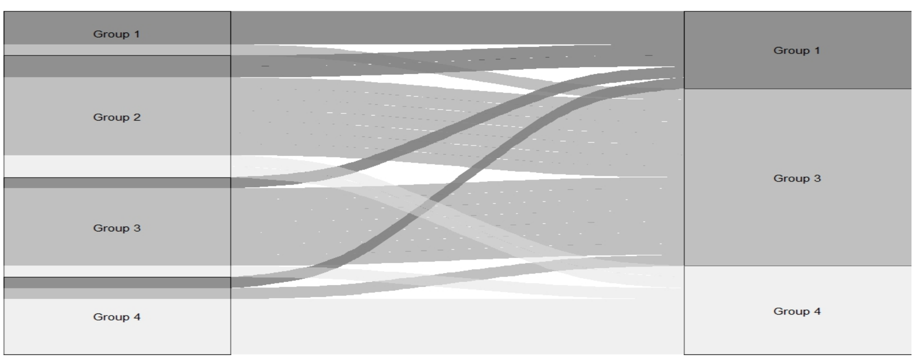
From the previous results, we can construct the errors of the model by following Equation

Table 3: Estimated groups with Breaks

Sample 1993-2007							
Grupo 1 (4)				Grupo 2 (11)			
EUR	GBP	**NZD**	**NOK**	JPY	**AUD**	**SEK**	DKK
				ZAR	**PLN**	**CZK**	HKD
				INR	**RUB**	**HUF**	
Grupo 3 (9)				Grupo 4 (7)			
TRY	MXN	BRL	CLP	**CAD**	CHF	SGD	**KRW**
COP	ARS	PEN	CNY	**TWD**	**MYR**	**IDR**	
ILS							
Sample 2007-2019							
Grupo 1 (7)				Grupo 2 (16)			
EUR	**NZD**	**NOK**	JPY	GBP	**AUD**	**SEK**	**ZAR**
CHF	DKK	ARS		TRY	**PLN**	**CZK**	SGD
				MXN	BRL	CLP	COP
				PEN	**RUB**	**HUF**	
Grupo 3 (8)							
CAD	HKD	**KRW**	**TWD**				
MYR	INR	**IDR**	CNY				

Notes: The table presents the estimated groups for each of the 31 exchange rates used in the model of Ando and Bai (2017) for the two periods. Bold names, are exchange rates that remain from the original group. In particular, groups one and two reflect that the exchange regime matters in transmitting shocks. Groups three and five represent the effect of the Eurozone. As the effect of the Euro-zone monetary policy is filtered through the Euro shadow rate, the groups are separated into the peripheral countries of the euro and the capital flow-dependent countries. Controlling for the West Texas Intermediate (WTI) eliminates the existence of a group with commodity currencies. *Sources:* Author's calculations.

Figure 5: Group Transition between 1993 to 2019



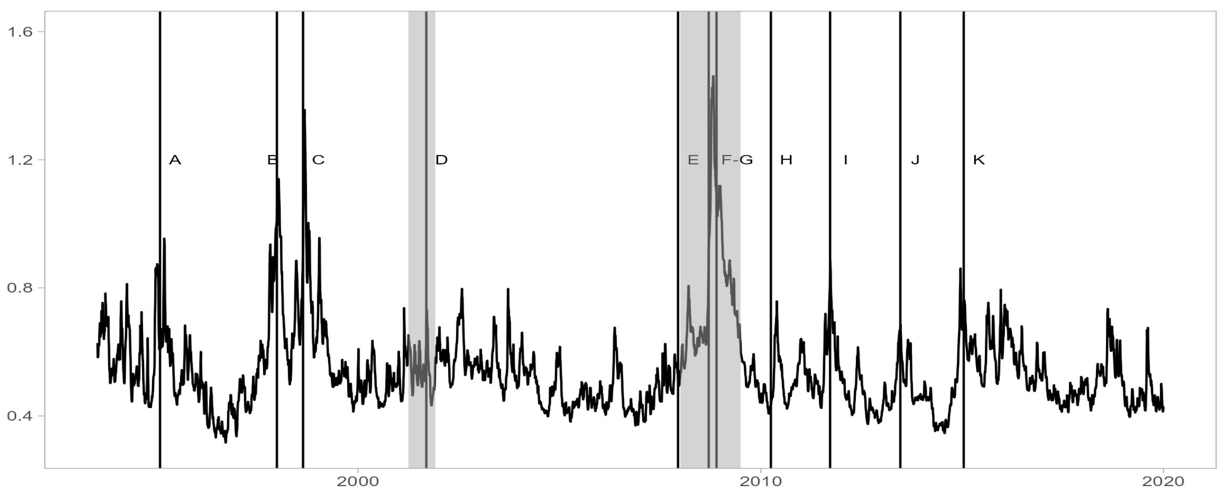
Note: The graph plots the change of the group membership between the sample 1993-2007 (left) and 2007-2019 (right) for each of the groups. *Sources:* Author' calculations.

10 and estimate the conditional volatility (uncertainties) of each one of the Exchange Rates using Equations 11 and 12. I calculate the value of the exchange rate uncertainties in Equation 13 by giving equal weight to each, which is such that $W_i = \frac{1}{N_i}$ as in Jurado et al. (2015) and Ludvigson et al. (2021) [10]. Figure 6 presents the result of the estimation of the

[10] I tried other specifications, such as using weights by turnover or trade, but it had a higher concentration only on the Euro, Yen, and Pound. This will reflect their market power and influence, but will underestimate the shocks coming from other developed and emerging countries.

general level of Uncertainty and the occurrence of events that coincide with the peaks of the distribution.

Figure 6: Exchange Rate Uncertainty Index with Breaks

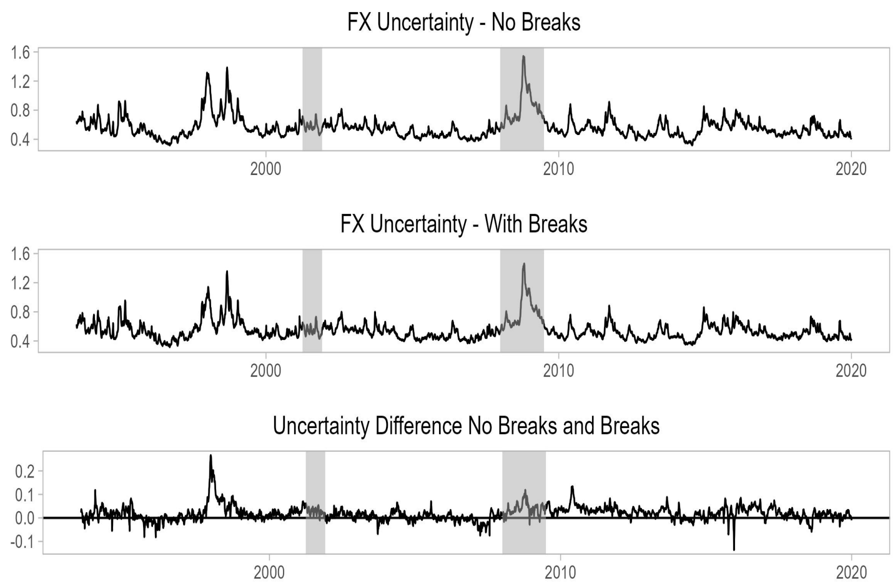


Note: The graph plots the general Exchange rate index calculated by the model. The letters in the plot correspond to events that affected the uncertainty level. A-Mexican Bail-out, B-Asian Crisis, C-Russian Bail-out, D-9/11, E-Term Auction Facility, F-Lehman Bankruptcy, G-Quantitative Easing, H-Quantitative Easing 2, I-Operation Twist, J-Bernanke's Taper Tantrum, K-Forward Guidance/Swiss Ending Peg, N-Brexit Vote. Shaded regions are the NBER recession dates for the periods. *Sources:* Author' calculations and NBER.

The uncertainty index reflects the market's economic conditions and mainly measures general economic Uncertainty. After the "Tequila" crisis ended, it decreased until 1997. In that year, the Asian exchange rate crisis of Hong Kong, Singapore, South Korea, and Taiwan occurred. The turmoil generated that most of the countries implicated abandoned a fixed/pegged exchange rate and converted to a (managed) floating exchange rate regime. The event might be part of the explanation behind the high level in this period. The developed countries started retrenching their capital from the developing countries, which devalued a significant amount of the emerging world exchange rates and impulsed a financial crisis that affected Russia, Brazil, and Latin American Countries. A considerable spike at the end of the 2000s represents the Great Financial Crisis of the USA that escalated quickly into a world financial crisis. The crisis created a financial flow from the affected countries to others that offered a higher return rate, as mentioned by Caballero et al. (2008a,b). Global imbalances generate capital migration and high exchange rate fluctuation.

