Uncovered Interest Rate Parity Redux: Non-Uniform Effects

Yin-Wong Cheung
Wenhao Wang

Abstract

Based on the $\beta$-estimate that captures the interest rate differential effect in uncovered interest rate parity (UIP) regressions, we show that an empirical model that includes proxy variables for unobservable factors and allows for variables to have time-varying weights and parameters can reduce the UIP deviation. However, the specification that alleviated UIP failure does not reduce the variability of the $\beta$-estimate. The explanatory variables exhibit time-varying coefficient estimates and shifting importance across exchange rates. These findings corroborate the scapegoat theory and suggest that the difficulty of rectifying the empirical UIP failure can be attributable to the shifting roles of explanatory variables and time-varying parameter effects.

JEL Classifications: F31, G15

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

Cheung: Department of Economics, University of California, Santa Cruz, USA.
E-mail: cheung@ucsc.edu

Wang, School of Finance, Shandong University of Finance and Economics, CHINA.
E-mail: andrew_wang9007@sdufe.edu.cn.

Acknowledgments: The authors thank Menzie Chinn and Michał Rubaszek for their comments and suggestions. Cheung and Wang gratefully thank the Hung Hing Ying and Leung Hau Ling Charitable Foundation for its continuing support via the Hung Hing Ying Chair Professorship of International Economics.
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.

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 $\beta$-estimate (henceforth, the “$\beta$-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 corroborates the reported carry trade profits, which are driven by the puzzling phenomenon that high yield currencies tend to appreciate.

Theoretically, the presence of risk premiums, expectational errors, and changing market beliefs can lead to UIP violations. The UIP puzzle has triggered numerous studies assessing the roles of risk premiums, expectational errors, and market’s shifting perceptions about exchange rate determinants in explaining the UIP failure. In general, UIP failure is a widespread finding in the empirical literature – the $\beta$-estimates from various empirical specifications are usually different from one, and even negative.

Different empirical UIP studies employed different empirical proxy variables for the unobservable risk premiums and expectational errors; these proxy variables 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 proxy variables capture the attributes of unobservable factors that are relevant to UIP? The answer to this question is complicated by the scapegoat theory that suggests the relative importance of determinants of exchange rates.

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


3 There are a few studies showing 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.
can shift across different time periods (Bacchetta and Van Wincoop, 2004, 2013). The change of the importance of determinants affects the arbitrage behavior between foreign exchange and money markets and, thus, the appropriate proxy variables for modelling the observed UIP relationship over time. There is uncertainty in selecting the relevant set of empirical proxy variables for unobservable terms in the UIP regression. The issue is further complicated by time-varying parameters and currency-specific behaviors (Baillie and Kilic, 2006; Rossi, 2013; Sarno and Valente, 2009).

Against this backdrop, we consider a modified UIP regression augmented with empirical proxy variables for covered interest rate parity (CIP) deviations, risk premiums, and expectational errors. Instead of creating our list of proxy variables, we draw from the existing studies 27 empirical proxy variables for these three augmented variables. We focus on the behavior of the $\beta$-estimate in the presence of these proxy variables and use it to infer the implications of these proxy variables for the empirical relevance of UIP.

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 shifting importance of proxy variables implied by the scapegoat theory and time-varying parameters. Since UIP connects the foreign exchange and money markets, we follow the explanatory, instead of the predictive, modelling approach, and assess the explanatory rather than the predictive power of the empirical model. Thus, we conduct retrospective statistical inferences that incorporate information in the entire sample. The resulting retrospective posterior distributions are used to infer the shifting importance of explanatory variables and provide a data-driven approach to assess the implication of scapegoat theory for the empirical UIP relation.

