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Uncovered Interest Rate Parity Redux: Non-Uniform Effects

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Abstract

An empirical model that includes proxies for unobservable factors and allows for non-uniform effects due to model uncertainty and time-varying parameters can reduce the deviation of uncovered interest rate parity (UIP) as measured by the β-estimate that captures the interest rate differential effect in UIP regressions. However, the specification that alleviated UIP failure does not reduce the variability of the β-estimate, exhibits composition changes and time-varying parameters, and varies across exchange rates. These findings collaborate the scapegoat theory, and suggest that shifting roles of explanatory variables and time-varying effects contribute to the difficulty of rectifying the empirical UIP failure.

JEL Classifications: F31, G15

Keywords: Dynamic Model Averaging; Model Uncertainty; Proxies for CIP Deviations, Risk Premiums and Expectational Errors; Scapegoat Theory, Time-Varying Parameters

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1. Introduction

The uncovered interest rate parity (UIP) hypothesis provides a key link between foreign exchange and money markets in theoretical models of international economics, open macroeconomics, and international asset pricing. The hypothesis states that, for a given period, the expected rate of appreciation of the home currency against the foreign currency is the same as the difference of the interest rates of these two currencies. Its validity depends on assumptions about capital mobility, rational expectations, risk neutrality, …, etc.

Despite UIP's prominent role in model building and related analytical work, its empirical applicability has been seriously challenged. It is commonly found that the Fama β-estimate (henceforth, the "β-estimate") – the estimate of the cross-country interest rate differential coefficient is typically deviated from the value of one predicted under UIP (Burnside, *et al.*, 2011; Chinn, 2006; Engel, 1996, 2014; Fama, 1984; Froot and Thaler, 1990; Hodrick, 1987; Lewis, 1995; Sarno, 2005).The finding of UIP violations collaborates the reported carry trade profits, which are driven by the puzzling phenomenon that high yield currencies tend to appreciate.

The UIP puzzle has triggered numerous studies assessing the roles of, say, risk premiums and expectational errors, market's shifting perceptions about exchange rate determinants, and estimation techniques in explaining the UIP failure.[1] Theoretically, the presence of risk premiums, expectational errors, and changing market beliefs can lead to UIP violations.[2] UIP failure indeed

[1] See Amat, *et al.* (2018), Ballie and Bollerslev (1990, 2000), Bacchetta and Van Wincoop (2004, 2010), Beckmann and Schüssler (2016), Bekaert, *et al*. (2007), Berg and Mark (2018a, b), Boudoukh, *et al.* (2016), Bussiere, *et al.* (2018), Cheung (1993), Chinn and Frankel (2019), Dornbusch (1976), Engel, *et al.* (2019), Gospodinov (2009), Gourinchas and Tornell (2004), Kellard and Sarantis (2008), Moran and Nono (2018), Sarno and Valente (2009). Gabaix and Maggiori (2015) examines the role of capital flows in imperfect financial markets.

[2] See, for example, Backus, *et al.* (2001), Bacchetta and Van Wincoop (2010, 2019), Gourinchas and Tornell (2004), Ilut (2012), and Leippold and Wu (2007).

is a widespread empirical finding – regressions based on various empirical specifications yield β-estimates that are different from one, and even negative.[3]

Different empirical UIP studies employed different empirical proxies for the unobservable risk premiums and expectational errors; these proxies were derived from similar or different theoretical models, and from either economic or non-economic data. A natural question to ask is: To what extent these empirical proxies capture the attributes of unobservable factors that are relevant to UIP? The answer to this question is complicated by the possible shift of factors that affect the arbitrage behavior between foreign exchange and money markets under UIP due to, say, the shift of determinants of exchange rates across different time periods as described under the scapegoat theory (Bacchetta and Van Wincoop, 2004, 2013). There is uncertainty in selecting the empirical UIP model with the appropriate set of proxies over time. The issue is further complicated by time-varying parameters and currency-specific behaviors (Baillie and Kilic, 2006; Rossi, 2013; Sarno and Valente, 2009). That is, the relevant set of empirical proxies for unobservable terms in the UIP regression can shift across time periods, and exhibits varying effects over time and across exchange rates.

Against this backdrop, we consider a modified UIP regression that is augmented empirical proxies for covered interest rate parity (CIP) deviations, risk premiums, and expectational errors. Instead of creating our list of proxies, we draw from the existing studies and collect a total of 27 empirical proxy variables for these three augmented variables. We focus on the behavior of the β-

[3] There are a few studies show that UIP holds better, say, in very short or very long time horizons (Chaboud and Wright, 2005; Chinn and Meredith, 2004), among developing economies (Bansal and Dahlquist, 2000), and for countries facing currency crises (Flood and Rose, 2002). Baillie and Chang (2011), Brunnermeier, *et al.*, (2008), Ismailov and Rossi (2018), Mulder and Tims (2018), and Ramirez-Rondan and Terrones (2019) show that the validity of UIP depends on market and exchange rate uncertainties.

estimate in the presence of these proxy variables, and use it to infer the implications of these proxies for the empirical relevance of UIP.

In view of non-uniform effects due to model uncertainty and time-varying parameters, we adopt the Bayesian dynamic linear model approach coupled with a modified dynamic model average procedure (Raftery, *et al.*, 2010; West and Harrison, 1997) to infer the varying degrees of importance of proxy variables and time-varying parameters. As UIP describes and explains the linkage between the foreign exchange and money markets, we assess the explanatory rather than the predictive power of the empirical model and, thus, follow the explanatory, instead of predictive, modelling approach for our empirical exercise.[4] In this regard, we conduct statistical inferences based on the retrospective perspective that incorporates information in the entire sample, and use the retrospective posterior distributions to study the shifting relevance of explanatory variables and the time-varying parameters.

We measure the degree of UIP failure by the deviation of the β-estimate from its theoretical value of one. Specifically, we compare the time-varying β-estimates from the canonical bivariate UIP specification and from specifications augmented with proxy variables. And, we assess if the presence of proxy variables leads to a reduction of the β-estimate's deviation from one, and test if the reduction is statistically significant.

To anticipate results, we affirm that the β-estimate – our measure of UIP behavior – is non-uniform over time and across the nine exchange rates against the US dollar derived from the G-10 currencies. Relatively speaking, the β-estimate tends to be negative before the 2007-8 global financial crisis (GFC) and positive after. Further, it exhibits large sampling uncertainty.

[4] Shmueli (2010), for example, discusses the differences between explanatory and predictive modelling, and suggests explanatory modelling is retrospective.

There is evidence that regressions augmented with empirical proxies for CIP deviations, risk premiums and expectational errors can reduce UIP deviations indicated by either a reduction in the mean deviation or in the mean absolute deviation of time-varying β-estimates from one. The composition of the set of relevant proxies changes over time; a finding that is in line with the scapegoat theory. Further, the set of empirical proxies that improves the UIP result, and the effects of individual proxies vary across exchange rates.

The non-uniform effects due to time-varying set of relevant proxies (model uncertainty) and time-varying parameters can contribute to the difficulty of revealing the UIP relationship. There are caveats to the reported improved UIP results. For instance, while the β-estimate is closer to its predicted value of one under UIP, the sampling uncertainty is not reduced in the presence of proxy variables. The improvement patterns also depend on the amount of data information used to compute the time-varying parameters.

Section 2 presents an empirical UIP framework that includes CIP deviations, risk premiums and expectational errors. Section 3 introduces the data and empirical proxy variables used in the study, and outlines the Bayesian dynamic linear model and modified dynamic model averaging setup. A more detailed discussion of the data and these empirical procedures is provided in the Appendix. Section 4 presents the empirical results. Section 5 offers some additional discussions. Section 6 concludes.

2. An Empirical UIP Framework

UIP is a key parity relation commonly used in models of international macroeconomics and finance, and it connects foreign exchange and money markets. Essentially, UIP condition states that the expected exchange rate movement will be offset by the difference in the domestic and foreign interest rates. Under log approximations, the parity relation can be written as:

$$E_{t-1}(s_t) - s_{t-1} = i_{t-1,t} - i^*_{t-1,t}, \tag{1}$$

where s_t is the logarithm of the spot exchange rate at time *t* that is quoted as domestic currency per unit of foreign currency, $E_t(\cdot)$ is the expectations operator conditional on information available at time *t*, $i_{t-1,t}$ and $i^*_{t-1,t}$ are 1-period domestic and foreign interest rates available at time *t*-1. Equation (1) states that expected depreciation of exchange rate is offset by cross-country interest rate differential (henceforth, "interest rate differential" for brevity). Arguably, equation (1) is only valid under some ideal conditions including capital mobility, rational expectations, and risk neutrality. Allowing for the deviation from UIP ($\mu^u_{t\text{-}1,t}$), the parity condition can be re-written as

$$E_{t-1}(s_t) - s_{t-1} = i_{t-1,t} - i^*_{t-1,t} + \mu^u_{t\text{-}1,t}. \tag{2}$$

The well-known empirical failure of UIP is typically illustrated by the regression:

$$y_t = \alpha + \beta \nabla i_t + \eta_t;\ t = 1, \ldots, T, \tag{3}$$

where $y_t \cong s_t - s_{t-1}$, $\nabla i_t \cong i_{t-1,t} - i^*_{t-1,t}$, T is the sample size, and the empirical β-estimate tends to be less than one or even negative. In view of (2), the residual term η_t comprises the usual random sampling error (ε_t), the UIP deviation ($\mu^u_{t\text{-}1,t}$) and the expectational error ($s_t - E_{t-1}(s_t)$).

To shed some insight on $\mu^u_{t\text{-}1,t}$, we consider the covered interest rate parity (CIP) with deviations ($\mu^c_{t\text{-}1,t}$s) given by

$$f_{t-1,t} - s_{t-1} = i_{t-1,t} - i^*_{t-1,t} + \mu^c_{t\text{-}1,t} \tag{4}$$

where $f_{t-1,t}$ is the logarithm of the 1-period forward exchange rate. It can be shown that

$$\mu^c_{t\text{-}1,t} = f_{t-1,t} - E_{t-1}(s_t) + \mu^u_{t\text{-}1,t}; \tag{5}$$

where $f_{t-1,t} - E_{t-1}(s_t)$ is the foreign exchange risk premium. That is, the wedge between the UIP and CIP deviations is the risk premium. In view of (5), the term η_t in (3) is the sum of the usual random sampling error (ε_t), the CIP deviation ($\mu^c_{t\text{-}1,t}$), the risk premium ($f_{t-1,t} - E_{t-1}(s_t)$), and the expectational error ($s_t - E_{t-1}(s_t)$). The canonical UIP regression (3) can be re-written as

$$y_t = \alpha + \beta \nabla i_t + \gamma z_t + \varepsilon_t \,, \tag{6}$$

where the vector z_t comprises a) $C\hat{I}Pd_{t-1}$ that includes empirical proxies for $\mu^c_{t\text{-}1,t}$, b) $R\hat{P}_{t-1}$ empirical proxies for ($f_{t-1,t} - E_{t-1}(s_t)$), and c) $E\hat{R}_t$ empirical proxies for ($s_t - E_{t-1}(s_t)$). For brevity, we call the elements of z_t the control variables.

Conceivably, estimating (3) without the proper set of control variables can lead to a biased β-estimate; the magnitude of biasedness depends on the association between the omitted control variables and the cross-country interest rate differential.

3. Data and Econometric Methodology

We consider end-of-quarter observations of the nine exchange rates against the US dollar derived from the G-10 currencies, the corresponding three-month forward exchange rates, and the three-month euro-currency deposit rates of the G-10 currencies from 1990Q1 to 2018Q4.[5] The G-10 currencies comprise Australian dollar (AUD), Canadian dollar (CAD), Euro (EUR), Japanese yen (JPY), New Zealand dollar (NZD), Norwegian krone (NOK), Pound sterling (GBP), Swedish krona (SEK), Swiss franc (CHF), and United States dollar (USD).[6]

The following subsections list the empirical proxy variables for CIP deviations, risk premiums, and expectational errors. Appendixes A.1 to A.3 describe the sample periods, data sources, and definitions/construction of these variables and other variables used in the study.

[5] 1990Q1 to 2018Q4 represents the maximum sample period. Due to data availability, some currencies have a shorter sample; for instance, Euro starts at 1999Q1; see Appendix A.1.

[6] The G-10 currencies and the Group of Ten Countries do not cover the same set of economies. See, for example, https://www.bis.org/list/g10publications/ for the G-10 countries.

Then, we outline the empirical methodology that includes the Bayesian dynamic linear model and modified dynamic model averaging. Appendix B offers additional discussions of these empirical methods.

3.1 The Proxy for CIP Deviations, $\hat{CIPd}_{t-1}$

For developed countries, the CIP deviations are typically small and transitory before the 2007-8 GFC, and have significantly increased after (Akram, *et al.*, 2008; Avdjiev, *et al.*, 2019; Baba and Packer, 2009; Cerutti, *et al.*, 2019; Du, *et al.*, 2018). The CIP deviation is commonly measured by the cross-country basis.

It is noted that the time gap between our data on euro-currency deposit rates and the corresponding spot and forward exchange rates is no longer than one hour. Our data are quite well synchronized for constructing exchange rate changes, interest rate differentials, and the cross-currency basis.

The plots of these CIP deviations (Appendix C.1) corroborate the usual notion that, with the exception of a few currencies in the beginning of the 1990s, the deviations tended to be small before the 2007-8 GFC, experienced large swings during the crisis, and have noticeably increased since.[7] However, there is not a clear pattern across these currencies.

3.2 Proxies for Risk Premiums, $\hat{RP}_{t-1}$

The risk premium ($f_{t-1,t} - E_{t-1}(s_t)$) is what required to compensate an investor to assume the foreign exchange risk in trading currency. Existing UIP studies have considered alternative

[7] These CIP deviations are not as significant as those reported in, say, Du, *et al.* (2018), who used New York closing of spot and forward exchange rates and LIBOR rates, which have a time gap of about 10 hours.

approaches to model and quantify the unobserved risk premium. We selected from existing studies 15 empirical proxies for the risk premium, and grouped them into three categories.

The first category includes eight proxy variables that are related to the relative *macroeconomic* environment. They are cross-country differences of inflation rates, interest rate changes, money supply growth rates, output growth rates, productivity growth rates and changes of unemployment rates, a macroeconomic uncertainty index (Jurado, *et al.*, 2015), and an economic policy uncertainty index (Baker, *et al.*, 2016).[8]

The second category includes three proxies for risks in the *US financial markets* and two proxies for the *global foreign exchange market*. Given her prominent position in the global market, risk and uncertainty in the US financial market are conceived to have effects on financial prices overseas and spillovers to exchange rates.[9] The three US-related proxy variables are the VIX index, the TED spread (the difference between three-month US Treasury bill rate and the three-month US dollar LIBOR), and a US financial uncertainty index (Jurado, *et al.*, 2015). The global foreign exchange market risk is captured by the realized upside and downside semi-variances (Barndorff-Nielsen, *et al.*, 2010; Menkhoff, *et al.*, 2012). The two global semi-variance measures are constructed from individual semi-variances with equal weights, and are used to capture the possible asymmetric effects of upside and downside volatilities faced by investors.[10]

The third category comprises two *country-specific* proxies for financial market risks. They are a) the cross-country difference of MSCI returns (Gavin, 1989; Hossfeld and MacDonald, 2015;

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8 These variables are considered by, for example, Amat, *et al.* (2018), Bacchetta and Van Wincoop (2010), Beckmann and Schüssler (2016), Berg and Mark (2018a, b), Boudoukh, *et al.* (2016), Cheung (1993), Dornbusch (1976), Engel, *et al.* (2019), Gourinchas and Tornell (2004), Husted, *et al.* (2018), Moran and Nono (2018), and Sarno and Valente (2009). Rogers and Xu (2019) assesses the performance of economic uncertainty measures.