From the figure, we can see that the index does not capture the 2001's dot-com bubble. It was just an event of the stock market and did not spill over to a world financial crisis; it did not generate disruption in the exchange markets. In which case, we can say that the uncertainty index itself is robust to measuring other types of uncertainties, such as the Economic Policy Index of Baker et al. (2016) or the macroeconomic and financial uncertainty indexes of Ludvigson et al. (2021)[11].

Figure 7: Exchange Rate Uncertainty Index with Breaks and No Breaks



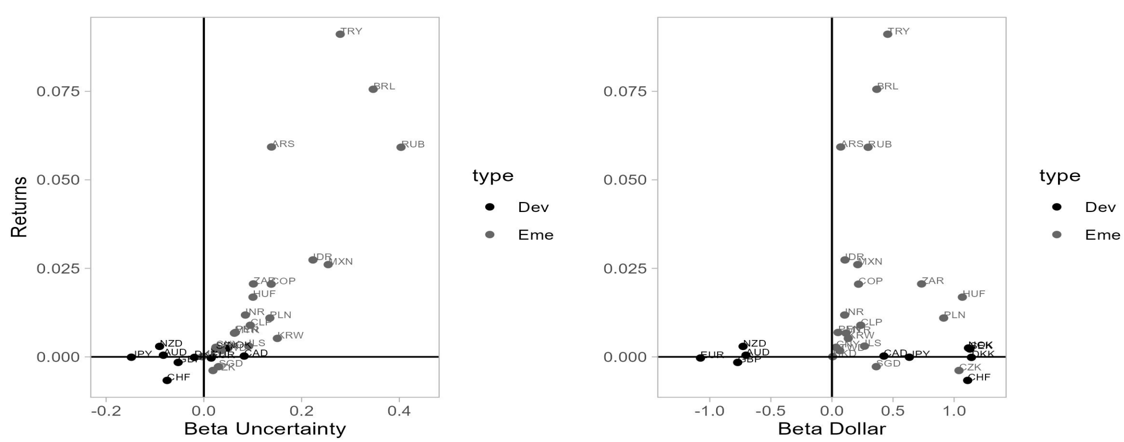
Note: The graph plots the Exchange Rate Uncertainty Index without taking into account the Breaks, with the breaks, and the difference between them. Shaded regions are the NBER recession dates for the periods. *Sources:* Author' calculations and NBER.

Two aspects need to be contrasted in the model: the difference between accounting or not for the breaks and the relationship between the changes in the level of Uncertainty and the dollar movements. In Figure 7 I plot the uncertainty without breaks (UN_{NB}), with breaks (UN_B), and the difference between them (UN_{NB} - UN_B). From the graph, we can see that both series have similar behavior, such that we can expect a high correlation. The last plot makes the difference clearer, as UN_{NB} has a bias toward the right side of the distribution, showing a higher level of Uncertainty. The difference is not related to episodes of crisis or recessions, except for the Asian crisis in the second part of the 90s. Then, I contrast the relationship between the Dollar and the Uncertainty by regressing the returns of each currency to the Uncertainty and the Dollar separately. Figure 8 plots the returns and the betas of each one of the currencies in a CAPM-like model to show the difference between the returns and Dollar effect and compare the results of Avdjiev et al. (2019) in which the VIX and Dollar captured similar effects. The graph shows that the effect of Uncertainty and the

[11]In appendix A.3 I compare the results of the index to the mentioned uncertainty measures, and some other commonly used in the literature.

Dollar, measured through the DXY dollar index, differs in both level and sign. There is no clear trend of the dollar beta with returns, but there is a higher level of Uncertainty with higher returns (depreciation), as a risk/return expected by the risk-return trade-off. The New Zealand dollar, the British Pound, and the Australian Dollar face both negative effects, the Uncertainty and the Dollar. In contrast, analogously, the Canadian Dollar, the Swedish Krona, and the Norwegian Krone positively affect both. On the other hand, the Japanese Yen, the Euro, the Danish Krone, and the Swiss Franc have a contrary sign. Then, we can see that a few currencies show that the Dollar and Uncertainty have similar effects.

Figure 8: Uncertainty and Dollar effects on Returns



Note: The figure plots the estimated beta between returns of each developed and emerging currency and both Uncertainty and the Dollar. The left panel presents the returns against the estimated parameters β of the regression against the logarithmic of the uncertainty measure. The right panel follows the same estimation but against the DXY dollar index. I estimate a lineal model using Newey and West (1987) and Newey and West (1994) lag selection procedure. Developed Markets are in black, while the emerging is in dark grey. *Sources:* Bloomberg and author's calculations.

3.2 Covered Interest Rate Parity

Previous literature as Brunnermeier et al. (2008), Berg and Mark (2018a), Berg and Mark (2018b), Husted et al. (2018), and Kalemli-Ozcan and Varela (2021) show the relationship between interest rate parity and uncertainty. Yet, they mostly focus on traditional measures of uncertainty that are not related to exchange rates, but rather macroeconomic or financial markets, such as the VIX as recent work by Avdjiev et al. (2019) and Cerutti et al. (2021), which find that by controlling for broad dollar variations, this variable loses significance. I argue that by constructing an exchange rate-specific uncertainty, we can show an innate variability in the currencies that are not accounted for in the broad index. In this section, I provide evidence of the significance of this result by comparing it to different traditional models in the literature. I center on the period of 2007-2019 using daily weekday data, the period after the financial crisis, as the previous variation of both Libor and Government cross-currency basis have low levels that can are not significant for arbitrage opportunities.

I will construct different measures of uncertainty to asses whenever they may have some power over explaining the basis to assess the effect of uncertainty on the Libor and Government Cross-currency Basis shown in Equations 2 and 3. I use both UNC_{NB} and UNC_B that I presented previously. I construct a group-specific uncertainty for the model considering the break and no break, such that I take the equal weight of the uncertainty specific to the group membership. Then, we will have the uncertainty for groups one and two with no breaks presented in Table 2; $UNC_{G1,NB}$ and $UNC_{G2,NB}$. If we account for breaks, then we will three groups as in Table 3 after 2007; $UNC_{G1,B}$, $UNC_{G2,NB}$, and $UNC_{G3,B}$. Additionally, I only consider the G10 currencies' uncertainty by assuming no break, $UNC_{10,NB}$, so I can assess the contribution of only the most commonly analyzed currencies.

Table 4: Dollar Factors and Uncertainty

	CIP	UNC_{NB}	UNC_B	$UNC_{G1,NB}$	$UNC_{G2,NB}$	$UNC_{10,NB}$	VIX	DXY	$UNC_{G1,B}$	$UNC_{G2,B}$	$UNC_{G3,B}$
CIP	1										
UNC_{NB}	-0.48	1									
UNC_B	-0.44	0.99	1								
$UNC_{G1,NB}$	-0.46	0.99	0.98	1							
$UNC_{G2,NB}$	-0.50	0.91	0.89	0.85	1						
$UNC_{10,NB}$	-0.46	0.89	0.89	0.86	0.92	1					
VIX	-0.47	0.79	0.78	0.77	0.76	0.77	1				
DXY	-0.01	0.01	0.01	0.01	0.005	0.01	0.09	1			
$UNC_{G1,B}$	-0.41	0.95	0.97	0.95	0.84	0.85	0.73	0.01	1		
$UNC_{G2,B}$	-0.42	0.89	0.89	0.86	0.89	0.95	0.74	0.01	0.83	1	
$UNC_{G3,B}$	-0.40	0.86	0.87	0.86	0.75	0.68	0.68	0.01	0.74	0.68	1

The table present the correlations between the different types of uncertainty and the average Cross-Currency Basis (CIP). UNC_{NB} is the calculated Uncertainty assuming no breaks, UNC_B assuming breaks, $UNC_{G1,NB}$ and $UNC_{G2,NB}$ are the ones formed by the estimated groups with no breaks, VIX is the Chicago Board Exchange's Volatility index for the S&P500, DXY is the DXY Dollar index, and $UNC_{i,B}$ are uncertainties formed by groups $i = G1, G2, G3$ with breaks.