We use the deviation of the $\beta$-estimate from its theoretical value of one to measure the degree of UIP failure. Specifically, we compare the time-varying $\beta$-estimates from the canonical bivariate UIP specification and specifications augmented with proxy variables. If the

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4 Bacchetta and Van Wincoop (2004) point out that the scapegoat theory is in line with the finding that some models with certain variables explain some exchange rates well in some periods but not others (Cheung et al., 2005), and market traders altered their views on the importance of determinants (Cheung and Chinn, 2001). Fratzscher et al. (2015) offer the first empirical test of the theory.

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

6 Fratzscher et al. (2015) use survey data to quantify scapegoat measures for testing the scapegoat theory. Market traders surveyed by Cheung and Chinn (2001) altered their perceived importance of determinants. Without survey data, our exercise infers from the data the change of importance of explanatory variables as implied by the scapegoat theory.
presence of proxy variables leads to a reduction of the $\beta$-estimate’s deviation from one, we test if the reduction is statistically significant.

Our exercise adds to the existing UIP studies in several aspects. First, we consider a large set of proxy variables for unobservable factors relevant to the empirical UIP formulation. Second, we adopt a modified dynamic model average procedure to estimate a Bayesian dynamic linear model. The setting allows us to infer the shifting importance of the proxy variables and, hence, provide (indirect) evidence of the scapegoat effect in a time-varying parameter environment. Third, the empirical setup allows us to evaluate the empirical UIP relation extensively. We document the presence of scapegoat effects in the UIP context, and the roles of changing roles of explanatory variables and time-varying effects in explaining UIP failure.

To anticipate results, we affirm that the $\beta$-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. Comparatively speaking, the $\beta$-estimate tends to be negative before the 2007-8 global financial crisis (GFC) and positive after. Further, it exhibits large sampling uncertainty.

There is evidence that including empirical proxy variables for CIP deviations, risk premiums and expectational errors can alleviate UIP deviations by either reducing the mean deviation or the mean absolute deviation of time-varying $\beta$-estimates from one. There are caveats to the reported improvement of UIP results. For instance, while the $\beta$-estimate is closer to its predicted value of one, 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.

The set of proxy variables that improves the UIP result is not constant over time. The importance of these proxy variables shifts over time, and the noticeable shifts tend to occur around crisis periods; a finding that is implied by the scapegoat theory. Further, the pattern of shifting importance, the set of proxy variables, and the effects of these proxy variables vary across exchange rates.

Our study affirms that the UIP relation goes beyond the simple bivariate relationship of exchange rate changes and interest rate differentials. In addition to CIP deviations, forward premiums, and expectational errors, the shifting roles of factors influenced by market perception on market dynamics can affect the observed link between exchange rate changes and interest rate differentials. Thus, the role of market sentiment and the fickleness of the
simple bivariate UIP formulation should be incorporated in policymaking, and in investment decisions.

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, 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 UIP estimation results with a focus on the deviations of the \( \beta \)-estimate from one. Section 5 reports the results on the shifting importance of empirical proxy variables and their time-varying effects. Section 6 offers some additional discussions, including results from two alternative approaches to reduce the dimensionality of the dataset. Section 7 concludes.

2. An Empirical UIP Framework

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

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

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 \( t \), \( i_{t-1} \) and \( i^*_{t-1} \) are 1-period domestic and foreign interest rates available at time \( t-1 \). Equation (1) states that the expected depreciation of the exchange rate is offset by the 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 (\( \mu^*_{t-1} \)), the parity condition can be re-written as

\[
E_{t-1}(s_t) - s_{t-1} = i_{t-1} - i^*_{t-1} + \mu^*_{t-1}, \tag{2}
\]

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

\[
y_t = \alpha + \beta V_t(i_t + \eta_t), \quad t = 1, \ldots, T, \tag{3}
\]

where \( y_t \equiv s_t - s_{t-1}, \quad V_t \equiv i_{t-1} - i^*_{t-1}, \quad T \) is the sample size, and the empirical \( \beta \)-estimate tends to be less than one or even negative. Given equation (2), the residual term \( \eta_t \) comprises the usual random sampling error (\( \varepsilon_t \)), the UIP deviation (\( \mu^*_{t-1} \)) and the expectational error (\( s_t - E_{t-1}(s_t) \)).
To shed some light on $\mu_{t,s}$, we consider the CIP with deviations ($\mu_{t,s}^d$, $s$) given by

$$f_{t-1,t} - s_{t-1} = l_{t-1,t} - l_{t-1,t}^* + \mu_{t,s}^d$$  \hspace{1cm} (4)