9 See, for example, Brunnermeier, *et al.* (2008), Bussiere, *et al.* (2018), Du, *et al.* (2018), Engel and Wu (2018), Husted, *et al.* (2018), and Ranaldo and Söderlind (2010).

10 Studies relate volatility to risk premiums include Li, *et al.* (2012) and Londono and Zhou (2017). Studies use downside risks include Ang, *et al.* (2006), Atanasov and Nitschka (2014) and Barndorff-Nielsen, *et al.* (2010).

Phylaktis and Ravazzolo, 2005; Ranaldo and Söderlind, 2010), and b) the lagged exchange rate changes (Baillie and Chang, 2011; Menkhoff, *et al.*, 2012).

Note that the risk premium enters equation (6) as $f_{t-1,t} - E_{t-1}(s_t)$. Thus, these risk premium proxies observed at time *t*-1 are included in the following regression exercise.

3.3 Proxies for Expectational Errors, $E\hat{R}_t$

The expectational error ($s_t - E_{t-1}(s_t)$) occurs where there are unforeseeable and unexpected shocks affecting the market between time *t*-1 and *t*. We consider 11 proxies for the expectational error, and group them into three categories. These proxy variables observed between *t*-1 and *t* are included in the following regression exercise.

Motivated by PPP and monetary models, the first category includes four proxies for *macro* shocks – three proxies capture shocks to the cross-country differences of inflation rates, money supply growth rates and output gaps, and one given by the contemporaneous change in interest rate differentials.

The second category comprises four proxies for shocks to the *US financial markets* and the *global foreign exchange market*. Specifically, the contemporaneous VIX index and TED spread are used to capture shocks to the US stock market and liquidity conditions (Engel, 2016; Habib and Stracca, 2012; Hossfeld and MacDonald, 2015; Menkhoff, *et al.*, 2012; Ranaldo and Söderlind, 2010). The realized upside and downside jump variables are used to represent shocks in the global foreign exchange market (Barndorff-Nielsen and Shephard, 2006; Barndorff-Nielsen, *et al.*, 2010).[11]

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[11] Individual exchange rate jumps are combined with equal weights to derive the corresponding global jump measures to capture unexpected upward and downward shocks to the global foreign exchange market.

The third category includes three *uncertainty* indexes – the macroeconomic uncertainty index and financial uncertainty index (Jurado, *et al.*, 2015) are based on prediction errors, and the economic policy uncertainty index (Baker, *et al.*, 2016) reflects economic policy-related uncertainty reported in newspapers.

In sum, we select a total of 27 empirical proxy variables for CIP deviations, risk premiums, and expectational errors. With the exceptions of the lead and the lag of the macroeconomic uncertainty index and of the lead and the lag of the financial uncertainty index, the correlation of these proxy variables is mostly less than 0.6. The results presented below indeed do not indicate issues attributable to collinearity of these proxy variables.

3.4 Econometric Methodology

There are some issues to consider before estimating (6). First, the effect of interest rate differential is time varying and exchange-rate specific **(**Bussiere, *et al.*, 2018; Ismailov and Rossi, 2018; Lothian and Wu, 2011). To accommodate time-varying and exchange-rate specific behavior, we consider an equation-by-equation time-varying set up.

Besides time varying effects, the composition of proxies of the vector z_t in (6) can change over time. We selected in the previous subsection 27 proxy variables as control variables. Different studies consider different proxies. We do not have a strong theory on which proxy is the best one for which unobserved variable. Or, shall all these proxies or just a subset of them be used at all time?

The scapegoat theory (Bacchetta and Van Wincoop, 2004; 2013) postulates that, as market participants alter their beliefs, the role of fundaments in the foreign exchange market can shift over time. Cheung and Chinn (2001) report that market participants do alter their views on the relative importance of macroeconomic variables. The scapegoat theory is in accordance with the finding of different empirical models perform differently in different historical time periods across currencies (Cheung, *et al*., 2005; Cheung, *et al*., 2019; Rossi, 2013).[12] Since UIP depends on arbitrage behaviors between foreign exchange and money markets, the shifting roles of exchange rate fundamentals in alternating market conditions can affect an investor's perception about the proxies for unobserved factors relevant to UIP. The composition of empirical proxies appropriate for the UIP regression can change over time. In the following, we use data-driven retrospective posterior distributions to assess the relevance of the empirical proxy variables and, hence, address model uncertainty.

To address both time-varying effects and model uncertainty, we adopt the Bayesian dynamic linear model (DLM) approach and a modified dynamic model averaging (DMA) procedure with a retrospective perspective (Raftery, *et al.*, 2010; West and Harrison, 1997). DLM allows time-varying parameters and DMA offers a tractable way to account for model uncertainty. As said before, we are interested in studying the in-sample β-estimate in the presence of control variables. Thus, we follow the retrospective perspective (Shmueli, 2010) and incorporate information from the entire sample to evaluate the empirical UIP relationship.

In that regard, we modify (6) and consider the DLM setup (Beckmann and Schüssler, 2016; Byrne, *et al.*, 2018; Koop and Korobilis, 2012; Raftery, *et al.*, 2010) given by

$$y_t = \boldsymbol{x}_t'\boldsymbol{\theta}_t + \varepsilon_t, \ \ \varepsilon_t \sim N(0,V), \text{ and} \tag{7}$$

$$\boldsymbol{\theta}_t = \boldsymbol{\theta}_{t-1} + \delta_t, \ \ \delta_t \sim N(0,\boldsymbol{W}_t), \tag{8}$$

[12] Some empirical studies on the scapegoat theory and exchange rate determination are Bacchetta and Van Wincoop (2013), Cao, *at al.* (2019), Fratzscher, *et al.* (2015), Markiewicz (2012), and Pozzi and Sadaba (2018).

where $x_t' \cong (1, \nabla i_t, z_t)$, $\boldsymbol{\theta}_t$ contains the corresponding time-varying parameters α_t, β_t, and γ_t, and $\boldsymbol{W}_t$ is the variance of the error term δ_t that defines the degree of parameter variability. If $\boldsymbol{W}_t = 0, \forall t$, the model is a static one.

Bayesian methods are used to recursively generate $\boldsymbol{\theta}_t$- estimates and their filtered distributions. The recursive estimation is initialized with the first 20 observations, and the initial values used to initialize the recursive procedure are given in Appendix B.4. The inference is based on the retrospective distribution of $\boldsymbol{\theta}_t$ and retrospective sample likelihood function from the retrospective estimation procedure.

The data driven retrospective likelihood values are used to determine the relative importance of alternative model specifications and to conduct the model averaging analysis. Suppose there are *K* model specifications constructed from our selected empirical proxy variables. Instead of exercising the latitude in selecting one of these *K* models, we employ the retrospective sample likelihood functions of all the *K* models and the retrospective posterior distributions of parameters of each of these *K* specifications. The retrospective sample likelihood functions are used to derive the retrospective model probabilities, which indicate the relative importance and relevance of these *K* models. These retrospective model probabilities are also used to construct weights to adjust the retrospective estimates from the *K* models to obtain the model averaging retrospective estimate of $\boldsymbol{\theta}_t$. The technique of model averaging offers a formal way to obtain combinations of estimates from multiple models.

The relative relevance of an empirical proxy variable is inferred from the sum of the retrospective probabilities of models that include the proxy; we label it the proxy's retrospective inclusion probability. If we associate this probability measure to the posterior inclusion probability of the usual Bayesian model averaging approach, we can label a proxy to have an acceptable, substantial, strong, or decisive effect if it has a retrospective inclusion probability between, respectively, 0.5 and 0.75, 0.75 and 0.95, 0.95 and 0.99, and 0.99 and 1. The proxy is not "important" if its retrospective inclusion probability less than 0.5.

A detailed description of the econometric setup and the calculation of retrospective model probabilities are given in Appendix B.

4. Empirical Analysis

As a reference point, we present results from bivariate UIP regressions. Then, we report the interest rate differential effect in the presence of control variables; that is, the empirical proxies for CIP deviations ($C\hat{I}Pd_{t-1}$), risk premiums ($R\hat{P}_{t-1}$), and expectational errors ($E\hat{R}_t$).

4.1 Bivariate UIP Regressions

Table 1 presents the results of estimating the canonical UIP time invariant regression (3). The currency labels indicate the exchange rates against the US dollar, and are arranged from left to right in the order of increasing average interest rate differential (against the US dollar interest rate) shown in the row labelled "Mean (∇i)".

The top panel presents results from the entire sample from 1990Q1 to 2018Q4. The β-estimate ranges between -1.421 and 1.307. The β-estimates of JPY, CHF, EUR, AUD and NZD are negative but insignificantly different from zero, but those of JPY and AUD are significantly different from one, which is the value under the UIP stipulation. Note that JPY, CHF and EUR have the three smallest average interest rate differentials and are commonly conceived as funding currencies of carry trade, while AUD and NZD have the two largest average interest rate differentials and are the typical target currencies. The remaining three exchange rates; namely, SEK GBP, and NOK yield β-estimates that are quite close to 1, but they are not statistically different from zero.

Our β-estimate results – insignificance due to large standard errors with a negative bias are largely in accordance with the existing studies (Bussiere, *et al.*, 2018; Chinn and Frankel, 2019; Engel, 2016; Ismailov and Rossi, 2018). Note that the intercept estimates (α-estimates) are insignificant, and the explanatory power of the model is quite limited as the adjusted R^2 estimates are quite small if not negative.

The remaining three panels in Table 1 present results from three subsamples; 1990Q1-1997Q2, 1997Q3-2007Q2 and 2007Q3-2018Q4 that are separated by the 1997 Asian Financial Crisis and the 2007-8 GFC. The β-estimates from these subsamples exhibit patterns that are more volatile than and different from those of the full sample, and are noticeably different across subsamples. In the first subsample period, four currencies have a negative β-estimate, and four have a positive one.[13] Three β-estimates reject the hypothesis of $\beta = 1$; two of which are negative and the remaining one is positive. All the nine β-estimates are negative in the second sub-sample period, and seven of them are significantly different from 1.[14] In the last sub-sample period, however, eight out of nine β-estimates are larger than 1, and one is significantly larger than 1 (Bussiere, *et al.*, 2018).[15] The explanatory power of the interest rate differential, according to the adjusted R^2 estimates, is small and even negative with the exception of the SEK case in the first subsample period.

These subsample results do not lend support to UIP, and are suggestive of time-varying behavior. There is no discernable association between UIP deviations and average interest rate

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13 The EUR data are not available for the first subsample.
14 Lothian and Wu (2011) shows that a negative estimate is specific to some historical periods like the 1980s.
15 If the subsample starts at 2009Q1, the resulting β-estimates become smaller, and some even turn negative.

differentials. The stark contrast between the β-estimates of the second and third subsample mirrors the very different economic conditions in these two historical periods. A time-invariant specification is likely to disguise the non-constant interest rate differential effect.

Table 2 summarizes the results of estimating the bivariate time-varying specification given by (7) and (8) with $x_t' \cong (1, \nabla i_t)$. We set the λ parameter for updating the variance W_t in (8) to 0.95. The choice of λ is analogous to the choice of an effective window size $(1-\lambda)^{-1}$ that determines the rate of discounting past observations; a larger λ implies a larger weight assigned to a past observation, and W_t is effectively zero at the limit of λ = 1.[16]

The average values of the retrospective intercept estimates ($\hat{\alpha}_{t|T}$) and of their standard errors are given in the rows labelled, respectively, "Mean α" and "Mean se α." There is no indication of a significant intercept estimate. "MAD α" gives the mean absolute value (MAD) of {$\hat{\alpha}_{t|T}$}. Note that "MAD α" is defined with reference to α's theoretical value of zero.

Similarly, the rows labelled "Mean β" and "Mean se β" gives the average values of $\hat{\beta}_{t|T}$ estimates and of their standard errors. The results affirm the finding that there is a high level of uncertainty associated with estimating β. Compared with results in the first panel of Table 1, EUR and NZD yield a positive average β-estimate instead of a negative β-estimate; accounting for time variability can affect the sign of the (average) β-estimate.

To gauge UIP deviations, we report the mean absolute deviation of $\hat{\beta}_{t|T}$ from 1 under the row labelled "MAD β" – that is, the MAD with reference to β's *theoretical value of one*. The MAD

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16 The practice of discounting past observations is discussed, for example, in Raftery, *et al.* (2010), and documented in learning experiments (Cheung and Friedman, 1997) and stock return modelling (Cassella and Gulen, 2018). Summary results based on λ = 0.96, 0.97, 0.98, and 0.99 are discussed in Subsection 5.3.

measure is typically large; AUD and NZD that are the typically carry trade target currencies display a high level of "MAD" that is larger than 2.

The time variability and the sampling uncertainty of the retrospective β-estimate ($\hat{\beta}_{t|T}$) are depicted in Figure 1. One striking observation is that the wide 95% credible interval literally makes it impossible to infer a precise value of β. Even allowing for time variations, the bivariate specification is not very informative about the UIP hypothesis. While the β-estimate tends to increase with time, the pattern of UIP deviations is non-constant across exchange rates.

4.2 Augmented UIP Regressions

In this subsection, we consider (7) and (8) with the z_t vector defined by alternative combinations of the 27 selected proxy variables. The total number of possible models is to 2^{27} (=134,217,728), which far exceeds our computing capacity. Thus, we have to consider these proxy variables in categories as listed in Subsections 3.1 to 3.3. Specifically, we conduct the retrospective analysis under the DLM-DMA setting first with each one of $C\hat{I}Pd_{t-1}$, $R\hat{P}_{t-1}$, and $E\hat{R}_t$ individually, and then with some synthetic combinations of these categories. For brevity, we focus on results pertaining to the β-estimate.[17]

4.2.1 The Proxy for CIP deviations, $C\hat{I}Pd_{t-1}$

The effect of including our proxy for CIP deviations – the cross-currency basis – on the β-estimate is summarized in Table 3.[18]

[17] The intercept α-estimates are in general small and insignificant in all these regressions.

[18] The coefficient estimates of CIP deviations are highly variable; the ranges of the mean values and of the mean standard errors are (-38.8, 9.9) and (13.2, 40.2). The presence of CIP deviation proxy also inflates the sampling uncertainty of the β-estimate.