In Table 4, I show the correlation of the different measures of uncertainty and the average level of Libor Cross-currency basis as the benchmark measure of future models. We can see a high correlation between the various measures and the ground, with low magnitudes of difference between them. Let's turn to the correlation between the uncertainties calculated. We can see that coherent to Figure 7, the break and no break uncertainties have a near one correlation, and the other groups have similar levels of correlation. The high relationship between them indicates that even accounting for the break in 2007, the uncertainty relationship is generally homogeneous between the currencies. The homogeneity of uncertainty suggests that currency variability loads heavily on a common variation of the dollar, but it is not captured by dollar index measures, such as the DXY. The VIX has a high correlation concerning the uncertainty level, which tells us that a significant part of the currencies fluctuations are due to the variations in the financial markets of the United States market.

Still, there is other information that is not contained in those fluctuations.

I then analyze the effect of Uncertainty on Libor's cross-currency basis. I follow a CAPM-like model to analyze the sensitivity of the Libor cross-currency basis from the uncertainty for 2007 to 2019. I estimate the following model,

$$\lambda_{t,t+n} = \alpha + \beta_1 UN_{i,t-1} + \varepsilon_t \tag{14}$$

where $\lambda^i_{t,t+n}$ is the 3-month Libor cross currency basis and $UN_{i,t} = \{\ UNC_{NB},\ UN_B,\ UN_{G,NB},\ UN_{G,B},\ UN_{10},\ VIX\ \}$ are the different types of uncertainty used. In Table 5, I present the results of each currency basis against each uncertainty, such that we can see if a single uncertainty provides a better fit or if the uncertainties vary with the currency. We can see that there are heterogeneous effects, where for the AUD and the JPY, I find no uncertainty measure provides enough statistical relevance to the basis. If we select based on how well the model in equation 14 explains the data, we can see that VIX has higher significance for the CAD, DKK, and NOK. At the same time, the rest of the countries have a better fit with either uncertainty measure. One important aspect of the result is that it provides evidence that it is not the case of a single measure that fits all but that every country has its idiosyncratic behavior. In most cases, high uncertainty increases the cross-currency basis, but for the CAD and NZD, which is positive. The highest exposure to uncertainty comes from DKK, GBP, and EUR, while the lowest comes from SEK and CHF.

Table 5: Libor CIP Deviations and the Uncertainty 2007-2019

	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
UN_{NB}	-6.777	16.182	-23.609	-76.653	-43.901	-56.901	-10.166	-47.959	8.761	-38.239
p-value	0.262	0.00002	0.019	0	0.0001	0.0001	0.198	0.00001	0.009	0.001
$Adj.r^2$	0.013	0.063	0.064	0.313	0.163	0.345	0.015	0.225	0.033	0.205
UN_B	-4.196	16.242	-20.934	-73.293	-39.971	-56.757	-7.651	-45.650	10.858	-37.108
p-value	0.505	0.00003	0.046	0	0.001	0.0002	0.347	0.0001	0.001	0.004
$Adj.r^2$	0.004	0.060	0.048	0.271	0.128	0.325	0.008	0.193	0.048	0.183
$UN_{G,NB}$	-7.329	14.603	-22.434	-72.052	-41.746	-45.159	-9.485	-45.093	2.727	-34.600
p-value	0.139	0.0001	0.021	0	0.0003	0.001	0.217	0.0001	0.435	0.001
$Adj.r^2$	0.020	0.052	0.059	0.281	0.150	0.284	0.013	0.202	0.004	0.220
$UN_{G,B}$	-1.501	14.771	-19.912	-62.445	-32.792	-40.248	-7.402	-36.683	9.837	-28.116
p-value	0.770	0.00002	0.026	0.00000	0.004	0.010	0.256	0.001	0.0004	0.017
$Adj.r^2$	0.001	0.063	0.055	0.250	0.110	0.217	0.009	0.159	0.052	0.139
UN_{10}	-8.388	18.068	-22.915	-75.635	-39.102	-50.650	-5.081	-46.270	3.760	-35.677
p-value	0.125	0.00001	0.035	0	0.001	0.001	0.460	0.00001	0.312	0.003
$Adj.r^2$	0.020	0.080	0.062	0.312	0.132	0.280	0.004	0.215	0.006	0.183
VIX	-4.846	19.863	-5.495	-49.079	-28.590	-33.166	6.008	-33.919	3.405	-19.761
p-value	0.117	0	0.467	0	0.0003	0.001	0.191	0.00000	0.121	0.024
$Adj.r^2$	0.018	0.257	0.009	0.347	0.187	0.317	0.014	0.305	0.013	0.148

The table shows the regression of different types of uncertainty against the LIBOR cross-currency basis for each currency. UN_{NB} is the uncertainty without taking into account breaks, UN_B is the uncertainty with breaks, $UN_{G,NB}$ is the uncertainty of the respective two groups without breaks, $UN_{G,B}$ is the group uncertainty. Still, for each of the three groups after the break, UN_{10} is the uncertainty of the Top 10 economies and the Chicago Board Exchange' Volatility Index VIX. The model is estimated following Newey and West (1987) with an optimal lag selection of Newey and West (1994).

If we apply the same CAPM model in equation 14 to the whole sample, we could test if the uncertainty has relevance in explaining the entire sample from 2000-2019. I take the Uncertainty with breaks, $UN_{t,B}$, as my benchmark uncertainty model, as I want to account for the change of the comovements of breaks and regress it against both the Libor and Government Cross-Currency basis. In table 6, we can see the general results of the model, where the uncertainty is significant for most currencies but the AUD in both Libor and Government basis, while compared to the previous results, JPY is significant for the Libor Basis. Uncertainty is not significant for the NZD and GBP on a government basis. The currencies, as mentioned earlier, and the AUD are coincidentally part of the Group 1 (1993-2007 sample) with NOK, which shows weak significance. Based on the results, we can expect uncertainty to be generally relevant to explain the cross-currency basis of both Libor and Government markets, with a higher magnitude for the Government deviations. The results are consistent with the theory and the effects of Jiang et al. (2021), as it suggests that higher levels of uncertainty and risk aversion increase the demand for safe assets and treasury bills, which in turn help the rates to stay low. At the same time, the international markets have the pressure to increase them (Gourinchas and Rey, 2007, 2014, 2022; Camanho et al., 2022).

Table 6: Libor Cross-currency Basis and Uncertainty - 2000-2019

	Libor CIP Deviations									
	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
α	2.67	-4.60^{*}	-30.63^{***}	-86.16^{***}	-44.64^{***}	-42.99^{***}	-25.48^{***}	-47.45^{***}	16.00^{***}	-40.03^{***}
	(3.54)	(2.58)	(6.24)	(10.53)	(8.54)	(10.46)	(4.68)	(7.60)	(2.09)	(8.33)
β_1	-0.21	9.63^{***}	-24.09^{***}	-75.30^{***}	-40.92^{***}	-46.20^{***}	-13.87^{**}	-41.96^{***}	13.43^{***}	-34.72^{***}
	(5.05)	(3.48)	(8.67)	(14.71)	(11.76)	(14.70)	(6.59)	(10.77)	(3.02)	(11.76)
R^2	0.00	0.02	0.05	0.16	0.11	0.25	0.02	0.15	0.05	0.14
$Adj.R^2$	-0.00	0.02	0.05	0.16	0.11	0.25	0.02	0.15	0.05	0.14
Num. obs.	5173	5173	5173	5173	5173	5173	5173	5173	5173	5173
	Government CIP Deviations									
	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
α	25.01^{*}	52.74^{***}	83.14^{***}	98.70^{***}	48.87^{***}	26.86^{**}	94.10^{***}	62.16^{**}	25.23	75.86^{**}
	(13.01)	(17.57)	(11.06)	(26.21)	(16.14)	(13.25)	(28.67)	(28.12)	(18.78)	(32.72)
β_1	26.01	52.44^{**}	74.43^{***}	85.84^{**}	42.70^{*}	21.50	86.33^{**}	68.47^{*}	44.69	88.33^{*}
	(18.66)	(25.32)	(15.35)	(37.59)	(23.08)	(19.07)	(41.24)	(40.57)	(27.49)	(46.70)
R^2	0.03	0.15	0.19	0.20	0.10	0.03	0.23	0.17	0.09	0.20
Adj. R^2	0.03	0.15	0.19	0.20	0.10	0.03	0.23	0.17	0.09	0.20
Num. obs.	5173	5173	5173	5173	5173	5173	5173	5173	5173	5173