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

$$\mu_{t,s}^d = f_{t-1,t} - E_{t,s}(s_t) + \mu_{t,s}^d;$$  \hspace{1cm} (5)

where $f_{t-1,t} - E_{t,s}(s_t)$ is the foreign exchange risk premium. That is, the wedge between the UIP and CIP deviations is the risk premium. Given equation (5), the term $\eta_t$ in equation (3) can be expressed as the sum of the usual random sampling error ($\varepsilon_t$), the CIP deviation ($\mu_{t,s}^d$), the risk premium ($f_{t-1,t} - E_{t,s}(s_t)$), and the expectational error ($s_t - E_{t,s}(s_t)$). That is, we can re-write the canonical UIP regression (3) as

$$y_t = \alpha + \beta^*_i + \gamma z_t + \varepsilon_t,$$  \hspace{1cm} (6)

where the vector $z_t$ comprises a) $\hat{CIPd}_{t,s}$ that includes empirical proxy variables for $\mu_{t,s}^d$, b) $R^\phi_{t,s}$ empirical proxy variables for ($f_{t-1,t} - E_{t,s}(s_t)$), and c) $ER^\phi$, empirical proxy variables for ($s_t - E_{t,s}(s_t)$). For brevity, we call the elements of $z_t$ the control variables.

Conceivably, estimating equation (3) without the proper set of control variables can lead to a biased $\beta$-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.\footnote{1990Q1 to 2018Q4 represents the maximum sample period. Due to data availability, some currencies have a shorter sample; for instance, the Euro starts at 1999Q1; see Appendix A.1.} 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).\footnote{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.}

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.

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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 definition/construction of these variables and other variables used in the study.

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 Variables 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 defined by the cross-currency basis.

The plots of CIP deviations considered in our exercise (Appendix C.1) corroborate the usual notion that, except for 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. However, there is not a clear pattern across these currencies.

3.2 Proxy Variables for Risk Premiums, \( \hat{RP}_{t-1} \)

The risk premium (\( f_{t-1} - E_{t-1}(s_t) \)) is what required to compensate an investor for assuming the foreign exchange risk in trading currency. Existing UIP studies have considered alternative approaches to model and quantify the unobserved risk premium. We selected 15 empirical proxy variables for the risk premium from existing studies and grouped them into three categories.

The first category includes eight proxy variables 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).10

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9 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.

The second category includes three proxy variables for risks in the *US financial markets* and two proxy variables 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.\(^{11}\) 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., 2012a). 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.\(^{12}\)

The third category comprises two *country-specific* proxy variables for financial market risks. They are a) the cross-country difference of MSCI returns (Gavin, 1989; Hossfeld and MacDonald, 2015; Phylaktis and Ravazzolo, 2005; Ranaldo and Söderlind, 2010), and b) the lagged exchange rate changes (Baillie and Chang, 2011; Menkhoff et al., 2012b).

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

### 3.3 Proxy Variables for Expectational Errors, \(E\hat{\epsilon}\)

The expectational error (\(s_t - E_{t-1}(s_t)\)) occurs where unexpected shocks affect the market between time \(t-1\) and \(t\). We consider 11 proxy variables 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 proxy variables for *macro* shocks – three proxy variables capture shocks to the cross-country differences of inflation rates, money supply growth rates and output gaps, and one proxy variable given by the contemporaneous change in interest rate differentials.

The second category comprises four proxy variables for shocks to the *US financial markets* and the *global foreign exchange market*. Specifically, the contemporaneous VIX index

\(^{11}\) 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).