Corresponding to the statistics reported in the rows labelled "Mean β" and "MAD β," we present respectively the ratios $|\Sigma_t(\hat{\beta}^{aug}_{t|T}-1)|/|\Sigma_t(\hat{\beta}^{biv}_{t|T}-1)|$ and $\Sigma_t|\hat{\beta}^{aug}_{t|T}-1|/\Sigma_t|\hat{\beta}^{biv}_{t|T}-1|$ that are derived from the absolute value of the mean deviation of β-estimates from one and the mean absolute deviation of β-estimate from one, where $\hat{\beta}^{biv}_{t|T}$ is the retrospective β-estimate in Table 2 and $\hat{\beta}^{aug}_{t|T}$ is the corresponding retrospective estimate in Table 3. A ratio less than one – indicated by bold figures – implies the estimated level of UIP deviation implied by $\hat{\beta}^{biv}_{t|T}$ is larger than the corresponding one implied by $\hat{\beta}^{aug}_{t|T}$; that is, the inclusion of the proxy for CIP deviations weakens the evidence on UIP failure.

According to these ratios, CHF, EUR, and AUD have a smaller absolute value of mean deviation from one and CHF, CAD, and AUD have a smaller mean absolute deviation from one. For other cases, the inclusion of the proxy does not improve the result, and actually leads to a larger degree of average UIP deviation.

To infer the significance of the MAD difference, we calculate the Diebold-Mariano (DM) type "loss differential": $T^{-1}\Sigma_t(|\hat{\beta}^{biv}_{t|T}-1|-|\hat{\beta}^{aug}_{t|T}-1|)$ (Diebold and Mariano, 1995), and report the DM statistics under the row labelled "DM." The reduction of MAD is statistically significant for CHF and AUD. Despite MAD is still large, the improvement to the level of 1.071 from 1.416 for CHF and to 2.307 from 2.513 for AUD is statistically significance. However, the CIP deviation proxy yields evidence that, relative to the bivariate reference specification, is less favorable to the UIP hypothesis for the cases of JPY and NZD.

In sum, the implications of the CIP deviation proxy for UIP are mixed across currencies, and the evidence on improving UIP result is limited.

4.2.2 Proxies for Risk Premiums, $\hat{RP}_{t-1}$

From existing studies, we selected 15 empirical proxy variables for risk premiums and grouped them into three categories (Subsection 3.2). We augment the bivariate specification with each of the seven possible combinations of the three categories of proxies. For each augmented specification, we adopt the DMA approach to find, period by period, the "best" model averaging representation. Since there are eight proxies under the macro category, five under the US-Global category, and two under the country-specific category, the number of potential models included in each of the seven combinations of proxy categories ranges from 4 (=2^2) to 32,768 (=2^{15}). The DLM-DMA setup allows, for each augmented specification, the set of relevant proxies and their effects to change over time.

Table 4 summarizes the β-estimates from specifications augmented with alternative combinations of categories of risk premium proxies. Again, the ratios $|\Sigma_t(\hat{\beta}^{aug}_{t|T}-1)|/|\Sigma_t(\hat{\beta}^{biv}_{t|T}-1)|$ and $\Sigma_t|\hat{\beta}^{aug}_{t|T}-1|/\Sigma_t|\hat{\beta}^{biv}_{t|T}-1|$ are presented underneath, respectively, the rows of "Mean β" and "MAD β." A ratio less than one – indicated by bold figures – suggests that, compared with the $\hat{\beta}^{biv}_{t|T}$ in Table 2, the $\hat{\beta}^{aug}_{t|T}$ from the augmented UIP regression indicated by the label in the first column yields a smaller degree of UIP failure.

A few observations are in order. First, out of the total 126 cases, there are 59 cases in which $\hat{\beta}^{aug}_{t|T}$ compared with $\hat{\beta}^{biv}_{t|T}$ is closer to unity by either the ratio based on the absolute value of mean deviation or the mean absolute deviation. The implication of a specific combination of categories for the β-estimate depends on whether the mean deviation or the absolute mean deviation criterion is considered.

Second, these 59 "improved" cases are not distributed evenly across these seven combinations of proxy categories. For example, the country-specific category yields 6 improved cases, while the combination of the US-Global and country-specific categories has 10 improved cases. Also, the ability of these proxy categories to enhance UIP results appears exchange-rate-specific. The AUD case offers the most encouraging finding; these combinations of proxy categories, with exception of the country-specific category, improve UIP results. These proxies, however, do not improve the UIP result for JPY.

Third, among the 32 cases in which the MAD ratio $\Sigma_t |\hat{\beta}_{t|T}^{aug} - 1| / \Sigma_t |\hat{\beta}_{t|T}^{biv} - 1|$ shows an improvement, 10 (17) cases are statistically significant at the 10% level of a two-sided (one-sided) test. JPY, CAD and NOK do not garner any significant improvement case. On the other hand, there are 22 cases in which the presence of proxy variables worsens the UIP result; indicating that some of these proxies are not relevant for alleviating the UIP failure.

4.2.3 Proxies for Expectational Errors, $E\hat{R}_t$

The implications of expectational errors are assessed using three categories of corresponding empirical proxy variables; namely the categories of macro shocks, of shocks to the US financial market and the global foreign exchange market, and of uncertainty indexes (Subsection 3.3). Similar to the previous Subsection, we consider the seven UIP regressions augmented with alternative combinations of these three categories of proxy variables, and summarize the resulting β-estimates in Table 5.

According to the ratios $|\Sigma_t(\hat{\beta}_{t|T}^{aug} - 1)| / |\Sigma_t(\hat{\beta}_{t|T}^{biv} - 1)|$ and $\Sigma_t |\hat{\beta}_{t|T}^{aug} - 1| / \Sigma_t |\hat{\beta}_{t|T}^{biv} - 1|$ underneath the "Mean β" and "MAD β" rows in Table 5, the inclusion of these empirical proxy variables for expectational errors improves 49 cases out of the total of 126 cases. The number of improved cases is slightly less than the 52 recorded in Table 4.

Similar to those in Table 4, these 49 improved cases are not distributed evenly either across the seven augmented UIP specifications or across the exchange rates. One observation is that UIP specifications augmented with a single category of proxies yields a larger number of improved cases than those augmented with multiple categories; indicating that these proxy categories are not necessarily complementary. Further, the effects of these proxies for expectational errors on the β-estimate are different from those for risk premiums. A case in point is AUD – the risk premium proxies yield an improved UIP result in 12 of 14 cases, while the expectational error proxies yield zero improved case.

The DM statistic indicates that, among the 34 cases in which the MAD ratio $\Sigma_t \,|\, \hat{\beta}_{t|T}^{aug} - 1 \,|\, / \Sigma_t \,|\, \hat{\beta}_{t|T}^{biv} - 1 \,|$ is less than one, 16 (20) cases show a significant reduction in MAD at the 10% level of a two-sided (one-sided) test. The relative number of significant cases is higher than the corresponding one in Table 4. The NZD highlights the role of these empirical proxies for expectational errors – in all seven augmented specifications, the MAD is smaller than the corresponding one in Table 2. There are three exchange rates; namely, JPY, SEK and AUD record no case of significant improvement. Further, Table 5 has 13 cases in which the degree of UIP failure is significantly worse than the bivariate setup, and Table 4 has 22 such cases.

4.3 Synthetic UIP Regression Specification

The individual roles of $C\hat{I}Pd_{t-1}$, $R\hat{P}_{t-1}$, and $E\hat{R}_t$ are presented in the previous subsections. The evidence of these selected empirical proxy variables to reduce the β-estimate's deviation from one is mixed. For instance, these results do not identify a consistent positive role of a given category of proxy variables. Our findings collaborate with the belief that these (proxies for) unobserved factors have different implications for the observed UIP failure, and their effects are non-uniform over time and exchange-rate specific.

In this subsection, we consider specifications with selected combinations of proxies for CIP deviations, risk premiums, and expectational errors. For each exchange rate, we refer to Tables 2, 3 and 4 and form synthetic augmented UIP models with the CIP deviation proxy, the category of risk premium proxies, and the category of expectational error proixes that lead to a significant reduction in MAD of the β-estimate. Given a synthetic specification we conduct the DLM-DMA retrospective analysis with model averaging applied to the included proxies. Table 6 summarizes the results of β-estimates from the synthetic models in the upper panel, and the corresponding included categories of proxy variables in the lower panel.

Because the JPY case does not yield any improved UIP result, the JPY result in Table 6 is the same as the one in Table 2.[19] In the following, we focus on the remaining eight cases. The synthetic specifications of CHF, EUR, AUD, and NZD include two categories from the three sources of $C\hat{I}Pd_{t-1}$, $R\hat{P}_{t-1}$ and $E\hat{R}_t$, while the remaining four cases include a single category. Each of $R\hat{P}_{t-1}$ and $E\hat{R}_t$ contributes five times to these synthetic specifications.

The ratio $|\Sigma_t(\hat{\beta}_{t|T}^{aug}-1)|/|\Sigma_t(\hat{\beta}_{t|T}^{biv}-1)|$ based on the absolute values of mean deviation indicates that the synthetic model yields $\hat{\beta}_{t|T}^{aug}$ that is, on average, closer to one than $\hat{\beta}_{t|T}^{biv}$ for five of the eight exchange rates; these five improved cases have a positive average $\hat{\beta}_{t|T}^{aug}$. For SEK, GBP, and NZD, the average $\hat{\beta}_{t|T}^{aug}$ is quite close to the UIP predicted value of one. Of these eight cases, only EUR has a negative average $\hat{\beta}_{t|T}^{aug}$.

The MAD ratio $\Sigma_t|\hat{\beta}_{t|T}^{aug}-1|/\Sigma_t|\hat{\beta}_{t|T}^{biv}-1|$ offers encouraging UIP results. With the exception of EUR, the $\hat{\beta}_{t|T}^{aug}$ from synthetic models has a MAD smaller than the MAD of the corresponding

19 The no-proxy-effect for JPY is unique to the case of λ = 0.95. Subsection 5.3 notes the sensitivity to the choice of λ value. Also, the SEK synthetic specification is the improved case based on a one-sided test in Table 4.

$\hat{\beta}^{biv}_{t|T}$. For six (seven) of these seven improved cases, the reduction in MAD is statistically significant at the 10% level of a two-sided (one-sided) test. The omission of these selected proxies can sway the β-estimate away from its predicted value of one.

Figure 2 plots, for each exchange rate, the empirical density distributions of $|\hat{\beta}^{biv}_{t|T}-1|$ (dashed line) and $|\hat{\beta}^{aug}_{t|T}-1|$ (solid line) of the corresponding synthetic model. The JPY case shows only the $|\hat{\beta}^{biv}_{t|T}-1|$ density plot, which is bi-modal. The synthetic model reduces the absolute deviation from one in different forms. The cases of CHF, SEK, GBP, NOK and NZD show a noticeable shift of the density mass towards zero, while CAD and AUD give density distributions with shapes similar to the corresponding bivariate $|\hat{\beta}^{biv}_{t|T}-1|$ setting, but with the mass shifted to the left.

We note that $|\hat{\beta}^{aug}_{t|T}-1|$ from the synthetic model of EUR has a density distribution more diffused/flattened than $|\hat{\beta}^{biv}_{t|T}-1|$. If we consider a synthetic model that augments the bivariate specification with either the two categories of risk premium proxies or the two categories of expectational errors proxies (Panel B, Table 6), then the $|\hat{\beta}^{aug}_{t|T}-1|$ from each of the two alternative augmented specifications has a density mass closer to zero than the corresponding $|\hat{\beta}^{biv}_{t|T}-1|$; these density plots are presented in Appendix C.2. The results are in line with the DM test results in Tables 4 and 5, and suggest the EUR synthetic model in Table 6 may suffer collinearity of explanatory variables.

These results based on the DM statistics and the ratios $|\Sigma_t(\hat{\beta}^{aug}_{t|T}-1)|/|\Sigma_t(\hat{\beta}^{biv}_{t|T}-1)|$ and $\Sigma_t|\hat{\beta}^{aug}_{t|T}-1|/\Sigma_t|\hat{\beta}^{biv}_{t|T}-1|$ indicate that the inclusion of an appropriate collection of empirical proxy variables can deliver a β-estimate that is close to its UIP predicted value of one.

To shed some insight on sampling uncertainty, we plot for each exchange rate the $\hat{\beta}_{t|T}^{biv}$ (dashed line) and the $\hat{\beta}_{t|T}^{aug}$ (solid line) in Figure 3. With the exception of JPY and EUR, $\hat{\beta}_{t|T}^{aug}$ is closer to its UIP predicted value of one than the corresponding $\hat{\beta}_{t|T}^{biv}$. The CAD case illustrates that, compared with the absolute value of mean deviation, the mean of absolute deviation can be a better measure as, before taking the absolute value, averaging can offset the effects of large deviations with opposite signs.

The 95% credible intervals of $\hat{\beta}_{t|T}^{aug}$ cover a wide range that includes the value of one, and tend to be larger towards the end of the sample period. While the presence of the selected proxies moves the β-estimate towards the value of one, it does not provide a precise inference. Given the wide credible interval, we are not sure if the true value of β is one.[20]

In sum, we have to exercise caution in interpreting the improved UIP result afforded by these empirical proxy variables.

5. Additional Discussions

In the previous section, we focused on the implications of empirical proxy variables for the interest rate differential effect, which is used to assess the relevance of UIP. In this Section, we use the case of NZD to illustrate, for a given selected empirical proxy variable, the time variation of its relevance and its time-varying effects. Then, we briefly discuss the results from varying the λ parameter that controls the amount of past information used to calculate the time-varying parameters, and carry trade.

5.1 Relevance or Irrelevance

[20] The wide 95% credible interval result also impairs our ability to find significant asymmetric interest rate differential effects (Bansal and Dahlquist, 2000; Bussiere, *et al.*, 2018).

Drawing insights from the scapegoat theory (Bacchetta and Van Wincoop, 2004, 2013), we anticipate that the appropriate set of proxies for augmented UIP specifications can vary in different historical time periods, and display non-uniform effects over time. The DLM-DMA framework allows us to assess a proxy's shifting role and its non-constant effect over time.

As an illustration, we consider the NZD synthetic specification that yields the most encouraging UIP result in Table 6. As the NZD specification includes, in addition to the interest rate differential variable, eight macro proxies for risk premiums and four US-Global proxies for expectational errors, there are $2^{12} = 4,096$ component models in the model space.

Figure 4 plots for each proxy its time-varying retrospective inclusion probability given by the sum of retrospective probabilities of models that include the proxy. All the 12 proxies have a retrospective inclusion probability larger than 0.5 for most of time during the sample period; indicating their relevance in the regression.[21] These retrospective inclusion probabilities vary over time; some display a jump – cross-country inflation rates, cross-country output growth rates and macroeconomic uncertainty index (Macro Risk Premium 1, 4, 7), some display an upward-trend – the TED spread and the realized upside jump variable (US-Global Shock 2, 4); and some are quite stable – the VIX and the realized downside jump variable (US-Global Shock 1, 3). The degree of relevance of these proxy variables changes over time.

Figure 5 shows the time-varying model averaging retrospective coefficient estimates. The effects of these proxy variables exhibit wide variations over time. Some proxy variables experience a steady increase of their impacts – cross-country money growth rates (Macro Risk Premium 3), and some steady decrease – the VIX index (US-Global Shock 1). And some proxy variables show

[21] The large retrospective inclusion probabilities can be an artifact that the synthetic model is the model averaging of the component models that represents the "best" estimate of the true model.

an increase (decrease) followed by a decrease (increase) – cross-country inflation rates and the realized upside jump variable (Macro Risk Premium 1, US-Global Shocks 4). Some of the estimated effects even change signs – cross-country money growth rates. These large swings, apparently, do not appear to match the sharp changes in retrospective inclusion probabilities in Figure 4.