The model is estimated following Newey and West (1987) with optimal lag selection of Newey and West (1994). The level of significance is given by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

I extended the CAPM model type regression used earlier with additional control variables to assess the robustness of the results. To this end, I follow the models of Du et al. (2018a), Verdelhan (2018),Avdjiev et al. (2019), and Cerutti et al. (2021), which are used in the literature as the benchmark to models to explain the deviations in Libor market. I estimate the following model,

$$\lambda_{t,t+n}^{CIP,i} = \alpha + \beta_1 TWDI_t + \beta_2 Unc_{B,t-1} + \beta_3 \Delta Unc_{B,t} + \beta \mathbf{X} + \varepsilon_t \tag{15}$$

where $\lambda_{t,t+n}^{i}$ is the 3-month cross currency basis for $CIP = Libor, Government$ and currency i, $TWDI_t$ are the logarithmic returns of the trade-weighted broad dollar index from the Federal Reserve of St. Louis Economic Database (FRED), $\mathbf{X} = ER_{i,t}, WTI_t - 1$ are control variables. $ER_{i,t}$ are the logarithmic exchange rate of i against the dollar, and the WTI is the West Texas Intermediate logarithmic returns. The inclusion of the Exchange rate and the Dollar index obeys to control for the effect of variations of the dollar and its implications of the "risk-taking channel" mechanism described in Bruno and Shin (2015a,b), Ivashina et al. (2015), Avdjiev et al. (2019), and Bräuning and Ivashina (2020). Following Bruno and Shin (2015a) and Avdjiev et al. (2019), I include both the level and logarithmic variation of the Uncertainty measure that I constructed to capture the variation and the general level of the uncertainty in the exchange rates. I include the change in the price of oil as the relationship between the predictability of commodity currencies and oil is a well-established stylized fact, as we can see in Amano and Van Norden (1998), Ferraro et al. (2015), Chen et al. (2016), and Boubakri et al. (2019).

Table 7 presents the results of the estimation of the univariate regression of equation 15. Even by including the dollar index, we can see that the uncertainty remains significant for both Government and Libor Basis. The level of uncertainty has a significant effect for almost all variables but the AUD and JPY, coherent with the previous result. I find evidence that an increase of 1 percent of the uncertainty increases the Libor basis by at most 75 basis points. Nevertheless, I find that the variations in the uncertainty level do not affect the basis. Coherent with the results in the literature, the effect of the dollar on the basis is prevalent for the Libor, and it is economically significant. One puzzling result is the lack of significance of the Oil price; other than for the SEK, there is only a statistically weak effect in other currencies such as CAD, CHF, and DKK. Due to the basis level, the increase in the oil price reduces the deviations, as it is traduced in further increases on capital outflows for the US, which reduce the gap.

The government basis has a particular behavior compared to the Libor Basis. Neither the dollar nor the oil price has a statistically significant effect. The only significant impact comes from the uncertainty level. Uncertainty increases the retrenchment of gross capital flows back to the US as it also increases the rates of the domestic economy relative to the US by changing the time-varying risk aversion, as mentioned by Bekaert et al. (2009). Then, the regression results show a relationship between the level of uncertainty and increases in the convenience yield of the US government treasury assets. For economies like Denmark and Sweden, an increase in the level of uncertainty increases the deviation by 115 and 119 basis points, an economically relevant amount.

I extend the model in 15 and include other macroeconomic variables to analyze the deviations from the parity. I base on the model proposed by Cerutti et al. (2021) of macro-financial variables to explain the basis of the different currencies. Kalemli-Ozcan and Varela (2021)

Table 7: Cross-Currency Basis and the Exchange Rate Uncertainty with Controls 2007-2019

	Libor CIP Deviations									
	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
Intercept	1.22	-6.69^{**}	-37.96^{***}	-105.23^{***}	-55.63^{***}	-53.95^{***}	-29.56^{***}	-58.02^{***}	19.93^{***}	-48.38^{***}
	(4.82)	(3.32)	(8.12)	(9.95)	(9.19)	(12.12)	(6.64)	(9.46)	(2.68)	(11.50)
$TWDI_t$	-51.11	-256.54^{***}	-185.17	-273.10	-305.30^{*}	-96.11	-428.96^{**}	-202.23	-25.75	-216.90^{***}
	(86.75)	(95.29)	(116.02)	(221.76)	(172.91)	(210.30)	(170.01)	(215.95)	(82.42)	(81.95)
ER_t	1.38^{**}	-0.19	-1.18^{**}	0.15	0.77	1.23	-0.34	0.21	-0.11	-0.23
	(0.56)	(0.53)	(0.50)	(1.13)	(0.76)	(0.88)	(0.67)	(0.65)	(0.39)	(0.23)
$UN_{B,t-1}$	-6.46	17.04^{***}	-21.83^{**}	-74.61^{***}	-41.14^{***}	-57.99^{***}	-6.86	-46.79^{***}	11.29^{***}	-37.24^{**}
	(6.79)	(4.26)	(11.12)	(13.72)	(12.03)	(16.87)	(9.39)	(12.79)	(3.92)	(16.66)
$\Delta UN_{B,t}$	-70.04	-29.11	-34.25	91.23	32.49	-4.98	-41.83	31.00	7.81	17.63
	(45.29)	(42.52)	(53.29)	(80.23)	(75.20)	(68.69)	(64.37)	(65.42)	(27.51)	(32.29)
WTI_{t-1}	-5.52	25.35^{*}	26.03^{*}	36.79^{*}	27.01	22.21	13.98	23.38	8.40	59.60^{***}
	(14.84)	(14.66)	(15.73)	(22.07)	(17.35)	(26.05)	(15.90)	(17.02)	(12.38)	(16.98)
R^2	0.03	0.07	0.06	0.29	0.15	0.34	0.02	0.21	0.05	0.20
Adj. R^2	0.03	0.07	0.06	0.29	0.15	0.34	0.01	0.21	0.05	0.20
Num. obs.	2759	2759	2759	2759	2759	2759	2759	2759	2759	2759
	Government CIP Deviations									
Intercept	33.87^{*}	69.27^{***}	98.94^{***}	125.52^{***}	60.85^{***}	39.97^{***}	116.26^{***}	79.27^{***}	28.75	89.95^{***}
	(17.84)	(19.73)	(10.10)	(24.10)	(18.24)	(15.42)	(28.07)	(22.83)	(18.31)	(28.25)
$TWDI_t$	124.52	136.20	-141.04	240.87	320.67	290.72	721.20	-101.03	283.38	87.88
	(279.61)	(215.15)	(200.69)	(376.99)	(276.10)	(374.72)	(489.68)	(308.35)	(285.05)	(413.20)
ER_t	-0.59	1.31	1.83^{**}	-0.26	-0.08	-0.62	-0.34	1.03	0.96	1.07
	(1.29)	(1.79)	(0.86)	(1.64)	(1.07)	(0.86)	(0.85)	(0.93)	(0.79)	(0.88)
$UN_{B,t-1}$	44.58^{*}	75.99^{***}	79.72^{***}	115.22^{***}	62.23^{**}	41.94^{*}	108.60^{***}	96.92^{***}	53.15^{**}	118.66^{***}
	(25.02)	(28.24)	(13.82)	(33.92)	(25.40)	(21.83)	(39.78)	(31.46)	(26.49)	(38.46)
$\Delta UN_{B,t}$	52.92	118.96	5.15	67.98	172.67	68.84	162.56	82.44	-24.85	162.74
	(137.83)	(111.26)	(95.68)	(171.53)	(161.43)	(127.86)	(194.69)	(132.19)	(82.02)	(149.05)
WTI_{t-1}	11.80	-27.73	-10.54	-25.16	-12.07	-5.48	-59.80	-40.19	-61.20	-53.93
	(34.12)	(38.14)	(33.59)	(44.19)	(26.41)	(34.68)	(40.77)	(40.46)	(45.54)	(37.67)
R^2	0.10	0.28	0.28	0.34	0.18	0.13	0.33	0.28	0.15	0.31
Adj. R^2	0.10	0.28	0.27	0.34	0.18	0.13	0.33	0.28	0.15	0.31
Num. obs.	2759	2759	2759	2759	2759	2759	2759	2759	2759	2759

The model is estimated following Newey and West (1987) with optimal lag selection of Newey and West (1994). The level of significance is given by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

show that for the Uncovered Interest Rate Parity, the fluctuations are highly correlated with variations in the interest rate differentials. Consequently, I include the variations on the domestic USD LIBOR benchmark rates as the domestic rate (r_t), the currency country LIBOR rate (r_t^*), and He et al. (2017)'s logarithmic returns of the squared leverage (L^2) as a measure of intermediary constraint, consistent with their paper and the literature of intermediary asset pricing effect on the carry trade and exchange rates such as Fang and Liu (2021), Du et al. (2022), and Niepmann and Schmidt-Eisenlohr (2023).