\(^{12}\) Studies that 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).
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., 2012a; 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).13

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 the collinearity of these proxy variables.

3.4 Econometric Methodology

There are some issues to consider before estimating equation (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 Bayesian dynamic linear model (DLM) set up.

Besides time varying effects, the importance of individual proxy variables can change over time. The scapegoat theory (Bacchetta and Van Wincoop, 2004, 2013) postulates that, as market participants alter their beliefs, the role of fundamentals in the foreign exchange market can shift over time.14 Since UIP depends on arbitrage behaviors between foreign exchange and money markets, the shifting roles of exchange rate fundamentals can shift an investor’s perception of the importance of the proxy variables in the UIP formulation. As their relative importance changes, the set of proxy variables that is relevant for equation (6) can vary over time; that is, there is model uncertainty over time. Further, previous studies consider different

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13 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.

14 The scapegoat theory is in accordance with the finding that different empirical models perform differently in different historical periods across currencies (Cheung et al., 2005; Cheung et al., 2019; Rossi, 2013). Cheung and Chinn (2001) report that market participants alter their views on the relative importance of macroeconomic variables. Some empirical studies on the scapegoat theory Cao et al. (2019), Fratzscher et al. (2015), Markiewicz (2012), and Pozzi and Sadaba (2018).
subsets of the 27 proxy variables selected in the previous subsection as control variables. We do not have a strong theory on which proxy variable is best for all historical periods.

To tackle the model uncertainty issue, we adopt a modified dynamic model averaging (DMA) framework with a retrospective perspective to estimate the DLM model (Raftery et al., 2010; West and Harrison, 1997). As said before, we are interested in studying the in-sample $\beta$-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. While DLM allows for time-varying parameters that are a feature of UIP relation, DMA offers a tractable way to extract information about the time-varying importance of individual explanatory variables and account for model uncertainty. The time-varying importance of individual explanatory variables is used as a data-driven measure to assess the shifting roles of empirical proxy variables implied by the scapegoat theory. In doing so, our empirical exercise accounted for the scapegoat effect by allowing the importance of individual proxy variables to vary over time.

To estimate the UIP in the DLM-DMA setup, we modify equation (6) to the DLM setup (Beckmann and Schüssler, 2016; Byrne et al., 2018; Koop and Korobilis, 2012; Raftery et al., 2010) given by

$$y_t = x_t' \theta_t + \varepsilon_t, \quad \varepsilon_t \sim N(0, V),$$  
and  
$$\theta_t = \theta_{t-1} + \delta_t, \quad \delta_t \sim N(0, W_t),$$  
where $x_t' \equiv (1, \sqrt{i_z}, z_t)$, $\theta_t$ contains the corresponding time-varying parameters $\alpha_t$, $\beta_t$, and $\gamma_t$, and $W_t$ is the variance of the error term $\delta_t$ that defines the degree of parameter variability. If $W_t = 0, \forall t$, the model is a static one.

Bayesian methods are used to generate $\theta_t$ estimates and their filtered distributions recursively. 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 $\theta_t$ and retrospective sample likelihood function from the retrospective estimation procedure.

The data-driven retrospective likelihood values are used to evaluate alternative model specifications and 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

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15 Fratzscher et al. (2015) present a direct test for scapegoat theory with scapegoat measures from survey data.
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 weights for adjusting the retrospective estimates from the $K$ models to obtain the model averaging retrospective estimate of $\theta$. The technique of model averaging offers a formal way to obtain combinations of estimates from multiple models.

The relative importance and relevance of a proxy variable is inferred from the sum of the retrospective probabilities of models that include the proxy variable; we label it the retrospective inclusion probability of the proxy variable. Following the posterior inclusion probability of the usual Bayesian model averaging approach, we label a proxy variable 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 (Kass and Raftery, 1995; Havranek et al., 2015). The proxy variable is not “important” if its retrospective inclusion probability is less than 0.5. That is, the retrospective inclusion probability of a proxy variable indicates its importance in the regression. The scapegoat theory stipulates the importance attributed to a proxy variable can change with market conditions. Appendix B gives a detailed description of the econometric setup and the calculation of retrospective model probabilities.