Comparing across different exchange rates, their synthetic UIP specifications comprise different sets of proxy variables, which display different patterns of retrospective inclusion probabilities, and time-varying model averaging retrospective estimates. These results are not reported for brevity, but are available upon request.

Our exercise reveals the shifting roles and the time-varying effects, which suggest that the use of the same set of proxy variables for unobserved variables and time-invariant specification can severely hamper the empirical analysis of UIP hypothesis.

5.2 Carry Trade

The UIP failure; especially the negative β-estimate echoes the success of the carry trade strategy, that involves buying the high yield currency and selling the low yield one. A common question is whether the excess carry trade return represents compensation for assuming risks. Apparently, it is hard to explain carry trade profits with empirical risk factors (Brunnermeier, *et al.*, 2008; Burnside, 2012; Menkhoff, *et al.*, 2012).

While our exercise does not directly address carry trade, our findings do not indicate a stable link between the β-estimate and the commonly perceived carry trade target (or funding) currency. Indeed, equation (6) indicates that the observed UIP failure can possibly be attributed to unobservable factors, which exhibit non-uniform effects over time.

Our empirical framework allowing for shifting roles and time-varying effects offers hope for rectifying the UIP deviation result. With the exception of JPY, the inclusion of selected empirical proxy variables can reduce the deviation of the β-estimate from its UIP predicted value of one. Possibly, the observed excess carry trade return is the realized compensation of assuming risks, which shift and display varying intensities over time. A caveat is that the role of these proxy variables is non-uniform over time and across exchange rates.

5.3 The λ parameter

The results presented in Section 4 are generated with the λ parameter equals to 0.95. The choice of λ is analogous to the choice of an effective window size $(1-\lambda)^{-1}$ that determines the amount of past observations used to estimate the time-varying parameters. To assess sensitivity, we conducted the DLM-DMA analysis also for λ = 0.96, 0.97, 0.98 and 0.99.[22]

We summarize the results pertaining to the β-estimate from synthetic models obtained under different values of λ in Appendix C.3. There are a few observations.

First, for a given exchange rate, the composition of its synthetic model changes across different values of λ. For example, the synthetic model of JPY includes no proxy variable when λ = 0.95, but different categories of proxy variables for other values of λ. Different exchange rates exhibit different patterns of changes in the compositions of their synthetic models.

Second, different values of λ imply different degrees of improvement of the UIP evidence for different exchange rates. Both the DM and "MAD β" statistics indicate that, for λ = 0.99, the $\hat{\beta}_{t|T}^{aug}$ from all the nine synthetic UIP models under consideration offers a more favorable evidence for UIP than the corresponding $\hat{\beta}_{t|T}^{biv}$. However, the "Mean β" statistic shows three exchange rates

[22] Koop and Korobilis (2012), for example, consider λ = 0.95 and 0.99 for quarterly data.

have an average negative β-estimate; a finding that is at odd with UIP. Noted that the average β-estimates of JPY and CHF under λ = 0.99 are further away from the value of one than the corresponding ones under λ = 0.95;

Third, we do not observe a specific category of proxy variables that plays a consistently primary role in alleviating the evidence of UIP failure for all exchange rates and under all λ values. There are complications and caveats in generalizing the implication of deploying these empirical proxy variables to account for the observed UIP failure.

6. Concluding Remarks

We consider 27 empirical proxies for CIP deviations, risk premiums and expectational errors, and investigate whether they play a role in explaining UIP failure. The dynamic linear model and a modified dynamic model averaging procedure are adopted in the retrospective framework to accommodate non-uniform effects due to shifting roles of proxies over time and time-varying parameters. Specifically, we infer the implications of these proxy variables based on the behavior of the β-estimate – the coefficient estimate of the interest rate differential variable in UIP regressions.

Our results show that the inclusion of these proxies to the canonical bivariate UIP regression can yield a β-estimate that is closer to the value of one predicted under UIP. There are, however, qualifications to the positive result. First, while the presence of proxies reduces the deviation of the β-estimate from one, it does not reduce its sampling uncertainty.

Second, the set of proxy variables that alleviates the degree of UIP failure is not the same for all exchange rates under consideration. Further, both its composition, and the effects of its components can display wide time variability.

Third, the combination of proxy variables that leads to an improved UIP result is sensible to the choice of λ – a parameter that determines the amount of information used to generate the time-varying estimates.

These findings corroborate the scapegoat theory that refers to shifting roles of determinants in foreign exchange markets, and is suggestive of factors that affect the arbitrage behavior between the foreign exchange and money markets can change over time and exhibit time-varying effects. It is conceivable that shifting roles and time-varying effects of proxies for unobservable factors due to, say, changes in market perceptions can contribute to the difficulty of rectifying the empirical UIP failure. Further, the exchange-rate specific results present challenges to develop a general explanation for the observed failure.

Undeniably, our exercise is mainly an empirical one that highlights non-uniform effects. It is beyond the scope of the current study to assess the extent to which these empirical proxy variables capture the attributes of the unobserved factors that are relevant for the UIP discussion, the conditions under which these proxy variables are good empirical proxies, and the factors that determine their shifting roles. Nonetheless, an empirical model for explaining UIP failure is likely to be one that allows for both a time-varying set of explanatory variables and time-varying parameters.

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Table 1. Bivariate UIP Regression: Different Sample Periods

Periods	Coef	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
1990Q2-2018Q4	Mean (∇i)	-0.534	-0.318	-0.090	0.096	0.187	0.299	0.327	0.503	0.624
	α	-0.712	-0.574	-0.227	0.128	0.098	0.011	-0.034	0.820	-0.029
		(0.723)	(0.676)	(0.642)	(0.381)	(0.522)	(0.468)	(0.553)	(0.783)	(1.343)
	β	-0.849*	-0.788	-0.865	0.098	1.307	0.891	0.906	-1.421*	-0.136
		(1.097)	(1.191)	(1.856)	(0.868)	(1.674)	(1.450)	(1.178)	(1.452)	(2.162)
	Adj.R2	-0.003	-0.004	-0.010	-0.009	0.015	-0.002	0.000	0.001	-0.009
1990Q2-1997Q2	Mean (∇i)	-0.458	-0.045	--	0.314	0.937	0.690	0.598	0.574	0.724
	α	-2.226*	0.036	--	0.679**	-2.759	-1.168	-0.763	0.161	0.181
		(1.156)	(1.359)	--	(0.330)	(2.420)	(1.007)	(1.424)	(1.363)	(2.131)
	β	-3.093**	-0.916	--	-0.301***	3.777*	2.090	1.836	0.273	-0.652
		(1.734)	(1.935)	--	(0.500)	(2.721)	(2.224)	(1.722)	(1.633)	(2.635)
	Adj.R2	0.065	-0.029	--	-0.031	0.172	0.011	0.024	-0.036	-0.033
1997Q3-2007Q2	Mean (∇i)	-0.930	-0.605	-0.134	-0.032	-0.160	0.298	0.189	0.312	0.568
	α	-1.697	-3.288**	-1.574*	-0.929	-1.025	-0.062	-0.384	1.078	1.771
		(1.792)	(1.295)	(0.685)	(0.595)	(0.676)	(0.783)	(0.739)	(1.109)	(1.373)
	β	-1.695	-4.530***	-4.505***	-3.185*	-3.883***	-1.779	-1.548*	-5.086***	-3.847***
		(1.989)	(1.839)	(1.647)	(2.545)	(1.349)	(1.786)	(1.341)	(2.405)	(1.853)
	Adj.R2	-0.010	0.072	0.087	0.022	0.098	0.002	0.010	0.118	0.051
2007Q3-2018Q4	Mean (∇i)	-0.223	-0.236	-0.058	0.069	0.008	0.047	0.275	0.627	0.609
	α	1.632	0.396	0.701	0.421	0.721	0.747	-0.145	0.528	-3.487*
		(1.169)	(1.054)	(0.796)	(0.851)	(0.990)	(0.750)	(1.093)	(1.498)	(2.358)
	β	7.421*	3.320	4.015	4.117	1.535	6.403	4.342	-0.025	6.164
		(3.306)	(3.121)	(2.839)	(4.903)	(2.492)	(4.554)	(3.651)	(2.842)	(3.623)
	Adj.R2	0.077	0.003	0.020	-0.005	-0.015	0.061	0.019	-0.023	0.085

Notes: The Table reports the OLS results of the regression $y_t = \alpha + \beta \nabla i_t + \eta_t$; $y_t = s_t - s_{t-1}$ and $\nabla i_t = i_{t-1,t} - i^*_{t-1,t}$. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses. *, **, *** indicate the rejection of α=0 or β=1 at the 10%, 5% or 1% level. The row of "Mean (∇i)" shows the average value of interest rate differential. See Appendix A.1 and the related text for exact sample periods of individual exchange rates.

Table 2. Bivariate UIP regression: Summary of DLM estimation results

Coef	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Mean α	-0.593	-0.649	0.093	-0.008	0.147	-0.037	0.020	0.496	-0.850
Mean se α	1.803	1.544	1.035	0.625	1.151	1.098	1.208	1.644	2.011
MAD α	1.121	0.698	0.445	0.291	0.373	0.345	0.400	0.645	1.534
Mean β	-0.111	-0.403	1.870	0.867	0.393	1.602	1.124	-1.513	1.066
Mean se β	2.559	2.947	3.502	2.600	2.237	2.848	2.299	2.744	2.861
MAD β	1.564	1.416	1.402	1.710	0.718	0.997	1.082	2.513	2.290

Notes: The Table reports the DLM estimation results of the regression $y_t = \alpha_t + \beta_t^{biv} x_t + \varepsilon_t$. The rows "Mean α" and "Mean se α" give the average value of retrospective intercept estimates $\{\hat{\alpha}_{t|T}\}$ and of their standard errors, the row "MAD α" the mean absolute deviation of α-estimates from 0, the rows "Mean β" and "Mean se β" the average value of retrospective of β-estimates $\{\hat{\beta}_{t|T}^{biv}\}$ and of their standard errors, and the row "MAD β" is the mean absolute deviation of β-estimates from 1. See the text for details.

Table 3. Summary of β-estimates: UIP Regressions Augmented with the Proxy for CIP deviations

Coef	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Mean β	-0.468	**-0.039**	**1.719**	1.430	0.304	2.072	1.348	**-1.307**	1.170
	[1.321]	**[0.741]**	**[0.827]**	[3.226]	[1.147]	[1.780]	[2.801]	**[0.918]**	[2.581]
MAD β	1.773	**1.071**	1.431	**1.596**	0.739	1.072	1.155	**2.307**	2.442
	[1.134]	**[0.756]**	[1.020]	**[0.933]**	[1.029]	[1.075]	[1.067]	**[0.918]**	[1.066]
DM	-2.001**	2.805***	-0.375	0.619	-0.590	-0.322	-1.033	4.800***	-1.923*

Notes: Summary of β-estimates from the regression $y_t = \boldsymbol{x}_t'\boldsymbol{\theta}_t + \varepsilon_t$; $\boldsymbol{x}_t = (1, \nabla i_t, C\hat{I}Pd_{t-1})'$ is presented. The rows "Mean β" and "MAD β" give the average value of retrospective of β-estimates and the mean absolute deviation of β-estimates from 1. Numbers in the squared brackets under "Mean β" and "MAD β" are, respectively, $|\Sigma_t(\hat{\beta}_{t|T}^{aug} - 1)| / |\Sigma_t(\hat{\beta}_{t|T}^{biv} - 1)|$ and $\Sigma_t |\hat{\beta}_{t|T}^{aug} - 1| / \Sigma_t |\hat{\beta}_{t|T}^{biv} - 1|$, and those in bold have a value less one. The row "DM" gives the DM statistics of the null hypothesis of $E\{(|\hat{\beta}_{t|T}^{biv} - 1| - |\hat{\beta}_{t|T}^{aug} - 1|)\} = 0$. *, **, *** indicate significance at the 10%, 5% and 1% level. See the text for details.

Table 4. Summary of β-estimates: UIP Regressions Augmented with Proxies of Risk Premiums

Variables	Coef	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Macro	Mean β	-0.751	-1.240	**1.425**	**0.948**	**0.743**	1.860	0.673	**-0.077**	0.669
		[1.576]	[1.596]	**[0.489]**	**[0.388]**	**[0.424]**	[1.428]	[2.628]	**[0.429]**	[5.034]
	MAD β	1.751	2.403	**1.218**	1.804	0.993	1.267	1.329	**1.848**	**2.044**
		[1.119]	[1.697]	**[0.869]**	[1.054]	[1.382]	[1.271]	[1.228]	**[0.735]**	**[0.893]**
	DM	-1.257	-2.636***	1.077	-2.177**	-1.568	-2.715***	-1.521	3.111***	1.880*
US-Global	Mean β	-1.496	**-0.181**	2.095	2.501	**1.294**	**1.201**	1.554	**0.046**	2.018
		[2.246]	**[0.841]**	[1.259]	[11.260]	**[0.485]**	**[0.333]**	[4.460]	**[0.380]**	[15.467]
	MAD β	2.639	**1.220**	1.622	2.990	**0.492**	**0.553**	1.428	**2.010**	**1.995**
		[1.687]	**[0.862]**	[1.157]	[1.748]	**[0.685]**	**[0.555]**	[1.320]	**[0.800]**	**[0.871]**
	DM	-3.281***	1.576	-2.668***	-2.453**	0.924	2.583**	-1.742*	3.149***	0.849
Country	Mean β	-0.213	**-0.374**	1.870	0.580	0.232	1.723	0.484	-1.704	**1.030**
		[1.091]	**[0.979]**	[1.000]	[3.149]	[1.265]	[1.201]	[4.149]	[1.076]	**[0.462]**
	MAD β	1.610	1.452	**1.298**	**1.575**	0.800	1.109	**0.895**	2.704	**2.212**
		[1.029]	[1.025]	**[0.926]**	**[0.921]**	[1.113]	[1.112]	**[0.827]**	[1.076]	**[0.966]**
	DM	-1.284	-0.858	1.572	1.175	-1.746*	-2.456**	0.929	-3.614***	2.931***
Macro, US-Global	Mean β	-2.150	-0.959	**1.277**	2.368	**0.838**	**1.337**	0.696	**1.051**	1.846
		[2.835]	[1.396]	**[0.319]**	[10.260]	**[0.266]**	**[0.559]**	[2.447]	**[0.020]**	[12.862]
	MAD β	3.150	2.344	**1.239**	2.712	**0.601**	**0.725**	1.256	**2.326**	**2.016**
		[2.014]	[1.655]	**[0.884]**	[1.586]	**[0.836]**	**[0.727]**	[1.161]	**[0.926]**	**[0.880]**
	DM	-4.372***	-2.850***	0.959	-2.111**	0.760	1.672*	-1.182	0.431	1.031
Macro, Country	Mean β	-0.775	-1.159	**1.286**	**0.956**	**0.434**	1.963	0.346	**-0.084**	0.513
		[1.598]	[1.539]	**[0.328]**	**[0.327]**	**[0.932]**	[1.599]	[5.257]	**[0.431]**	[7.406]
	MAD β	1.775	2.449	**1.041**	**1.690**	0.775	1.332	**1.059**	**1.786**	**2.014**
		[1.135]	[1.729]	**[0.742]**	**[0.988]**	[1.079]	[1.337]	**[0.979]**	**[0.711]**	**[0.879]**
	DM	-1.381	-2.931***	2.125**	0.435	-0.701	-3.683***	0.099	3.622***	1.524
US-Global, Country	Mean β	-1.538	**-0.305**	2.084	2.168	**1.186**	**1.205**	**0.999**	**0.080**	1.972
		[2.284]	**[0.930]**	[1.246]	[8.760]	**[0.306]**	**[0.340]**	**[0.010]**	**[0.366]**	[14.764]
	MAD β	2.716	**1.309**	1.562	2.673	**0.432**	**0.555**	1.303	**2.158**	**2.062**
		[1.736]	**[0.924]**	[1.114]	[1.563]	**[0.602]**	**[0.557]**	[1.204]	**[0.859]**	**[0.900]**
	DM	-3.445***	1.236	-2.024**	-2.320**	1.393	2.667***	-1.712*	1.867*	0.673
Macro, US-Global, Country	Mean β	-2.201	-1.020	**1.135**	2.129	**0.742**	**1.355**	0.537	**1.099**	1.807
		[2.881]	[1.440]	**[0.155]**	[8.469]	**[0.424]**	**[0.590]**	[3.726]	**[0.040]**	[12.267]
	MAD β	3.201	2.357	**1.145**	2.496	**0.522**	**0.737**	1.154	**2.374**	**1.997**
		[2.046]	[1.664]	**[0.817]**	[1.459]	**[0.726]**	**[0.740]**	[1.067]	**[0.945]**	**[0.872]**