Table 8: Extended Libor and Government basis regressions

	Libor CIP Deviations									
	AUD	CAD	CHF	DKK	EUR	GBP	JPY	NOK	NZD	SEK
Intercept	1.08	-9.31^{***}	-37.76^{***}	-105.78^{***}	-53.47^{***}	-53.75^{***}	-33.04^{***}	-58.58^{***}	19.32^{***}	-48.34^{***}
	(5.30)	(3.08)	(6.59)	(10.65)	(7.48)	(10.06)	(4.21)	(8.05)	(2.64)	(7.30)
$TWDI_t$	-100.96	-247.52^{***}	-357.38^{***}	-344.75	-330.80^{*}	-179.98	-354.89^{**}	-186.50	24.29	-289.87^{**}
	(135.03)	(94.44)	(134.70)	(228.35)	(192.50)	(185.28)	(171.02)	(159.25)	(83.60)	(140.33)
r_t^*	-4.13	-11.80	189.79^{**}	96.39^{*}	399.91^{***}	136.10^{**}	-22.42	25.60^{*}	-0.79	103.44^{***}
	(13.14)	(46.58)	(75.12)	(55.29)	(155.02)	(69.29)	(201.92)	(15.16)	(12.84)	(33.49)
r_t	-135.11^{***}	-124.22^{***}	-231.23^{***}	-135.34	-270.63^{***}	-147.96	-312.19^{***}	-106.46^{*}	-38.28^{**}	-83.07^{*}
	(51.20)	(27.42)	(54.05)	(92.88)	(70.75)	(91.92)	(48.46)	(64.40)	(18.84)	(50.32)
$UN_{B,t-1}$	-5.86	11.50^{***}	-20.23^{**}	-73.49^{***}	-36.44^{***}	-57.63^{***}	-12.01^{**}	-46.36^{***}	10.13^{**}	-36.58^{***}
	(7.58)	(3.85)	(9.15)	(15.32)	(10.29)	(14.15)	(5.94)	(11.23)	(3.97)	(10.48)
$\Delta UN_{B,t}$	-63.16	-35.02	-24.79	93.05	19.40	6.42	-22.69	31.18	14.22	23.15
	(43.36)	(40.82)	(59.43)	(76.72)	(70.05)	(65.85)	(46.45)	(71.14)	(28.41)	(54.93)
L^2	-15.86	8.62	32.55	20.84	12.14	5.45	15.64	16.85	-1.52	8.04
	(12.02)	(12.69)	(24.24)	(21.90)	(18.18)	(19.58)	(13.91)	(16.64)	(7.23)	(21.25)
R^2	0.07	0.09	0.12	0.29	0.19	0.36	0.17	0.20	0.05	0.21
Adj. R^2	0.07	0.09	0.12	0.29	0.19	0.36	0.17	0.20	0.05	0.21
Num. obs.	2708	2708	2708	2708	2708	2708	2708	2708	2708	2708
	Government CIP Deviations									
Intercept	32.57^{**}	67.87^{***}	96.99^{***}	125.83^{***}	63.23^{***}	40.72^{***}	118.96^{***}	78.04^{***}	26.60	88.68^{***}
	(15.41)	(19.18)	(11.48)	(21.65)	(17.53)	(14.08)	(25.35)	(25.31)	(16.36)	(27.31)
$TWDI_t$	79.42	222.34	75.90	223.84	287.19	288.57	553.90	-16.79	174.25	170.84
	(372.58)	(338.02)	(250.69)	(446.19)	(297.96)	(284.48)	(500.94)	(288.52)	(264.12)	(437.94)
r_t^*	-66.20	-220.95^{**}	-168.69^{**}	115.82	159.18	-75.04	649.76	-67.08	-104.42^{*}	-83.84
	(48.87)	(109.06)	(65.67)	(82.33)	(287.00)	(51.22)	(563.13)	(46.53)	(54.89)	(56.14)
r_t	117.21	103.21	103.05	131.29	205.93	232.85	265.35	60.94	35.85	92.91
	(182.17)	(194.43)	(116.60)	(213.49)	(201.42)	(168.61)	(226.38)	(195.61)	(90.16)	(242.37)
$UN_{B,t-1}$	43.12^{**}	75.29^{***}	74.45^{***}	113.21^{***}	63.92^{***}	43.23^{**}	111.93^{***}	94.20^{***}	48.98^{**}	114.68^{***}
	(21.99)	(28.11)	(15.66)	(31.04)	(24.56)	(20.03)	(37.09)	(35.56)	(23.65)	(37.60)
$\Delta UN_{B,t}$	34.67	118.10	-9.03	43.39	158.95	50.40	138.62	87.47	-22.96	140.00
	(148.73)	(111.34)	(95.27)	(170.37)	(136.71)	(111.33)	(170.59)	(132.08)	(86.34)	(156.54)
L^2	5.34	-18.62	-18.09	-16.18	-11.34	-11.57	0.29	-12.70	-12.68	6.45
	(26.68)	(28.48)	(27.65)	(35.01)	(35.38)	(19.01)	(34.44)	(30.10)	(19.59)	(41.04)
R^2	0.10	0.29	0.26	0.33	0.19	0.16	0.35	0.27	0.14	0.29
$Adj.R^2$	0.10	0.29	0.26	0.33	0.19	0.16	0.35	0.27	0.14	0.29
Num. obs.	2708	2708	2708	2708	2708	2708	2708	2708	2708	2708

The model is estimated following Newey and West (1987) with optimal lag selection of Newey and West (1994). The level of significance is given by $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

In Table 8, I present the results of the univariate regression by currency for Libor and Government basis. The dollar factor is again relevant in the models for each currency but the AUD, NOK, GBP, and NZD. The basis from those currencies was also not statistically significant in the previous model in Table 7, which shows the consistency of the effect of the dollar appreciations. The changes in the domestic rate are consistent and significant in explaining the basis for all currencies except the DKK and the GBP, which have a significant effect on their rate. In particular, CHF, EUR, and SEK have their interest rate and the US interest rate as significant effects. In this model, the level of uncertainty is again significant, but not for the AUD only. Like the results in Cerutti et al. (2021), I find that the increase in the leverage of the intermediaries does not have statistical significance in explaining the effect of the changes on the basis when the Dollar Index is present on the regression model. For the Government basis, the results also remain consistent, as the central variable that explains the government basis is the level of uncertainty, which has a magnitude higher than the Libor basis. The foreign interest rate for the CAD and CHF is significant in explaining the convenience yield of their currency.