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 proxy variables for CIP deviations ($\hat{CIPd}_{it}$), risk premiums ($\hat{RP}_{it}$), and expectational errors ($\hat{ER}_{it}$). The focus is on the implications of the presence of these control variables for the $\beta$-estimate.

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 ($\nabla_i$)”.

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The top panel presents results from the entire sample from 1990Q1 to 2018Q4. The β-estimate ranges between -1.421 and 1.307. While the β-estimates of JPY, CHF, EUR, AUD, and NZD are negative but insignificantly different from zero, 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 close to one but 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). The intercept estimates (α-estimates) are insignificant, and the explanatory power of the model is quite limited as the adjusted R² 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 are noticeably different across subsamples. These subsample β-estimates also exhibit more volatile patterns than and different from those of the full sample. In the first subsample period, four currencies have a negative β-estimate, and four have a positive one.16 Three β-estimates reject the hypothesis of β = 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 one.17 In the last subsample period, however, eight out of nine β-estimates are larger than one, and one is significantly larger than one (Bussiere et al., 2018).18 The explanatory power of the interest rate differential, according to the adjusted R² 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 differentials. The stark contrast between the β-estimates of the second and third subsample mirrors the different economic conditions in these two historical periods. A time-invariant specification is likely to disguise the non-constant interest rate differential effect.

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16 The EUR data are not available for the first subsample.
17 Lothian and Wu (2011) show that a negative estimate is specific to some historical periods like the 1980s.
18 If the subsample starts at 2009Q1, the resulting β-estimates become smaller, and some even turn negative.
Table 2 summarizes the results of estimating the bivariate time-varying version of equations (7) and (8) with \( x_t \approx \{ 1, V_t \} \). To implement the Bayesian estimation procedure, we have to pre-determine the value of the \( \lambda \) parameter introduced in Appendix B.1 to update the variance \( W \) in (8). Intuitively, the \( \lambda \) parameter determines the choice of an effective window size \((1 - \lambda)^{-1}\) that is related to the rate of discounting past observations; a larger \( \lambda \) implies a larger weight assigned to past observations, and \( W \) is effectively zero at the limit of \( \lambda = 1 \). In the current exercise, we set \( \lambda = 0.95 \). The results based on \( \lambda = 0.96, 0.97, 0.98, \) and 0.99 are discussed in subsection 6.2.

The average values of the retrospective intercept estimates (\( \hat{a} \)) and of their standard errors are given in the rows labelled, respectively, “Mean \( a \)” and “Mean se \( a \).” There is no indication of a significant intercept estimate. “MAD \( a \)” gives the mean absolute value (MAD) of \{ \( \hat{a} \) \}. Note that “MAD \( a \)” is defined with reference to \( a \)’s theoretical value of zero.

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

To gauge UIP deviations, we report the mean absolute deviation of \( \hat{\beta} \) from 1 under the row labelled “MAD \( \beta \)” – that is, the MAD with reference to \( \beta \)’s theoretical value of one. The MAD measure is generally large; the usual carry trade target currencies AUD and NZD display a high level of “MAD” larger than 2.

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

4.2 Augmented UIP Regressions

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19 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).
In this subsection, we consider equations (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 \( 2^{27} (=134,217,728) \), 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 first conduct the retrospective analysis under the DLM-DMA setting with individual \( \hat{CIP}_{t-1}, \hat{R}_{t-1}, \) and \( \hat{E}_{t} \), and then with some synthetic combinations of these three categories. For brevity, we focus on the \( \beta \)-estimate which is our measure of UIP deviations.