DM	-4.359***	-2.876***	1.439	-1.968*	1.628	1.641	-0.396	0.313	1.144

Notes: Summary of β-estimates from the regression $y_t = \boldsymbol{x}_t'\boldsymbol{\theta}_t + \varepsilon_t$; $\boldsymbol{x}_t = (1, \nabla i_t, R\hat{P}_{t-1})'$ is presented. The first column lists the categories of proxies for risk premiums included in the augmented UIP regression specifications. "Macro" refers to the category comprises eight proxies that are related to the relative macroeconomic environment, "US-Global" the category comprises five proxies for risks in the US financial markets and the global foreign exchange market, and "Country" the category comprises two country-specific proxies for financial market risks. See the text for details. Also, see the notes to the previous tables.

Table 5. Summary of β-estimates: UIP Regressions Augmented with Proxies of Expectational Errors

Variables	Coef	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Macro	Mean β	-0.341	**-0.165**	**1.271**	-0.029	-0.318	**0.767**	0.186	-2.141	1.417
		[1.207]	**[0.830]**	**[0.312]**	[7.717]	[2.171]	**[0.387]**	[6.545]	[1.250]	[6.339]
	MAD β	1.915	**1.192**	**0.756**	**1.550**	1.322	**0.957**	**0.962**	3.141	**1.966**
		[1.224]	**[0.842]**	**[0.539]**	**[0.906]**	[1.840]	**[0.960]**	**[0.889]**	[1.250]	**[0.859]**
	DM	-4.191***	0.873	2.884***	0.507	-5.580***	0.139	0.533	-3.925***	2.448**
US-Global	Mean β	**-0.021**	-0.531	**0.895**	0.269	-0.134	0.263	0.494	-1.626	1.375
		[0.919]	[1.091]	**[0.121]**	[5.484]	[1.869]	[1.224]	[4.072]	[1.045]	[5.703]
	MAD β	**1.543**	1.535	**0.668**	**1.363**	1.134	**0.743**	**0.515**	2.626	**0.677**
		[0.986]	[1.083]	**[0.476]**	**[0.797]**	[1.579]	**[0.745]**	**[0.475]**	[1.045]	**[0.296]**
	DM	0.412	-1.231	2.983***	1.271	-3.510***	0.747	3.325***	-0.295	6.030***
Uncertainty	Mean β	**0.167**	**-0.148**	**0.877**	-0.105	**0.432**	**1.032**	0.520	-1.991	1.373
		[0.749]	**[0.818]**	**[0.142]**	[8.289]	**[0.936]**	**[0.053]**	[3.863]	[1.190]	[5.670]
	MAD β	1.642	**1.149**	**0.752**	2.230	0.721	**0.715**	**0.937**	2.991	**1.666**
		[1.050]	**[0.811]**	**[0.537]**	[1.304]	[1.004]	**[0.717]**	**[0.866]**	[1.190]	**[0.727]**
	DM	-0.611	1.842*	2.540**	-2.068**	-0.029	1.310	0.693	-2.800***	3.385***
Macro, US-Global	Mean β	-0.405	-0.722	0.122	0.376	-0.475	-0.305	0.072	-1.699	1.469
		[1.265]	[1.227]	[1.009]	[4.680]	[2.430]	[2.167]	[7.465]	[1.074]	[7.123]
	MAD β	1.988	1.727	**0.932**	**0.962**	1.475	1.305	**0.928**	2.699	**0.798**
		[1.271]	[1.219]	**[0.665]**	**[0.562]**	[2.053]	[1.309]	**[0.858]**	[1.074]	**[0.349]**
	DM	-3.243***	-1.275	1.967*	2.617**	-4.419***	-0.965	1.309	-0.537	5.576***
Macro, Uncertainty	Mean β	-0.188	**-0.219**	0.014	-1.115	-0.408	**0.655**	-0.051	-2.474	2.221
		[1.069]	**[0.869]**	[1.133]	[15.862]	[2.319]	**[0.572]**	[8.458]	[1.382]	[18.553]
	MAD β	1.938	**1.222**	**1.024**	2.417	1.422	**0.796**	1.204	3.474	**1.630**
		[1.239]	**[0.863]**	**[0.730]**	[1.413]	[1.979]	**[0.799]**	[1.113]	[1.382]	**[0.712]**
	DM	-3.864***	0.506	1.524	-1.360	-4.205***	0.674	-0.490	-4.225***	1.689*
US-Global, Uncertainty	Mean β	**0.142**	**-0.333**	**0.957**	-0.345	0.154	0.330	0.485	-1.520	1.535
		[0.772]	**[0.950]**	**[0.049]**	[10.091]	[1.393]	[1.114]	[4.139]	[1.003]	[8.130]
	MAD β	1.715	**1.334**	**0.622**	1.765	0.848	**0.670**	**0.772**	2.520	**0.684**
		[1.096]	**[0.942]**	**[0.443]**	[1.032]	[1.181]	**[0.673]**	**[0.713]**	[1.003]	**[0.299]**
	DM	-1.122	0.906	3.520***	-0.140	-1.533	1.113	1.747*	-0.022	7.111***
Macro, US-Global, Uncertainty	Mean β	-0.649	-0.566	0.001	-0.196	-0.367	-0.232	0.102	-1.806	1.724
		[1.484]	[1.116]	[1.149]	[8.968]	[2.253]	[2.046]	[7.226]	[1.117]	[11.005]
	MAD β	2.373	1.566	**1.015**	**1.387**	1.367	1.232	**0.904**	2.806	**0.838**
		[1.517]	[1.106]	**[0.724]**	**[0.811]**	[1.904]	[1.236]	**[0.835]**	[1.117]	**[0.366]**

DM	-3.794***	-0.593	1.485	0.852	-4.868***	-0.726	0.840	-1.273	6.182***

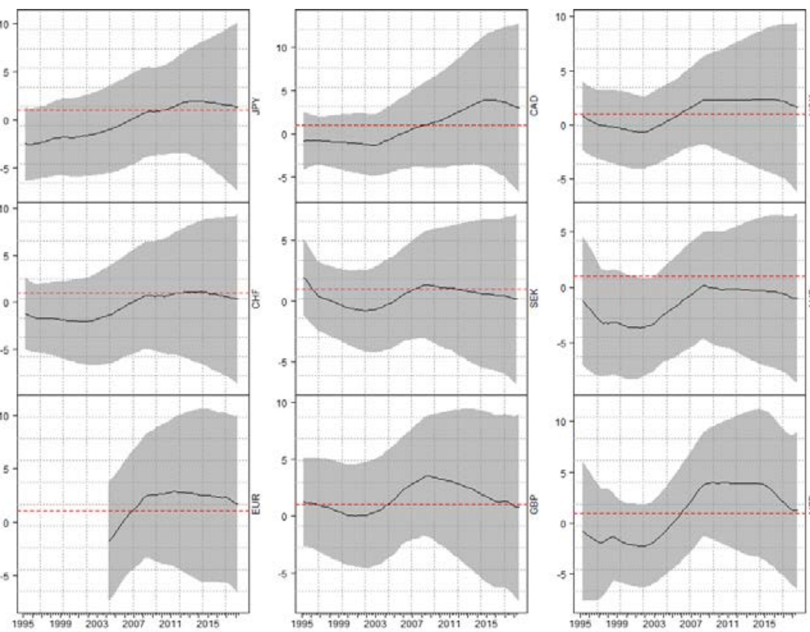
Notes: Summary of β-estimates from the regression $y_t = \boldsymbol{x}_t'\boldsymbol{\theta}_t + \varepsilon_t$; $\boldsymbol{x}_t = (1, \nabla i_t, E\hat{R}_t)'$ is presented. The first column lists the categories of proxies for expectational errors included in the augmented UIP regression specifications. "Macro" refers to the category comprises four proxies for macro shocks, "US-Global" the category comprises four proxies for shocks to the U.S. financial markets and the global foreign exchange market, and "Uncertainty" the category comprises three uncertainty indexes. See the text for details. Also, see the notes to the previous tables.

Table 6. Summary of β-estimates: UIP Regressions Augmented with Synthetic Categories of Proxies

	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Panel A									
Mean β	-0.111	**0.446**	-0.513	0.376	**1.186**	**1.201**	0.494	**0.147**	**0.945**
	[1.000]	**[0.394]**	[1.739]	[4.680]	**[0.306]**	**[0.333]**	[4.072]	**[0.339]**	**[0.843]**
MAD β	1.564	**0.692**	1.513	**0.962**	**0.432**	**0.553**	**0.515**	**1.789**	**0.437**
	[1.000]	**[0.489]**	[1.079]	**[0.562]**	**[0.602]**	**[0.555]**	**[0.475]**	**[0.712]**	**[0.191]**
DM	--	2.899***	-0.277	2.617**	1.39	2.583**	3.325***	2.923***	6.629***
Panel B									
$C\hat{I}Pd_{t-1}$	--	$C\hat{I}Pd_{t-1}$	--	--	--	--	--	$C\hat{I}Pd_{t-1}$	--
$R\hat{P}_{t-1}$	--	--	Macro, Country	--	US-Global, Country	US-Global	--	Macro, Country	Macro
$E\hat{R}_t$	--	Uncertainty	US-Global, Uncertainty	Macro, US-Global	--	--	US-Global	--	US-Global

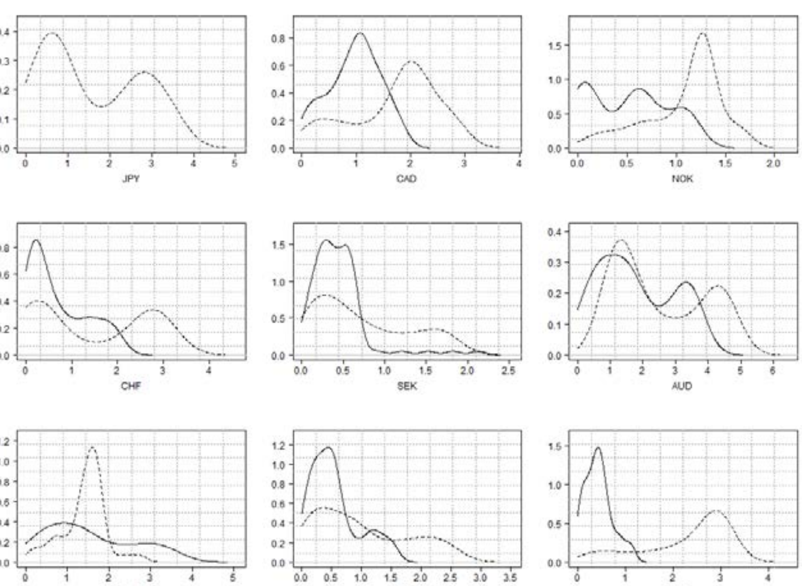
Notes: Panel A presents the summary of β-estimates from synthetic UIP regressions with selected categories of proxies for CIP deviations ($C\hat{I}Pd_{t-1}$), risk premiums ($R\hat{P}_{t-1}$), and expectational errors ($E\hat{R}_t$). Panel B presents, for each exchange rate, the specific categories of proxies in the synthetic UIP regression. See the notes to the previous tables.

Figure 1. β-estimates from the Bivariate DLM UIP Specification



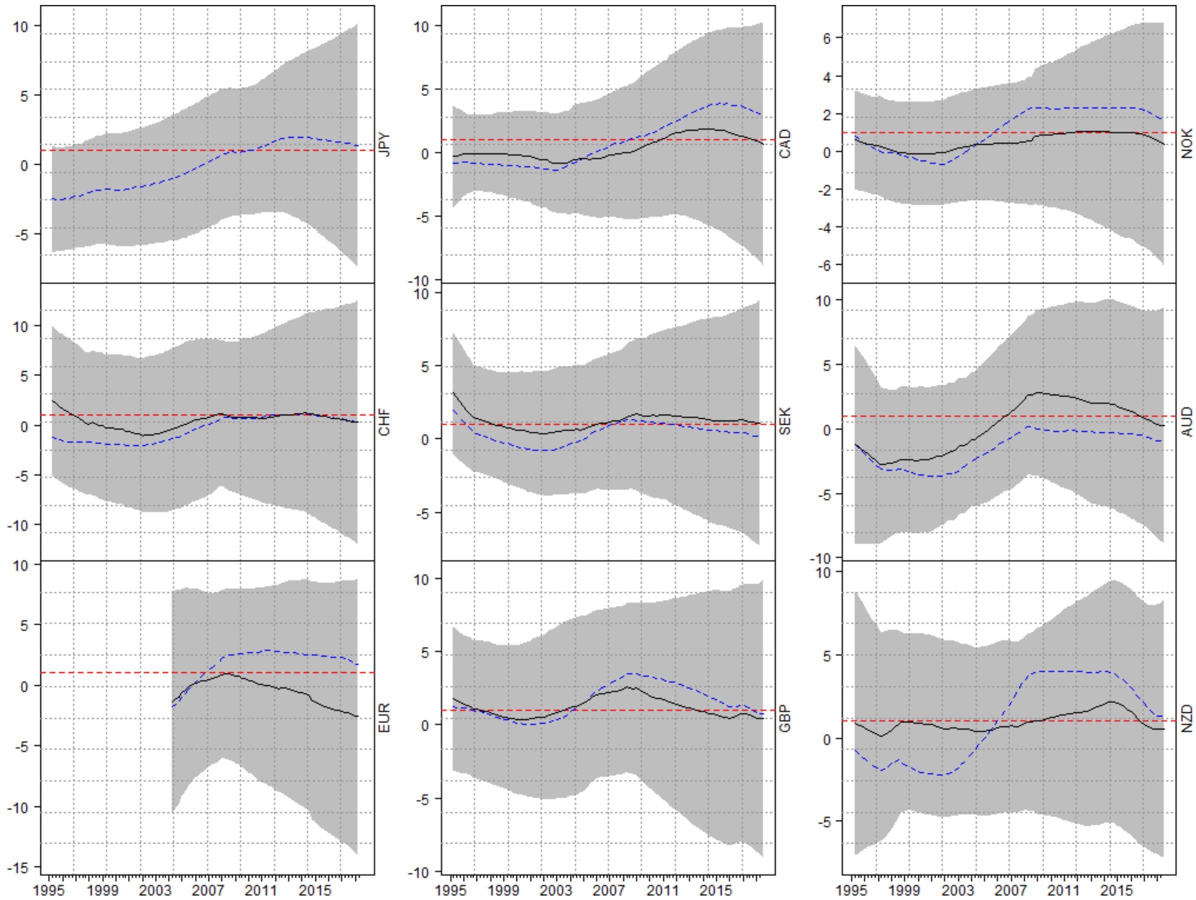
Notes: The solid line gives the β-estimate from the bivariate DLM regression $y_t = \alpha_t + \beta_t^{biv} x_t + \varepsilon_t$. The gray area represents the 95% credible region. The dash horizon line is the unity horizon line.