Table 9: Panel Model for Uncertainty and the Cross-Currency Basis

	Models									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$UN_{B,t-1}$	-25.88^{***}	-26.38^{***}	-26.35^{***}	-28.24^{***}	-28.51^{***}					
	(8.66)	(8.85)	(8.84)	(9.74)	(9.66)					
$\Delta UN_{B,t}$	-17.21	-9.00	-12.21	-2.13	5.71					
	(33.00)	(32.26)	(33.21)	(24.88)	(27.23)					
VIX_{t-1}						-15.10^{**}	-16.42^{**}	-16.55^{**}		
						(6.29)	(6.63)	(6.55)		
ΔVIX_t						-6.39	-6.41^{*}	-5.73		
						(4.27)	(3.87)	(3.52)		
VXO_{t-1}									-14.31^{**}	
									(6.21)	
ΔVXO_t									-5.43	
									(3.39)	
$UN_{NB,t-1}$										-30.38^{***}
										(8.69)
$\Delta UN_{NB,t}$										20.76
										(29.00)
$TWDI_t$		-257.80^{**}	-270.15^{**}	-202.76^{**}	-193.29^{*}	-288.62^{**}	-234.19^{**}	-228.23^{*}	-229.31^{**}	-187.82^{*}
		(104.85)	(108.78)	(96.63)	(99.71)	(120.22)	(113.71)	(117.48)	(116.81)	(96.14)
ER_t			0.03	-0.04	-0.14		-0.02	-0.12	-0.13	-0.14
			(0.26)	(0.28)	(0.29)		(0.28)	(0.30)	(0.30)	(0.30)
SR_{US}			-40.76^{*}							
			(21.31)							
r_t				-141.55^{***}	-149.14^{***}		-145.78^{***}	-151.77^{***}	-148.70^{***}	-150.34^{***}
				(32.02)	(34.07)		(34.67)	(37.87)	(37.99)	(32.61)
WTI_{t-1}					22.53^{**}			20.26^{*}	21.67^{**}	23.09^{***}
					(8.91)			(10.53)	(10.75)	(8.79)
Adjusted R^2	0.043	0.046	0.047	0.06	0.063	0.043	0.058	0.06	0.056	0.074
N	32420	32420	32420	32420	32420	32420	32420	32420	32420	32420

Notes: The Table reported the regression results of the daily panel for the G10 currencies in 2007-2019. I estimate the standard errors robust to the Cross-sectional and Serial correlation of Driscoll and Kraay (1998) with the Newey and West (1994) automatic lag selection. The statistical significance follows $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

The previous results suggest that uncertainty is relevant to explain the Libor and Government Basis variations. Still, we are yet to see if the effect is consistent in the aggregate. As such, I estimate a Panel Model for all the G10 currencies using the relevant control variables from the univariate model and contrasting the result with different measures of uncertainty and volatility commonly used. One additional explanatory variable I add is the CBOE Volatility Index for the $S\&P100$ firms (VXO) to the other uncertainty measures used previously, the CBOES VIX, and the exchange rate uncertainty with and without breaks UN_B and UN_{NB}. I include the US's Shadow Short Rate (SSR) as a control variable from

Krippner (2013b, 2014). The shadow rates capture the effect of conventional and unconventional rates on exchange rates, policies which Inoue and Rossi (2019) show had an impact on exchange rates.

I run the panel regression and show the results in Tables 9 and 10 for the Libor and Government Cross-currency basis. In each column, I run different models to compare the fit of each uncertainty measure and the consistency under other control variables. We can see that for the Libor Basis, the logarithmic returns of the dollar index have statistical significance under any model specification. As shown by Gopinath et al. (2020) and Boz et al. (2022), the dollar has the status as the dominant currency in which a considerable proportion of the trades are invoice, so we can expect that the fluctuations it has been translated on the deviations that the country may have. Including the shadow rate is not traduced in a better fit than using the domestic Libor rate; in both cases, we can see that a change in the US rate increases the deviation of the CIP, as it modifies the interest rate parity. The Oil price is statistically significant and reduces the basis, as an increase in the prices translates into higher capital flows and the demand for foreign currency, which appreciates the money. The uncertainty measures reflect that the Exchange Rate Uncertainty has a higher magnitude effect than the VIX or VXO over the currency basis, almost doubling one of the volatility indices. The Goodness of fit suggests that the entire model with the Exchange Rate Uncertainty under no break and break provides a better fit for the Libor basis.

Table 10 shows the Government Basis panel regression results with different uncertainty models. Consistently with the univariate results, the only variables that have statistical significance are the uncertainty measures. Like in the Libor results, the Exchange Rate Uncertainty effect doubles the magnitude of the impact over the VIX and VXO. If we compare the goodness of fit, we have again that the Exchange rate Uncertainty does a better job adjusting to the basis than the other traditional measures.

Compounding the results obtained from the univariate and the panel model, we can conclude that the Exchange Rate Uncertainty provides a better fit than other volatility measures, especially for the benchmark used in most papers, the VIX. Although for some univariate models, that index provides a higher R^2 than the uncertainty. As the construction of the uncertainty measures comes from the exchange rate itself rather than from the financial markets specific to the United States, it captures other international shocks that may have less impact in the domestic country but are highly relevant internationally. Along the same line, having a global measure allows us to weigh the difference between idiosyncratic and common shocks. Events such as the 2001's crisis and terrorist attacks have implications for the domestic market, but it will not be the case for the international.

Table 10: Panel Model for Uncertainty and the Government Convenience Yield

	Models									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$UN_{B,t-1}$	74.72***	78.05***	77.85***	79.77***	81.90***					
	(26.37)	(26.71)	(26.47)	(28.67)	(29.29)					
$\Delta UN_{B,t}$	94.62	82.69	81.37	76.48	81.21					
	(112.46)	(109.01)	(107.29)	(93.15)	(94.60)					
VIX_{t-1}						45.25***	46.56***	47.35***		
						(15.75)	(16.83)	(17.16)		
ΔVIX_t						25.14*	25.21**	21.87*		
						(12.98)	(12.57)	(12.07)		
VXO_{t-1}									43.62***	
									(15.89)	
ΔVXO_t									19.22**	
									(9.63)	
$UN_{NB,t-1}$										80.45***
										(28.39)
$\Delta UN_{NB,t}$										75.62
										(96.09)
$TWDI_t$		231.32	215.66	178.92	186.29	308.95	253.77	289.45	295.74	183.45
		(275.88)	(255.57)	(233.66)	(230.38)	(336.35)	(296.19)	(298.07)	(298.87)	(229.63)
ER_t			0.18	0.14	0.45		0.09	0.37	0.38	0.45
			(0.45)	(0.42)	(0.43)		(0.39)	(0.39)	(0.39)	(0.43)
r_g^*			−14.62							
			(20.30)							
r_t				131.10	158.06		144.64	166.55	164.58	152.28
				(135.82)	(135.65)		(131.81)	(134.81)	(129.31)	(134.15)
WTI_{t-1}					−27.15			−22.58	−23.39	−31.36
					(26.07)			(33.77)	(33.64)	(27.11)
Adjusted R^2	0.168	0.179	0.179	0.185	0.195	0.17	0.176	0.182	0.186	0.199
N	32420	32420	32420	32420	32420	32420	32420	32420	32420	32420

Notes: The Table reported the regression results of the daily panel for the G10 currencies in 2007-2019. I estimate the standard errors robust to the Cross-sectional and Serial correlation of Driscoll and Kraay (1998) with the Newey and West (1994) automatic lag selection. The statistical significance follows $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$

4 Conclusion

In this paper, I presented a model that measures exchange rate uncertainty by combining the base model of Jurado et al. (2015) and the Ando and Bai (2017), which allows me to construct a world and group-specific uncertainty index. This methodology takes advantage of the daily information accounted for by other exchange rates and exogenous variables used in the literature. I construct an index that captures the daily shocks and variations in the currencies that reflect on common shocks that generate fluctuations in the exchange market. The index captures high-uncertainty events, such as the Asian and global financial crises, yet differs from traditional uncertainty measures centered around a particular financial market. It is also robust to the changes of other economic variables or events not related to the general conditions of the exchange rate market, as it does not capture the financial crisis of 2000.

In the construction of the Uncertainty index, I find that if we omit the existence of breaks, the behavior of the exchange rates can be characterized by a single common factor and two group-specific factors, one that has the majority of currencies. The existence of a single common factor and a group with the majority of currencies goes in hand with the global financial cycle hypothesis of Rey (2015). Nevertheless, I find a break in the common factor of the currencies in July of 2007, per the assumptions made in the literature on the effect of the Great Financial Crisis on the world markets and the Exchange Rate Reconnect of Lilley et al. (2022). If we divide the sample, we get that there are not only two groups, but four for the earlier sample and three for the second. The changes in groups preserve clusters of currencies that obey in majority to geographical proximity.

I use the exchange rate uncertainty index to analyze the deviations of the Covered Interest Rate Parity puzzle for both the Libor and the Government basis. I find that the effect of uncertainty, as expected, is heterogeneous. By running different univariate regressions for each G10 currency, I show that either delay or volatilities increase the cross-currency basis to most currencies. Still, it is not the case for AUD and JPY. The Dollar is a significant factor in explaining the Libor but not the Government basis. Contrary to the results of Avdjiev et al. (2019) and Cerutti et al. (2021), I find that the dollar returns are not entirely related to the uncertainty level. So, both are statistically significant in the univariate and panel models. In terms of goodness of fit, the exchange rate uncertainty has a better fit and has a higher effect on both the Libor and Government Basis, which almost doubles the magnitude of the VIX or VXO.