### 4.2.1 The Proxy variables for CIP deviations, \( \hat{CIP}_{t-1} \)

The effect of including the proxy variable for CIP deviations – the cross-currency basis – on the \( \beta \)-estimate is summarized in Table 3. Corresponding to the statistics reported in the rows labelled “Mean \( \beta \)” and “MAD \( \beta \),” we present respectively the ratios \( \frac{\Sigma |I(\hat{\beta}_{\text{biv}} - 1)|}{\Sigma |I(\hat{\beta}_{\text{aug}} - 1)|} \) and \( \frac{\Sigma |I(\hat{\beta}_{\text{biv}}^{\text{aug}} - 1)|}{\Sigma |I(\hat{\beta}_{\text{aug}}^{\text{aug}} - 1)|} \) that are derived from the absolute value of the mean deviation of \( \beta \)-estimates from one and the mean absolute deviation of \( \beta \)-estimate from one, where \( \hat{\beta}_{\text{biv}} \) is the retrospective \( \beta \)-estimate in Table 2 and \( \hat{\beta}_{\text{aug}}^{\text{aug}} \) is the corresponding retrospective estimate in Table 3. The two ratios offer two alternative perspectives on evaluating deviation from the theoretical value of one. The mean deviation measure allows positive and negative deviations to offset each other. The former ratio focuses on the relative size of the average deviations. The latter ratio, on the other hand, treats positive and negative deviations as non-offsetting quantities and compares the cumulative sums of the magnitudes of deviations.

When the ratio is less than one (indicated by bold figures in the table), the estimated level of UIP deviation implied by \( \hat{\beta}_{\text{biv}} \) is larger than the corresponding one implied by \( \hat{\beta}_{\text{aug}}^{\text{aug}} \); that is, the inclusion of the proxy variable for CIP deviations weakens the evidence on UIP failure.

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20 The use of principal component analysis and partial least squares regression to reduce the dimensionality of parameter space is discussed in the next section.

21 A significant \( \alpha \)-estimate is an evidence of UIP violation. The intercept \( \alpha \)-estimates are in general small and insignificant in the current exercise.

22 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 variables also inflates the sampling uncertainty of the \( \beta \)-estimate.

23 Consider \( \frac{\Sigma |I(\hat{\beta}_{\text{biv}} - 1)|}{\Sigma |I(\hat{\beta}_{\text{aug}} - 1)|} \) and \( \frac{\Sigma |I(\hat{\beta}_{\text{biv}}^{\text{aug}} - 1)|}{\Sigma |I(\hat{\beta}_{\text{aug}}^{\text{aug}} - 1)|} \). If the \( \hat{\beta}_{\text{biv}}^{\text{aug}} \) series assumes the value of \(+1\) and \(-1\). Then the first ratio is zero while the second one is not. The relative merit of these ratios depends on the purposes of the analysis.
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 in the presence of the CIP proxy variable. For other cases, the inclusion of the proxy variable does not improve the result, but 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”: \( T \cdot \Sigma_t (| \hat{\beta}_{it}^{\text{aug}} - 1 | - | \hat{\beta}_{it}^{\text{biv}} - 1 |) \) (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. That is, the proxy variable improves the UIP result by significantly reducing \( \beta \)-estimate’s MAD. However, the CIP deviation proxy variable 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 variable for UIP are mixed across currencies, and the evidence on improving the UIP result is limited.

4.2.2 Proxy variables for Risk Premiums, \( r_{RP}^{t-1} \)

We selected 15 empirical proxy variables for risk premiums from existing studies 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 proxy variables. We adopt the DMA approach for each augmented specification to find, period by period, the “best” model averaging representation. Since there are eight proxy variables 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 variables categories ranges from 4 (=2^2) to 32,768 (=2^15). The DLM-DMA setup allows, for each augmented specification, the “best” set of proxy variables and their effects to change over time.