Figure 2. The Empirical Density Distributions of $|\hat{\beta}_{t|T}^{biv} - 1|$ and $|\hat{\beta}_{t|T}^{aug} - 1|$



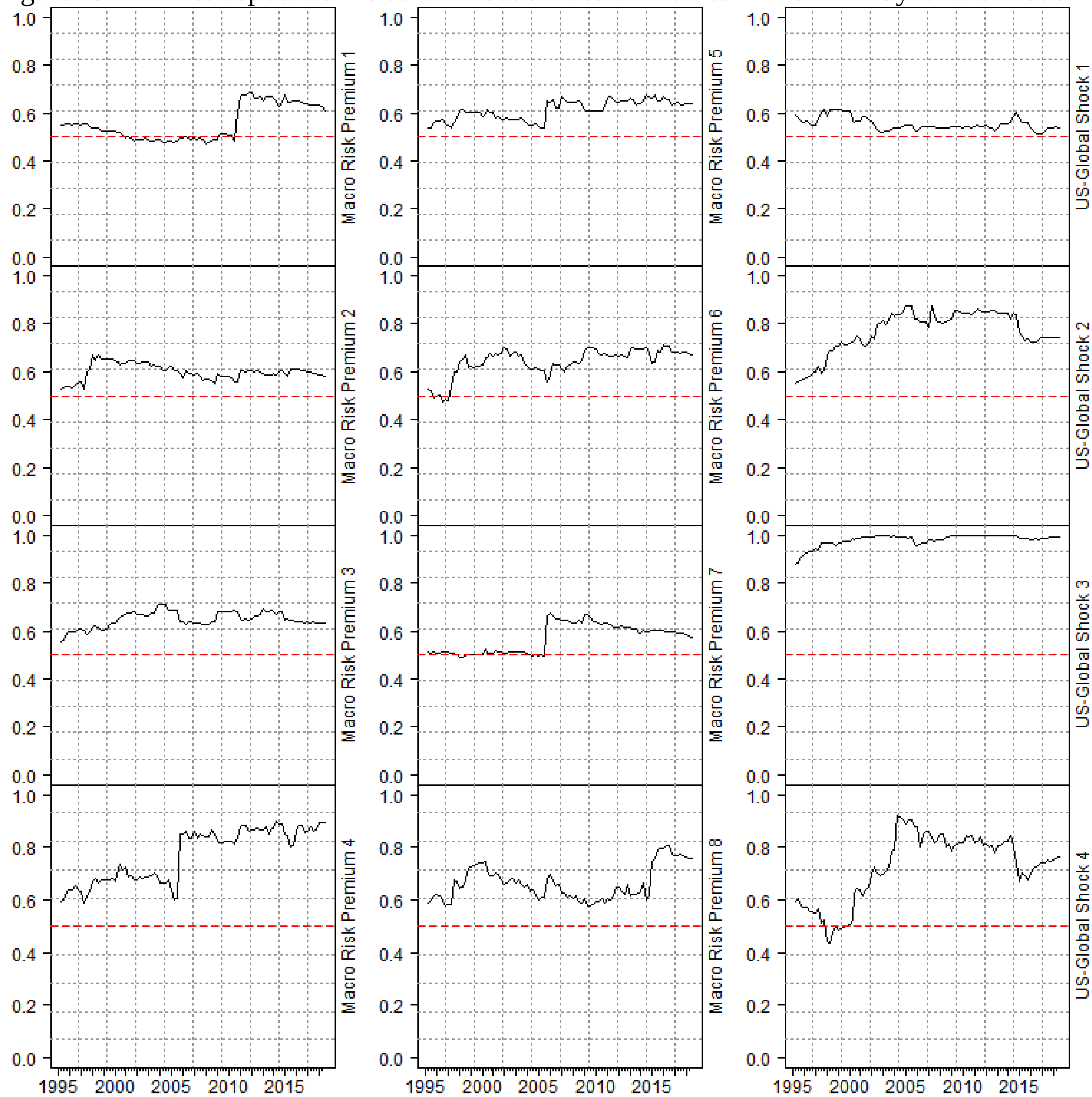
Note: For each exchange rate, the empirical density distributions of absolute deviations of β-estimates from one are plotted. The solid curve is for $|\hat{\beta}_{t|T}^{aug} - 1|$ based on β-estimates from the synthetic UIP regression reported in Table 6, and the dash curve is for $|\hat{\beta}_{t|T}^{biv} - 1|$ from the corresponding bivariate UIP regression in Table 2.

Figure 3. β-estimates from Bivariate and Synthetic UIP Regressions



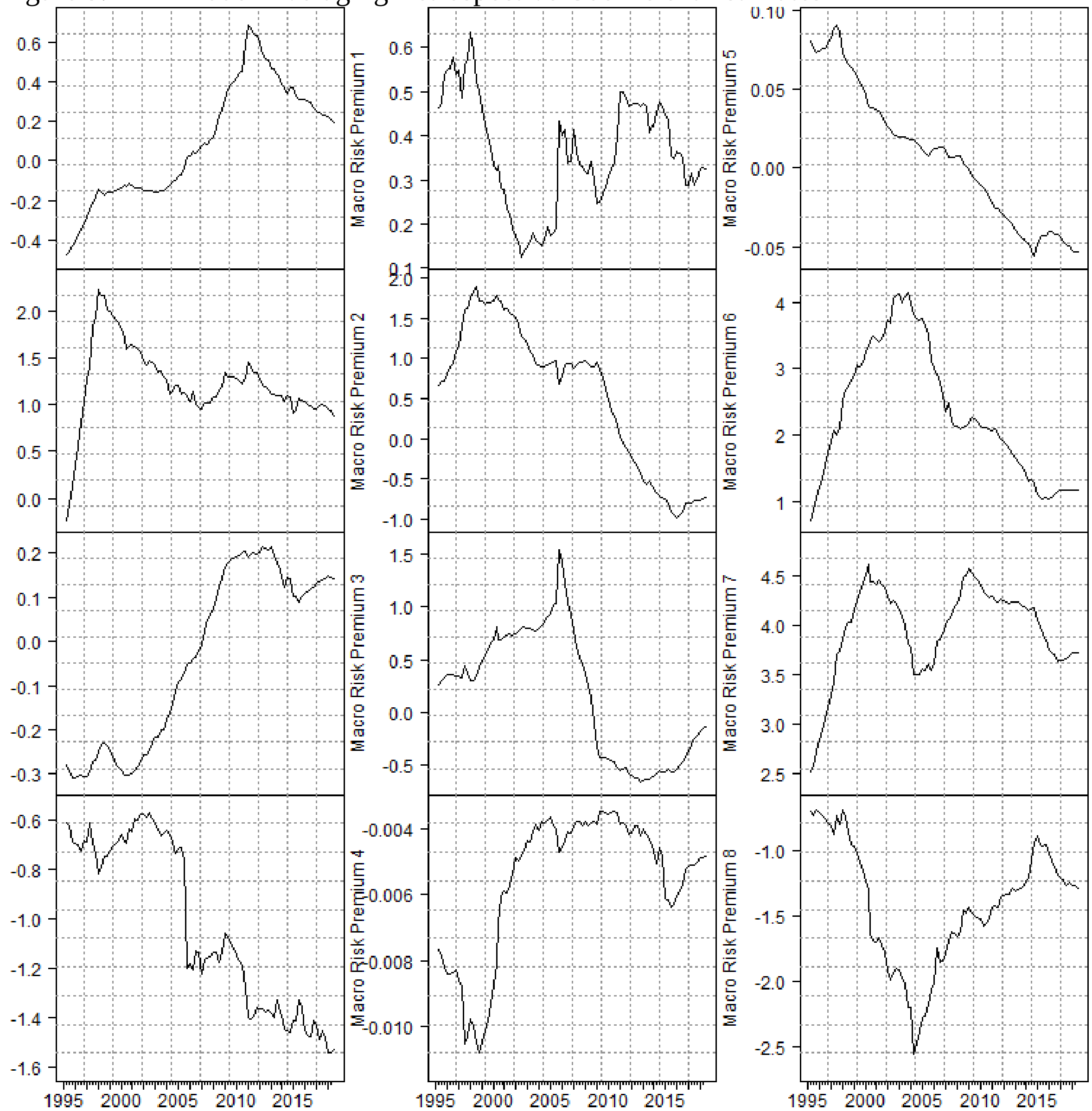
Notes: For each exchange rate, the solid and dash curve lines trace β-estimates ($\hat{\beta}_{t|T}^{aug}$) from the synthetic UIP specification in Table 6 and β-estimates ($\hat{\beta}_{t|T}^{biv}$) from the corresponding bivariate UIP regression in Table 2. The grey area gives the 95% credible region of $\hat{\beta}_{t|T}^{aug}$. The horizontal dash line is the unity line.

Figure 4. Retrospective Inclusion Probabilities of Proxies in the NZD Synthetic Model



Notes: For each proxy, the figure plots its time-varying retrospective inclusion probability. The 0.5 reference is given by the horizon dash line. Macro Risk Premium 1 to Macro Risk Premium 6 are lagged cross-country differences of inflation rates, interest rate changes, money growth rates, GDP growth rates, productivity growth rates, and unemployment rates, Macro Risk Premium 7 is the macroeconomic uncertainty index, and Macro Risk Premium 8 is the lagged economic policy uncertainty index. US-Global Shock 1 and 2 are the contemporaneous VIX and the contemporaneous TED, and US-Global Shock 3 and 4 are contemporaneous realized downside and upside jumps variables. See the text and the Appendix for a more detailed description of these variables.

Figure 5. Model Averaging Retrospective Coefficient Estimates



Notes: The time-varying model averaging retrospective coefficient estimates of each proxy in the NZD synthetic model are plotted. See the notes to the previous Table.

(online appendix, not intended for publication)

Appendix A. Data – Sample Periods, Sources, Definitions

A.1 Sample Period

The sample period, subject to data availability, starts from 1990Q1 and ends at 2018Q4. The actual sample periods for individual exchange rates are:

AUD: 1990Q1-2018Q4; **CAD:** 1990Q1-2018Q4; **CHF:** 1990Q1-2018Q3
EUR: 1999Q1-2018Q3; **GBP:** 1990Q1-2018Q4; **JPY:** 1990Q1-2018Q3
NOK: 1990Q1-2018Q4; **NZD:** 1990Q1-2018Q4; **SEK:** 1990Q1-2018Q3

A.2 Sources

(1) End-of-quarter data on spot exchange rates, 3-month forward rates, and MSCI indexes are collected from Bloomberg. Spot and forward exchange rates are New York closing rates.
(2) End-of-quarter data on 3-month euro-currency deposit rates are collected from DataStream. Due to data availability, in early years of the sample, New Zealand 3 month deposit rates, Norway 3 month Interbank rates, Sweden 90-Day Treasury Bill rates, and Australia Dealer 90 Day Bill rates are used.
(3) Seasonally adjusted data on board money, gross domestic product, number of employed persons, unemployment rates, and consumer price index are collected from DataStream, OECD Main Economic Indicators, and International Financial Statistics. M4 is used for the UK, and M1 for Japan.
(4) End-of-quarter data on the VIX index and the TED spread are collected, respectively, from the CBOE website and the FRED, Federal Reserve Bank of St. Louis. Data on Economic Policy Uncertainty index are from http://www.policyuncertainty.com/us_monthly.html, and Macro and Finance Uncertainty Indexes are from https://www.sydneyludvigson.com/data-and-appendixes/.

A.3 Definitions

Left-Hand-Side variable

Exchange rate change: $y_t = s_t - s_{t-1} = \Delta \ln(S_t)$, where S_t is the exchange rate at time *t*, $\ln(\cdot)$ is the log operator, and "Δ" is the first-difference operator. It is expressed in percentage term.

Right-Hand-Side variables

(1) Interest rate differential: $(1+i_{t-1,t})^{1/4} - (1+i^*_{t-1,t})^{1/4}$, where $i_{t-1,t}$ and $i^*_{t-1,t}$ are, respectively, 3 month home currency and USD euro-currency deposit rates. It is expressed in percentage term.

CIP Deviations, $\hat{CIPd}_{t-1}$

(2) Cross-currency basis: $[\ln(F_{t-1,t}) - \ln(S_{t-1})] - [(1+i_{t-1,t})^{1/4} - (1+i^*_{t-1,t})^{1/4}]$, where $F_{t-1,t}$ is the 3-month forward rate. It is expressed in percentage term.

Proxies for Risk Premiums, $\hat{RP}_{t-1}$

(3) – (8) Cross-country differences of (a) inflation rates: $\Delta \ln(CPI_{t-1}) - \Delta \ln(CPI^*_{t-1})$, (b) interest rate changes: $\Delta (1+i_{t-1,t})^{1/4} - \Delta (1+i^*_{t-1,t})^{1/4}$, (c) money supply growth rates: $\Delta \ln(M_{t-1}) - \Delta \ln(M^*_{t-1})$, (d) output growth rates: $\Delta \ln(GDP_{t-1}) - \Delta \ln(GDP^*_{t-1})$, (e) productivity growth rates: $\Delta \ln(GDP_{t-1} / labor_{t-1}) - \Delta \ln(GDP^*_{t-1} / labor^*_{t-1})$, and (f) changes of unemployment rates: $\Delta Uem_{t-1} - \Delta Uem^*_{t-1}$; where CPI_t is the CPI,

M_t is the money supply, GDP_t is the GDP, $labor_t$ is the number of employed persons, and Uem_t is the unemployment rate at time *t* in the home country. A "*" indicates an US variable. These cross-country differences are expressed in percentage term.

(9) – (10) Macroeconomic uncertainty index is developed by Jurado, *et al.* (2015), and economic policy uncertainty index is by Baker, *et al.* (2016). The quarterly data are given by the sum of the corresponding monthly data.

(11) End-of-quarter VIX index is from CBOE, which provides information on the construction of the index.