One limitation of the model is that as I focus on daily data, Du et al. (2018b) and Du and Schreger (2022) show that some seasonal effects may be generating problems of misspecification of the models. Further works should focus on extending the models to a monthly context such that the data does not suffer from these effects. Alternatively, it will be easier to model or use a methodology that seasonally adjusts them, like the X13-ARIMA-SEATS used by the Census Bureau. Another venue for research is on extending the model from Covered to Uncovered Interest Rate Parity. As many markets have constrained intermediaries, Forwards supply is scarce and costly, so firms decide to assume the exchange risk. In that case, the uncertainty may provide explanatory power for the deviation, as Kalemli-Ozcan and Varela (2021) show in their paper with an EPU-type measure.

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A Appendix

A.1 Descriptive Statistics

In this section, I present the descriptive statistics of the data of the exchange Rates shown in Table **??** used in the calculation of the Uncertainty measure of the Ando and Bai (2017) model. In these tables, the underlying statistics reflect their general behavior and allow us to see both databases' stylized facts.

Table 11: Descriptive Statistics - Exchange Rates

	Obs.	Mean	Std. Dev.	Skew	Kurtosis	Std. Error	Sharpe	Corr. USD	Corr. Unc.
AUD	5174.00	0.00	0.78	-0.34	9.74	0.01	0.00	-0.55	-0.03
CAD	5174.00	-0.00	0.55	0.10	2.99	0.01	-0.00	0.50	0.04
CHF	5174.00	-0.01	0.70	-3.76	118.95	0.01	-0.01	0.74	-0.00
DKK	5174.00	-0.00	0.61	-0.06	1.68	0.01	-0.00	0.92	0.01
EUR	5174.00	0.00	0.60	0.05	1.67	0.01	0.00	-0.93	-0.01
GBP	5174.00	-0.00	0.57	-0.76	10.77	0.01	-0.01	-0.68	-0.04
JPY	5174.00	0.00	0.61	-0.06	4.15	0.01	0.00	0.40	-0.04
NOK	5174.00	0.00	0.74	0.15	2.64	0.01	0.00	0.75	0.03
NZD	5174.00	0.01	0.80	-0.31	2.84	0.01	0.01	-0.53	-0.04
SEK	5174.00	0.00	0.74	0.04	2.56	0.01	0.00	0.78	0.02
BRL	5174.00	0.02	1.04	0.10	6.56	0.01	0.02	0.23	0.04
CLP	5174.00	0.01	0.63	0.28	4.48	0.01	0.01	0.23	0.04
CNY	5174.00	-0.00	0.14	0.04	28.67	0.00	-0.02	0.13	0.02
COP	5174.00	0.01	0.71	-0.02	8.84	0.01	0.01	0.21	0.03
HUF	5174.00	0.00	0.88	0.31	3.99	0.01	0.00	0.73	0.03
IDR	5174.00	0.01	0.59	-0.47	23.95	0.01	0.02	0.08	0.05
ILS	5174.00	-0.00	0.46	0.19	4.15	0.01	-0.01	0.36	0.04
INR	5174.00	0.01	0.39	0.27	9.10	0.01	0.02	0.17	0.05
KRW	5174.00	0.00	0.64	-0.69	54.97	0.01	0.00	0.14	0.04
MXN	5174.00	0.01	0.70	0.78	11.58	0.01	0.02	0.23	0.05
MYR	5174.00	0.00	0.34	-0.40	8.55	0.00	0.00	0.14	0.04
PEN	5174.00	-0.00	0.28	0.09	13.95	0.00	-0.00	0.14	0.03
PHP	5174.00	0.00	0.39	-5.00	141.30	0.01	0.01	0.12	0.05
PLN	5174.00	-0.00	0.84	0.25	4.65	0.01	-0.00	0.66	0.05
RUB	5174.00	0.01	0.77	0.43	102.28	0.01	0.02	0.22	0.03
THB	5174.00	-0.00	0.31	0.26	10.44	0.00	-0.01	0.21	0.03
TRY	5174.00	0.05	1.14	6.94	199.80	0.02	0.04	0.24	0.04
ZAR	5174.00	0.02	1.09	0.87	10.48	0.02	0.01	0.40	0.02

Notes: The table presents the descriptive statistics and the moments of the exchange rates used to estimate the uncertainty model. All series are in logarithmic returns. The range is the difference between the Maximum and the minimum value in the whole sample. I also calculate the Sharpe measure, the correlation with respect to the dollar, and uncertainty.

A.2 Unit-Root Test

In this section, I present the results of the Augmented-Dickey Fuller test on the exogenous variables used in the Ando and Bai (2017) part of the model. Under this test, the Null hypothesis is a non-stationary behavior (unit-root process). So, if the test statistic is in the accepting region, we must transform the series to make them approximately stationary. The table presents the statistics and critical values at 95% confidence for the endogenous and exogenous variables used in the methodology and the regressions. The last column represents the transformation of made to the variable according to McCracken and Ng (2016), where; 2-Δx, 3-$\Delta^2 x$, 4-$\log(x)$, and 5-$\Delta \log(x)$

Table 12: Unit Root Test - Explanatory Variables

Variable	Stat.	Diff.	Trans.
MSCI WI	-1.64	1.77	5
$S\&P500$	-0.28	3.13	5
VIX	-7.39	-3.98	4
DXY	-1.79	1.62	5
B. Comm.	-1.48	1.93	5
FF4	-1.56	1.85	2
CL3	-1.72	1.69	5
3M	-1.56	1.85	2
10Y	-3.83	-0.42	2
WTI	-2.10	1.31	5
SSR_{US}	-1.34	2.07	2

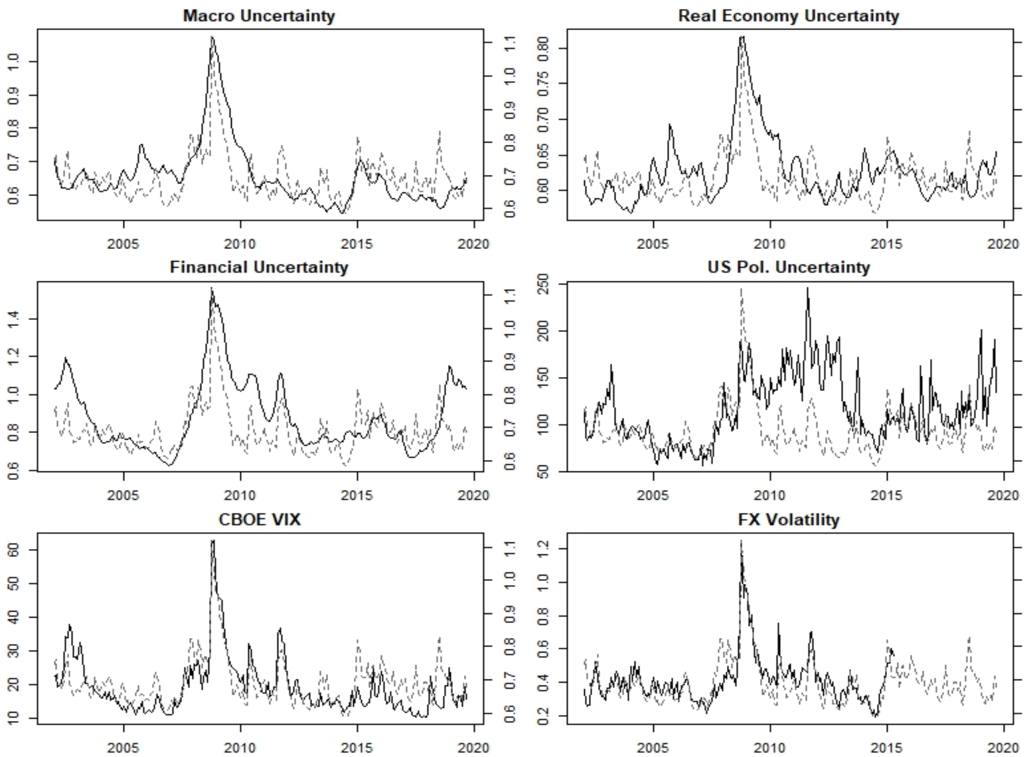
Notes: The table presents the Augmented Dickey-Fuller test for each explanatory variable. I did the test for the full sample from 2007 to 2019. The test run in the table is the specification with the trend. For each, I present the test statistic and the difference concerning the critical value on the 95%. A negative difference value will imply insufficient evidence that the series has a unit root.