Table 4 summarizes the \( \beta \)-estimates from specifications augmented with alternative combinations of categories of risk premium proxy variables. Again, the ratios \( | \Sigma_t (\hat{\beta}_{it}^{\text{aug}} - 1) | / | \Sigma_t (\hat{\beta}_{it}^{\text{biv}} - 1) | \) and \( | \Sigma_t (\hat{\beta}_{it}^{\text{aug}} - 1) | / | \Sigma_t (\hat{\beta}_{it}^{\text{biv}} - 1) | \) are presented underneath, respectively, the rows of “Mean \( \beta \)” and “MAD \( \beta \).” A ratio less than one – indicated by bold figures – suggests that, compared with the \( \hat{\beta}_{it}^{\text{biv}} \) in Table 2, the \( \hat{\beta}_{it}^{\text{aug}} \) 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 $\hat{\beta}_{augT}^{\beta}$ compared with $\hat{\beta}_{bivT}^{\beta}$ 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 $\beta$-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 the seven combinations of proxy variables categories. For example, the country-specific category yields six improved cases, while the combination of the US-Global and country-specific categories has ten improved cases. Also, the ability of these proxy variables categories to enhance UIP results appears exchange-rate-specific. The AUD case offers the most encouraging finding; these combinations of proxy variables categories, except for the country-specific category, improve UIP results. These proxy variables, however, do not improve the UIP result for JPY.

Third, among the 32 cases in which the MAD ratio $\Sigma_{t} |\hat{\beta}_{augT}^{\beta} - 1| / \Sigma_{t} |\hat{\beta}_{bivT}^{\beta} - 1|$ 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 proxy variables are not relevant for alleviating the UIP failure.

### 4.2.3 Proxy variables for Expectational Errors, $E\hat{r}$

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

According to the ratios $|\Sigma_{t}(\hat{\beta}_{augT}^{\beta} - 1)| / |\Sigma_{t}(\hat{\beta}_{bivT}^{\beta} - 1)|$ and $|\Sigma_{t}(\hat{\beta}_{augT}^{\beta} - 1)| / |\Sigma_{t}(\hat{\beta}_{bivT}^{\beta} - 1)|$ underneath the “Mean $\beta$” and “MAD $\beta$” 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 59 recorded in Table 4.

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

The DM statistic indicates that, among the 34 cases in which the MAD ratio $\Sigma |\hat{\beta}_m - 1| / \Sigma |\hat{\beta}_m ^{\text{aug}} - 1|$ 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 proxy variables 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 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 $\hat{\epsilon}_t$, $\hat{\epsilon}_t^{\text{RP}}$, and $\hat{\epsilon}_t^{\text{ER}}$ are presented in the previous subsections. The evidence of these selected empirical proxy variables to reduce the $\beta$-estimate’s deviation from one is mixed. These results do not identify a consistent positive role of a given category of proxy variables. Our findings collaborate with the belief that these (proxy variables 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 proxy variables. For each exchange rate, we refer to Tables 2, 3 and 4 and form synthetic augmented UIP models with the CIP deviation proxy variables, the risk premium proxy variables, and the expectational error proxy variables that lead to a significant reduction in MAD of the $\beta$-estimate. Table 6 summarizes the $\beta$-estimates from the DLM-DMA retrospective analysis of individual synthetic models in the upper panel, and the categories of proxy variables included in the corresponding synthetic models 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 in Table 2. 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

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24 The no-proxy variables-effect for JPY is unique to the case of $\lambda = 0.95$. Subsection 5.3 notes the sensitivity to the choice of $\lambda$ value. Also, the SEK synthetic specification is the improved case based on a one-sided test in Table 4.
sources of $C_iP_{d_i}$, $R_{t-1}$, and $E_{t}$, while the remaining four cases include a single category. Each of $R_{t-1}$ and $E_{t}$ contributes five times to these synthetic specifications.

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

The MAD ratio $\Sigma |\hat{\beta}_{i/t}^{aug} - 1| / \Sigma |\hat{\beta}_{i/t}^{biv} - 1|$ offers encouraging UIP results. With the exception of EUR, the $\hat{\beta}_{i/t}^{aug}$ from synthetic models has a MAD smaller than the MAD of the corresponding $\hat{\beta}_{i/t}^{biv}$. 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 inclusion of these proxy variables reduces the mean absolute deviation of the $\beta$-estimate from its theoretical value of one. The omission of these proxy variables can sway the $\beta$-estimate away from its predicted value of one.