(12) The TED spread is given by the difference of the three-month US Treasury bill rate and the three-month US dollar LIBOR.

(13) US financial uncertainty is developed by Jurado, *et al.* (2015).

(14) – (15) The global realized upside and downside semi-variances are constructed from the averages of the corresponding semi-variances of individual exchange rate series: $m_{t-1}^{-1}\Sigma_i[\Sigma_{j=1}^{n_{t-2}}\{(R_{i,t-2+j/n_{t-2}})^2 I(R_{i,t-2+j/n_{t-2}} > 0)\}]^{1/2}$ and $m_{t-1}^{-1}\Sigma_i[\Sigma_{j=1}^{n_{t-2}}\{(R_{i,t-2+j/n_{t-2}})^2 I(R_{i,t-2+j/n_{t-2}} \le 0)\}]^{1/2}$, where m_t is the number of available currencies at time *t*, $R_{i,t+j/n_t} = \ln(S_{i,t+j/n_t} / S_{i,t+(j-1)/n_t}) - [(1+i_{t,t+1})^{1/4} - (1+i_{t,t+1}^*)^{1/4}]/n_t$, $S_{i,t+j/n_t}$ is the *i*-th exchange rate observed on day $t + j/n_t$, n_t is the number of observations between time *t* to *t*+1, and $I(\cdot)$ is an indicator function. They are expressed in percentage term.

(16) Cross-country difference of MSCI returns: $\Delta\ln(MSCI_{t-1}) - \Delta\ln(MSCI_{t-1}^*)$, where $MSCI_t$ is the home country MSCI stock index at time *t*, and the US index is indicated by an "*." It is expressed in percentage term.

(17) Lagged exchange rate changes: $\Delta\ln(S_{t-1})$ expressed in percentage term.

Proxies for Expectational Errors, $E\hat{R}_t$

(18) – (20) Shocks to the cross-country differences of (a) inflation rates: $\Delta\widetilde{\ln(CPI_t)} - \Delta\widetilde{\ln(CPI_t^*)}$, where $\widetilde{X}$ is the cyclical component of *X* obtained by detrending it with the HP filter with a parameter of 1600, (b) money supply growth rates: $\Delta\widetilde{\ln(M_t)} - \Delta\widetilde{\ln(M_t^*)}$, and (c) output gaps: $\tilde{y}_t - \tilde{y}_t^*$, where $\tilde{y}_t$ and $\tilde{y}_t^*$ are HP filter generated output gaps in the home country and in the US respectively. They are expressed in percentage term.

(21) Contemporaneous changes of interest rate differential: $\Delta(1+i_{t,t+1})^{1/4} - \Delta(1+i_{t,t+1}^*)^{1/4}$, expressed in percentage term.

(22) – (23) Contemporaneous VIX index and Contemporaneous TED spread.

(24) – (25) The global realized upside and downside jumps are the averages of the corresponding jumps of individual exchange rates given by: $m_t^{-1}\Sigma_i[QJPP_{n_{t-1}} I(QJPP_{n_{t-1}} > 0)]^{1/2}$ and $m_t^{-1}\Sigma_i[QJPN_{n_{t-1}} I(QJPN_{n_{t-1}} > 0)]^{1/2}$, where $QJPP_{n_t} = \Sigma_{j=1}^{n_t}(R_{i,t+j/n_t})^2 I(R_{i,t+j/n_t} > 0) - \frac{\pi}{4}\Sigma_{j=1}^{n_t-1}|R_{i,t+j/n_t}\cdot R_{i,t+(j+1)/n_t}|$ and $QJPN_{n_t} = \Sigma_{j=1}^{n_t}(R_{i,t+j/n_t})^2 I(R_{i,t+j/n_t} \le 0) - \frac{\pi}{4}\Sigma_{j=1}^{n_t-1}|R_{i,t+j/n_t}\cdot R_{i,t+(j+1)/n_t}|$. They are expressed in percentage term.

(26) – (28) Contemporaneous macroeconomic, financial, and economic policy uncertainty indexes are obtained from Jurado, *et al.* (2015) and Baker, *et al.* (2016).

Appendix B. Econometric Methodology

We adopt the dynamic linear model (DLM) approach to estimate the time-varying retrospective coefficient estimates, and employ the dynamic model averaging (DMA) procedure to conduct the model averaging analysis (Raftery, *et al.*, 2010; West and Harrison, 1997).

B.1 Estimation of Dynamic Linear Model, DLM

Suppose there are K models in the model space. For clarity, we add the subscript "k" to (7) and (8) for the k-th model in the model space:

$$y_t = \boldsymbol{x}'_{t,k}\boldsymbol{\theta}_{t,k} + \varepsilon_{t,k}, \varepsilon_{t,k} \sim N(0, V_k), \tag{B.1.1}$$

$$\boldsymbol{\theta}_{t,k} = \boldsymbol{\theta}_{t-1,k} + \delta_{t,k}, \delta_{t,k} \sim N(0, \boldsymbol{W}_{t,k}). \tag{B.1.2}$$

The data y_t used in the text do not exhibit significant ARCH effects. Suppose the number of the observations is T. Bayesian methods are used to recursively estimate the parameters.

Let $Y_t = \{y_1, y_2, ..., y_t\}$ and the parameter vector $\boldsymbol{\theta}$ estimate at time t-1 derived from information from time 1 to t-1 follows $\boldsymbol{\theta}_{t-1,k} \mid Y_{t-1} \sim N(\hat{\boldsymbol{\theta}}_{t-1|t-1,k}, \boldsymbol{\Sigma}_{t-1|t-1,k})$. Then, given B.1.2,

$$\boldsymbol{\theta}_{t,k} \mid Y_{t-1} \sim N(\hat{\boldsymbol{\theta}}_{t-1|t-1,k}, \boldsymbol{R}_{t,k}), \tag{B.1.3}$$

where $\boldsymbol{R}_{t,k} \equiv \boldsymbol{\Sigma}_{t-1|t-1,k} + \boldsymbol{W}_{t,k}$. Following Raftery, *et al.* (2010), we set $\boldsymbol{W}_{t,k} = (1-\lambda)\lambda^{-1}\boldsymbol{\Sigma}_{t-1|t-1,k}$, where λ is the so-called "forgetting" factor, and obtain $\boldsymbol{R}_{t,k} = \lambda^{-1}\boldsymbol{\Sigma}_{t-1|t-1,k}$.

From B.1.3 and B.1.1, we have the distribution of the predicted y_t,

$$y_{t,k} \mid Y_{t-1} \sim N(\boldsymbol{x}'_{t,k}\hat{\boldsymbol{\theta}}_{t-1|t-1,k}, \hat{V}_{t-1|t-1,k} + \boldsymbol{x}'_{t,k}\boldsymbol{R}_{t,k}\boldsymbol{x}_{t,k}). \tag{B.1.4}$$

The estimate $\hat{V}_{\cdot,k}$ is obtained via the exponentially weighted moving average (EWMA) setup; $\hat{V}_{t|t,k} = \kappa\hat{V}_{t-1|t-1,k} + (1-\kappa)(e_{t,k})^2$, where $e_{t,k} = y_t - \boldsymbol{x}'_{t,k}\hat{\boldsymbol{\theta}}_{t-1|t-1,k}$ (Koop and Korobilis, 2012).

Given the distributions of $y_{t,k} \mid Y_{t-1}$ and $\boldsymbol{\theta}_{t,k} \mid Y_{t-1}$ (B.1.4, B.1.3), the Bayes' theorem implies

$$\boldsymbol{\theta}_{t,k} \mid Y_t \sim N(\hat{\boldsymbol{\theta}}_{t|t,k}, \boldsymbol{\Sigma}_{t|t,k}), \tag{B.1.5}$$

where $\hat{\boldsymbol{\theta}}_{t|t,k} = \hat{\boldsymbol{\theta}}_{t-1|t-1,k} + \boldsymbol{R}_{t,k}\boldsymbol{x}_{t,k}(\hat{V}_{t|t,k} + \boldsymbol{x}'_{t,k}\boldsymbol{R}_{t,k}\boldsymbol{x}_{t,k})^{-1}e_{t,k}$ and $\boldsymbol{\Sigma}_{t|t,k} = \boldsymbol{R}_{t,k} - \boldsymbol{R}_{t,k}\boldsymbol{x}_{t,k}(\hat{V}_{t|t,k} + \boldsymbol{x}'_{t,k}\boldsymbol{R}_{t,k}\boldsymbol{x}_{t,k})^{-1}\boldsymbol{x}'_{t,k}\boldsymbol{R}_{t,k}$.

By repeating the procedure, we recursively estimate the parameter vector $\boldsymbol{\theta}$, and obtain the distribution of $\boldsymbol{\theta}_{t,k} \mid Y_t$; $t = 1, 2, ..., T$.

The retrospective distributions of $\boldsymbol{\theta}_{t,k}$ and $y_{t,k}$ that incorporates information from the entire sample Y_T are given by (West and Harrison, 1997; chapter 4, p.112-115)

$$\boldsymbol{\theta}_{t,k} \mid Y_T \sim N(\hat{\boldsymbol{\theta}}_{t|T,k}, \boldsymbol{\Sigma}_{t|T,k}), \tag{B.1.6}$$

$$y_{t,k} \mid Y_T \sim N(\boldsymbol{x}'_{t,k}\hat{\boldsymbol{\theta}}_{t|T,k}, \hat{V}_k + \boldsymbol{x}'_{t,k}\boldsymbol{\Sigma}_{t|T,k}\boldsymbol{x}_{t,k}). \tag{B.1.7}$$

where $\hat{\boldsymbol{\theta}}_{t|T,k} = \hat{\boldsymbol{\theta}}_{t|t,k} + \lambda(\hat{\boldsymbol{\theta}}_{t+1|T,k} - \hat{\boldsymbol{\theta}}_{t|t,k})$, $\boldsymbol{\Sigma}_{t+1|T,k} = \boldsymbol{\Sigma}_{t|t,k} + \lambda^2(\boldsymbol{\Sigma}_{t+1|T,k} - \lambda^{-1}\boldsymbol{\Sigma}_{t|t,k})$, and $\hat{V}_k = T^{-1}\Sigma_{t=1}^{T}(y_t - \boldsymbol{x}'_{t,k}\hat{\boldsymbol{\theta}}_{t|T,k})^2$.

B.2 Estimation of Model Probabilities

Model probabilities that indicate the relative importance of models in each period are used to conduct dynamic model averaging. The model probability in the current exercise is derived from the retrospective distributions of $\boldsymbol{\theta}_{t,k}$ and $y_{t,k}$ for $t = 1, 2, ..., T$, $k = 1, 2, ..., K$, and a given λ value. Let $L_t = k$ be the event that the k-th model is the true model at time t.

Let $\pi_{t-1|t-1,k} = P(L_{t-1} = k \mid \boldsymbol{F}_{t-1})$ be the model probability of model k at time t-1 based on sample information available from time 1 to t-1; where $P(\cdot)$ is the probability operator, and $\boldsymbol{F}_{t-1}$ includes the retrospective likelihood of all K models at time t-1. Assume the time t predicted model probability $\pi_{t|t-1,k} = P(L_t = k \mid \boldsymbol{F}_{t-1})$ follows a Markov process given by the *K*x*K* transition matrix $Q_{t-1} = [q_{t-1,\ell k}]$, where $q_{t-1,\ell k} = P(L_t = k \mid \boldsymbol{F}_{t-1}, L_{t-1} = \ell)$. Thus,

$$\pi_{t|t-1,k} = P(L_t = k \mid \boldsymbol{F}_{t-1}) = \Sigma_{\ell=1}^{K} \pi_{t-1|t-1,\ell} q_{t-1,\ell k}. \qquad \text{(B.2.1)}$$

Defining a forgetting factor τ, (B.2.1) could be simplified and re-written as

$$\pi_{t|t-1,k} = [(\pi_{t-1|t-1,k})^{\tau} + c][\Sigma_{\ell=1}^{K} (\pi_{t-1|t-1,\ell})^{\tau} + c]^{-1}, \qquad \text{(B.2.2)}$$

where *c* is a small positive number to avoid a zero model probability caused by aberrant observations.

Given (B.2.2) and (B.1.7),

$$\pi_{t|t,k} = P(L_t = k \mid \boldsymbol{F}_t) = \pi_{t|t-1,k} f_k(y_t \mid Y_T)[\Sigma_{\ell=1}^{K} \pi_{t|t-1,\ell} f_\ell(y_t \mid Y_T)]^{-1}, \qquad \text{(B.2.3)}$$

where $f_\ell(y_t \mid Y_T)$ is the retrospective likelihood value of the ℓ-th model at time *t*.[23]

The model probability $\pi_{t|t,k}$ is recursively estimated for $t = 1, 2, ..., T$ and $k = 1, 2, ..., K$. Then, the retrospective model probability is given by (see Appendix B.5)

$$\pi_{t|T,k} = P(L_t = k \mid \boldsymbol{F}_T) = \pi_{t|t,k} \Sigma_{\ell=1}^{K} q_{t,k\ell} (\pi_{t+1|T,\ell})(\pi_{t+1|t,\ell})^{-1}, \qquad \text{(B.2.4)}$$

where $t = 1, 2, ..., T-1$, $k = 1, 2, ..., K$. Assuming $q_{t,k\ell}$'s are the same for $k = 1, 2, ..., K$, then $\pi_{t|T,k} = \pi_{t|t,k}$.

B.3 Parameter Averaging

The retrospective model averaging estimates of y_t and parameters are given by $\hat{y}_t^{DMA} = \Sigma_{k=1}^{K} \pi_{t|T,k} \boldsymbol{x}'_{t,k} \hat{\boldsymbol{\theta}}_{t|T,k}$, and $\hat{\theta}_t^{DMA} = \Sigma_{k=1}^{K} \pi_{t|T,k} \hat{\boldsymbol{\theta}}_{t|T,k}$, where $\pi_{t|T,k}$ is the retrospective model probability (B.2.4). The *i*-th parameter's retrospective inclusion probability is $RIP_t^{DMA}(\theta_i) = \Sigma_{k=1}^{K} \pi_{t|T,k} \boldsymbol{I}_k(\theta_i)$ for all *i*, where $\boldsymbol{I}_k(\theta_i)$ is the indicator function that equals 1 if θ_i is included in the *k*-th model. The variance of the retrospective parameter $\hat{\theta}_{i,t}^{DMA}$ is $\Sigma_{k=1}^{K} \pi_{t|T,k} [\mathrm{var}(\hat{\theta}_{i,t,k}^{DMA}) + \hat{\boldsymbol{\theta}}_{t|T,k}^2] - (\hat{\boldsymbol{\theta}}_t^{DMA})^2$.

B.4 Initial Values in the Estimation

Category	Parameters	Initial Values
DMA setup	τ in DMA	0.99
	κ for EWMA	0.98
	V_0 for EWMA	variance of OLS residuals
	$\boldsymbol{\Sigma}_{0\|0,k}$ for all *k*	diagonal elements are var(*y*)/var(x_i)#, non-diagonal elements are 0
	$\pi_{0\|0,k}$ for all *k*	1/*K*
	c	0.001/*K*
UIP setup	α_0, intercept	0
	β_0 of ∇i_t	1
	$\theta_{i,0}$ *of* $C\hat{I}Pd_{t-1}$	1
	$\theta_{i,0}$'s for $R\hat{P}_{t-1}$ and $E\hat{R}_t$	0

Notes: # "*y*" is the LHS variable, "x_i" is the RHS variable in the *k*-th model.