A.3 Uncertainty Comparisons

In Figures 9 and 10, I compare the most used uncertainty measures in the literature and the exchange rate uncertainty calculated previously. The selection depends on the data to have monthly periodicity and the indices to be public, the methodology available to replicate, or the data provided by the authors. As the FX index is daily, I transform it into monthly by taking the monthly median. I compare my exchange rate uncertainty index with the Macroeconomic, Real Economy, and Financial uncertainty indexes of Jurado et al. (2015) and Ludvigson et al. (2021), the US and Global Economic Policy Uncertainty Indices of Baker et al. (2016), the Chicago Board of Exchange Volatility Index (VIX), the FX Volatility Index of Menkhoff et al. (2012b), Monetary Policy Uncertainty Index of Husted et al. (2020), Global Uncertainty Index of Ozturk and Sheng (2018), Subjective Interest Rate Uncertainty of Istrefi and Mouabbi (2018), Trade Uncertainty index of Baker et al. (2016), and the Geopolitical Risk Index of Caldara and Iacoviello (2018).

The Exchange rate uncertainty index correlates with the FX volatility index and the VIX, with 0.72 (up until 2012) and 0.78, respectively. By construction, the FX volatility index will have a common relationship by taking individual volatility of exchange rates. The VIX captures the effect of expectations of the US market, the dominant currency, and the liquid exchange rate. The correlation with the macroeconomic and financial uncertainty indices is relatively high, with ranges between 0.65 to 0.47. They differ in the persistence of the exchange rate uncertainty. Being the exchange rate inherently liquid, the shocks will dilute in time faster than macroeconomic shocks. The surprising result is the low correlation with the US Economic Policy Uncertainty (0.28), Trade (0.01), and Geopolitical Risk (-0.11), which is due to the relationship to the dependence on the exchange rate, which we could expect to be higher.

Figure 9: Uncertainty Measure Comparisons ER and Reference Models

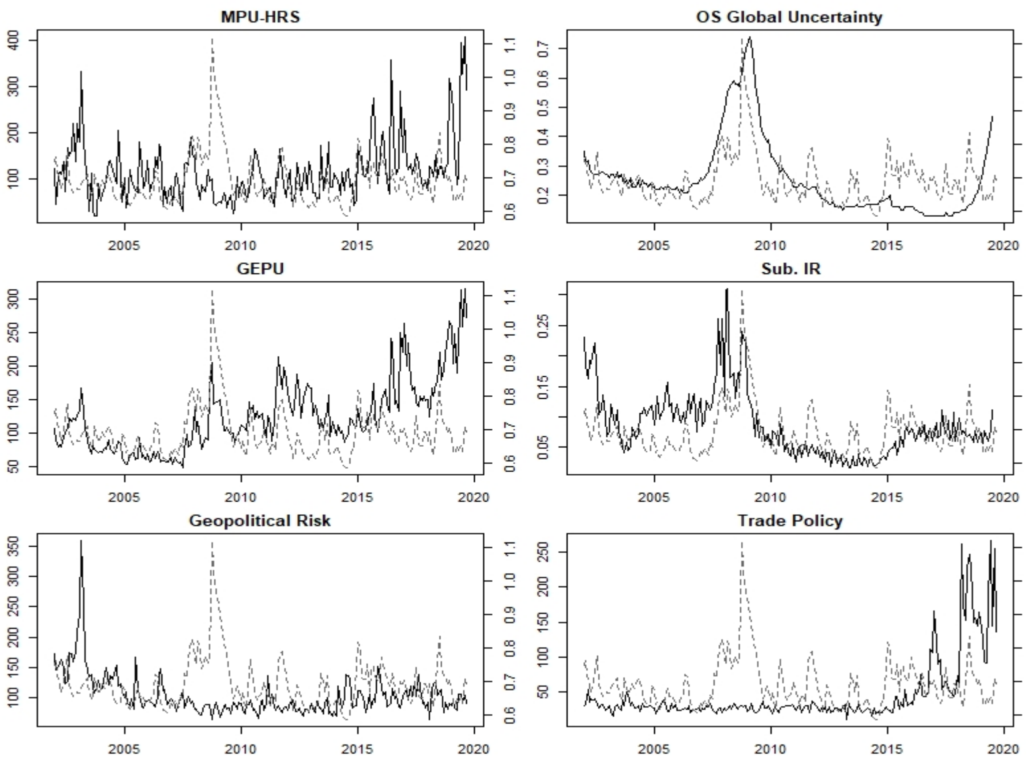


Note: The Figure plots different Uncertainty Indices against the Exchange Rate Uncertainty proposed. The left y-axis corresponds to the value of the contrasted index. The top-left panel is the Macroeconomic Uncertainty Index of Jurado et al. (2015). The top-right and center-Left are the Real Economies and Financial Uncertainty Indices of Ludvigson et al. (2021). The center-right is the United States Economic Policy Uncertainty of Baker et al. (2016). The lower-left panel is the CBOE VIX. The lower-right panel is the FX Volatility Index of Menkhoff et al. (2012b). *Sources:* The macroeconomic. real, and financial uncertainty indices come from their author's webpage, the US Economic Policy Uncertainty, and the VIX from the Federal Reserve of St. Louis, and the authors provided the FX Volatility.

A.4 Dickey-Fuller Test on CIP

In the literature, some authors have differentiated the series of CIP to avoid possible cases of unit root on the individual currencies, such as the case of Jiang et al. (2021), Avdjiev et al. (2019), and Cerutti et al. (2021). Nevertheless, to avoid possible misspecifications of the model, I ran An Augmented Dickey-Fuller test on each of the calculated cross-currency basis. In Table 13, I present the test for each sample used in the paper. From it, we can see that we did not find enough evidence for every currency to accept the null hypothesis that the series has a unit root process. As such, I will not differentiate the series in the cross-currency models.

Figure 10: Uncertainty Measure Comparisons ER and Reference Models



Note: The Figure plots different Uncertainty Indices against the Exchange Rate Uncertainty proposed. The left y-axis corresponds to the value of the contrasted index. The top-left panel is the Monetary Policy Uncertainty Index of Husted et al. (2020). The top-right is the Global Uncertainty Index of Ozturk and Sheng (2018). The Center-Left is the Global Economic Policy Uncertainty Index of Baker et al. (2016). The center-right is the Subjective Interest Rate Uncertainty of Istrefi and Mouabbi (2018). The lower-left panel is the Geopolitical Risk Index of Caldara and Iacoviello (2018). The lower-right panel is the Trade Uncertainty index calculated by Baker et al. (2016). *Sources:* Economic Policy Uncertainty webpage, the authors provided the Subjective interest rate uncertainty and Monetary Policy Uncertainty Indices and their calculations.

Table 13: CIP Augmented Dickey-Fuller Test

	Full Sample		1993-2007 Sample		2007-2019 Sample	
	Stat.	Diff.	Stat.	Diff.	Stat.	Diff.
AUD	-18.84	-15.43	-18.67	-15.26	-14.47	-11.06
CAD	-14.92	-11.51	-9.62	-6.21	-12.51	-9.10
CHF	-12.39	-8.98	-27.80	-24.39	-10.45	-7.04
DKK	-6.11	-2.70	-19.29	-15.88	-7.07	-3.66
EUR	-7.39	-3.98	-23.14	-19.73	-6.96	-3.55
GBP	-8.25	-4.84	-14.91	-11.50	-7.22	-3.81
JPY	-14.54	-11.13	-23.30	-19.89	-10.79	-7.38
NOK	-7.47	-4.06	-32.33	-28.92	-6.18	-2.77
NZD	-18.71	-15.30	-22.92	-19.51	-12.85	-9.44
SEK	-9.03	-5.62	-24.64	-21.23	-7.22	-3.81

Notes: The table presents the Augmented Dickey-Fuller test for each daily currency cross-currency basis ($\lambda_{i,t}$). I did the test for the full sample before the 2007 break, and after. The test run in the table is the specification with the trend. For each, I present the test statistic and the difference with respect to the critical value on the 95%. A negative difference value will imply insufficient evidence that the series has a unit root.