[23] As discussed, (B.2.3) is based on retrospective distributions. For the typical DMA based on "forecasts," (B.2.3) is modified to $\pi_{t|t,k} = P(L_t = k \mid \boldsymbol{F}_t) = \pi_{t|t-1,k} f_k(y_t \mid Y_{t-1})[\Sigma_{\ell=1}^{K} \pi_{t|t-1,\ell} f_\ell(y_t \mid Y_{t-1})]^{-1}$, where the likelihood value is based on (B.1.4).

B.5 Derivation of (B.2.4).

The retrospective model probability of the *k*-th model is

$$\pi_{t|T,k} = P(L_t = k \mid \boldsymbol{F}_T) = \Sigma_{\ell=1}^{K} P(L_t = k \mid \boldsymbol{F}_T, L_{t+1} = \ell) P(L_{t+1} = \ell \mid \boldsymbol{F}_T) . \quad \text{(B.5.1)}$$

The Bayes' theorem implies,

$$P(L_t = k \mid \boldsymbol{F}_T, L_{t+1} = \ell)$$
$$= P(L_t = k \mid \boldsymbol{F}_t, L_{t+1} = \ell) P(\boldsymbol{F}_{t+1/T} \mid \boldsymbol{F}_t, L_t = k, L_{t+1} = \ell)[P(\boldsymbol{F}_{t+1/T} \mid \boldsymbol{F}_t, L_{t+1} = \ell)]^{-1}$$
$$= P(L_t = k \mid \boldsymbol{F}_t, L_{t+1} = \ell) \quad \text{(B.5.2)}$$
$$= P(L_t = k \mid \boldsymbol{F}_t) P(L_{t+1} = \ell \mid \boldsymbol{F}_t, L_t = k)[P(L_{t+1} = \ell \mid \boldsymbol{F}_t)]^{-1} \quad \text{(B.5.3)}$$
$$= \pi_{t|t,k} q_{t,k\ell} (\pi_{t+1|t,\ell})^{-1} . \quad \text{(B.5.4)}$$

where (B.5.2) follows from $\boldsymbol{F}_{t+1/T} = \{\boldsymbol{F}_{t+1}, ..., \boldsymbol{F}_T\}$, $\boldsymbol{F}_t$ and $\boldsymbol{F}_{t+1/T}$ are independent of the state of L_t, and, thus, the two terms $P(\boldsymbol{F}_{t+1/T} \mid \cdot)$ cancel out, (B.5.3) follows from the Bayes' theorem.

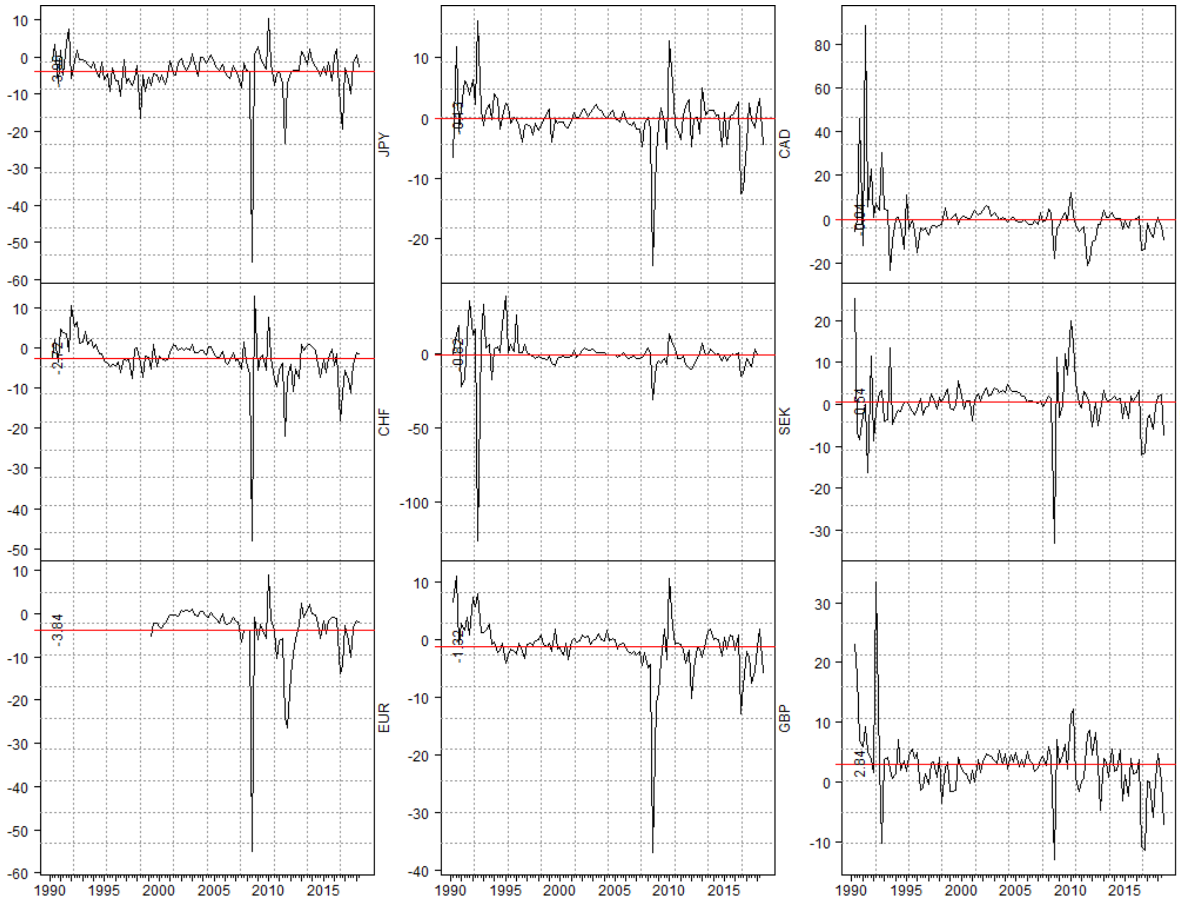
Substituting (B.5.4) into (B.5.1), we obtain (B.2.4):

$$\pi_{t|T,k} = P(L_t = k \mid \boldsymbol{F}_T) = \pi_{t|t,k} \Sigma_{\ell=1}^{K} q_{t,k\ell} (\pi_{t+1|T,\ell})(\pi_{t+1|t,\ell})^{-1} .$$

The retrospective model probability depends on the transition matrix $Q_t = [q_{t,k\ell}]$. The data do provide enough information about the transition matrix. Without any restrictions, there are infinite ways to define the transition matrix. However, most of these feasible transition matrices do not have a clear economic meaning. For simplicity purpose, we assume that all $q_{t,k\ell}$'s are the same for $k = 1, 2, ..., K$, and then, $q_{t,k\ell} = \pi_{t+1|t,\ell}$, and $\pi_{t|T,k} = \pi_{t|t,k}$. This assumption implies all the states are the same and with the same probability to transfer to the same state in the next period.

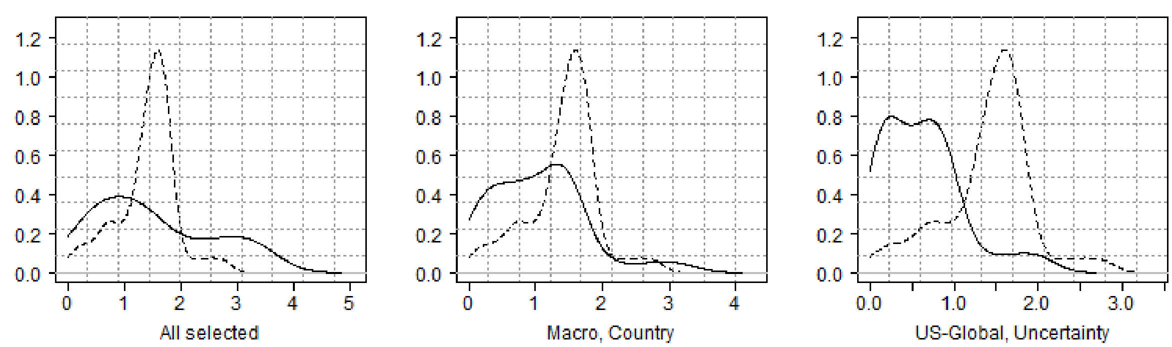
Appendix C. Additional Results

C.1 CIP deviations



Notes: The cross-country basis is used as the proxy for CIP deviations. The red horizon line is the average of cross-country bases. The unit is basis point.

C.2 The Empirical Density Distributions of $|\hat{\beta}^{aug}_{t|T} - 1|$ in Different Augmented UIP Regressions for EUR



Notes: The solid line is the density distribution of $|\hat{\beta}^{aug}_{t|T} - 1|$ in different augmented UIP regressions, and the dash line is the density distribution of $|\hat{\beta}^{biv}_{t|T} - 1|$.

C.3 Results of Synthetic UIP Models: Different λ values

λ	Estimator	JPY	CHF	EUR	CAD	SEK	GBP	NOK	AUD	NZD
Panel A										
0.96	Mean β	-0.214	**0.625**	-0.355	-0.173	**1.188**	1.333	0.404	**-0.054**	0.490
		[1.005]	**[0.253]**	[3.657]	[2.693]	**[0.342]**	[1.000]	[36.641]	**[0.407]**	[1.161]
	MAD β	**1.284**	**0.669**	1.355	**1.173**	**0.280**	0.599	**0.596**	**1.454**	**0.567**
		[0.908]	**[0.452]**	[1.448]	**[0.935]**	**[0.470]**	[1.000]	**[0.790]**	**[0.561]**	**[0.336]**
	DM	3.436***	2.360**	-1.581	0.457	1.926*	--	1.708*	8.002***	3.604***
0.97	Mean β	**-0.181**	**0.642**	0.811	0.277	**1.161**	1.076	0.861	**-0.166**	**0.931**
		[0.897]	**[0.229]**	[1.204]	[1.000]	**[0.347]**	[1.000]	[1.000]	**[0.440]**	**[0.080]**
	MAD β	**1.183**	**0.806**	**0.351**	0.902	**0.175**	0.321	0.457	**1.236**	**0.272**
		[0.899]	**[0.516]**	**[0.702]**	[1.000]	**[0.346]**	[1.000]	[1.000]	**[0.466]**	**[0.227]**
	DM	2.652***	2.578**	3.886***	--	2.885***	--	--	9.613***	3.282***
0.98	Mean β	**-0.387**	**0.169**	**0.463**	**0.897**	**1.127**	0.854	0.774	**0.546**	**1.052**
		[0.960]	**[0.506]**	**[0.757]**	**[0.109]**	**[0.378]**	[1.000]	[1.000]	**[0.169]**	**[0.043]**
	MAD β	**1.387**	**0.895**	**0.537**	**0.489**	**0.144**	0.192	0.238	**0.972**	**0.387**
		[0.960]	**[0.545]**	**[0.757]**	**[0.513]**	**[0.388]**	[1.000]	[1.000]	**[0.362]**	**[0.317]**
	DM	2.209**	2.709***	2.331**	4.064***	3.081***	--	--	14.655***	3.153***
0.99	Mean β	**-0.526**	**-0.019**	**0.305**	**1.423**	**1.106**	**0.950**	**1.056**	**-0.738**	**0.717**
		[0.952]	**[0.600]**	**[0.540]**	**[0.386]**	**[0.633]**	**[0.161]**	**[0.214]**	**[0.648]**	**[0.189]**
	MAD β	**1.526**	**1.019**	**0.695**	**0.423**	**0.110**	**0.084**	**0.126**	**1.738**	**0.304**
		[0.952]	**[0.600]**	**[0.540]**	**[0.386]**	**[0.574]**	**[0.269]**	**[0.481]**	**[0.648]**	**[0.203]**
	DM	2.600**	3.923***	17.006***	7.260***	1.989**	14.579***	3.556***	60.702***	22.450***
Panel B										
0.96	$\widehat{CIPd}_{t-1}$	--	$\widehat{CIPd}_{t-1}$	--	--	--	--	--	$\widehat{CIPd}_{t-1}$	--
	$\widehat{RP}_{t-1}$	--	US-Global	Macro, Country	Macro, Country	US-Global, Country	--	--	Macro, Country	Macro
	$\widehat{ER}_t$	US-Global	Uncertainty	US-Global, Uncertainty	Macro, US-Global	--	--	US-Global	--	US-Global, Uncertainty
0.97	$\widehat{CIPd}_{t-1}$	--	$\widehat{CIPd}_{t-1}$	--	--	--	--	--	$\widehat{CIPd}_{t-1}$	--
	$\widehat{RP}_{t-1}$	--	US-Global	Country	--	US-Global, Country	--	--	US-Global	--
	$\widehat{ER}_t$	Uncertainty	Macro, Uncertainty	--	--	--	--	--	--	Macro, US-Global, Uncertainty
0.98	$\widehat{CIPd}_{t-1}$	--	$\widehat{CIPd}_{t-1}$	--	$\widehat{CIPd}_{t-1}$	--	--	--	$\widehat{CIPd}_{t-1}$	$\widehat{CIPd}_{t-1}$
	$\widehat{RP}_{t-1}$	--	--	--	Macro, US-Global, Country	US-Global, Country	--	--	Macro, US-Global, Country	US-Global

	$\hat{ER}_t$	Uncertainty	Macro, Uncertainty	US-Global, Uncertainty	--	--	--	--	--	Macro, Uncertainty
0.99	$\hat{CIPd}_{t-1}$	--	$\hat{CIPd}_{t-1}$	--	$\hat{CIPd}_{t-1}$	--	--	$\hat{CIPd}_{t-1}$	$\hat{CIPd}_{t-1}$	$\hat{CIPd}_{t-1}$
	$\hat{RP}_{t-1}$	--	--	--	US-Global	US-Global, Country	Macro, Country	--	Macro, US-Global, Country	US-Global, Country
	$\hat{ER}_t$	Macro, Uncertainty	Macro, Uncertainty	US-Global, Uncertainty	Macro, US-Global	--	--	--	US-Global	Macro, Uncertainty

Notes: Panel A presents, for a given λ value, the summary of β-estimates from synthetic UIP regressions with selected categories of empirical proxies for CIP deviations ($\hat{CIPd}_{t-1}$), risk premiums ($\hat{RP}_{t-1}$), and expectational errors ($\hat{ER}_t$). Panel B presents, for each currency and λ value, the specific categories of empirical proxies included the synthetic UIP regression. See the notes to the previous tables.

"Mean β" and "MAD β" present, respectively, the means of β-estimates and the means of absolute deviation of β-estimates from unity for synthetic UIP Models defined by the categories listed in the corresponding entries in Panel B. "DM" give the Diebold-Mariano statistics for testing the equality of the means of absolute deviation of β-estimates from unity in synthetic UIP model and the corresponding bivariate UIP regression. *, ** and *** indicate rejections of DM test at 10%, 5% and 1% level. The bold numbers indicate the corresponding β-estimates are closer to its theoretical value.