Additional insights of the effects of these proxy variables on the $\beta$-estimate are illustrated by Figures 2 and 3. Figure 2 shows the implication of these proxy variables for the empirical distribution of the $\beta$-estimate; it plots for each exchange rate the empirical density distributions of $|\hat{\beta}_{i/t}^{biv} - 1|$ (dashed line) and $|\hat{\beta}_{i/t}^{aug} - 1|$ (solid line) of the corresponding synthetic model. The JPY case shows only the $|\hat{\beta}_{i/t}^{biv} - 1|$ 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. The empirical density distributions of $|\hat{\beta}_{i/t}^{aug} - 1|$ and $|\hat{\beta}_{i/t}^{biv} - 1|$ estimates of CAD and AUD have similar shapes, though that of the former is positioned closer to zero.

We note that $|\hat{\beta}_{i/t}^{aug} - 1|$ from the synthetic model of EUR has a density distribution more diffused/flattened than $|\hat{\beta}_{i/t}^{biv} - 1|$. If we consider a synthetic model that augments the bivariate specification with either the two categories of risk premium proxy variables or the two categories of expectational errors proxy variables (Panel B, Table 6), then the $|\hat{\beta}_{i/t}^{aug} - 1|$ from each of the two alternative augmented specifications has a density mass closer to zero than the corresponding $|\hat{\beta}_{i/t}^{biv} - 1|$; 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.

Figure 3 graphically illustrates the sampling uncertainty associated with the \( \beta \)-estimate; it plots for each exchange rate the time-varying \( \hat{\beta}_{\text{biv}}^{\text{est}} \) (dashed line) and \( \hat{\beta}_{\text{aug}}^{\text{est}} \) (solid line). With the exception of JPY and EUR, \( \hat{\beta}_{\text{aug}}^{\text{est}} \) is closer to its UIP predicted value of one than the corresponding \( \hat{\beta}_{\text{biv}}^{\text{est}} \). 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 \( \hat{\beta}_{\text{aug}}^{\text{est}} \) cover a wide range that includes the value of one, and tend to be larger towards the end of the sample period. While the selected proxy variables move the \( \beta \)-estimate towards the value of one, they do not provide a precise inference. Given the wide credible interval, we are not sure if the true value of \( \beta \) is one.\(^{25}\)

In sum, Figures 2 and 3 affirm that the presence of these proxy variables reduces the deviation of the \( \beta \)-estimate from its theoretical value of one. They corroborate these results based on the DM statistics that the inclusion of these empirical proxy variables can deliver a \( \beta \)-estimate that is close to its UIP predicted value of one. However, we have to exercise caution in interpreting these findings because the set of empirical proxy variables that yields the improved UIP result is exchange-rate specific and the \( \beta \)-estimate displays large sampling uncertainty.

5. Shifting Importance and Time-Varying Effect

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 present the evidence on the shifting importance of empirical proxy variables. The scapegoat theory suggests that the importance of these variables as perceived by market participants can shift with market conditions. Taking advantage of the DLM-DMA framework, the current exercise adopts the data-driven approach to infer the shift of importance.

As pointed out in subsection 3.4, the time-varying retrospective inclusion probability given by the sum of retrospective probabilities of models that include the proxy variables is employed to infer the importance of an empirical proxy variable.\(^{26}\) Following the usual model

\(^{25}\) 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).

\(^{26}\) See Appendix B.2 and B.3 for the calculation of retrospective model probability and retrospective
average practice, if the retrospective inclusion probability falls between 0.5–0.75, 0.75–0.95, 0.95–0.99 and 0.99–1, we consider the corresponding proxy variable is important and has an acceptable, substantial, strong, or decisive effect (Kass and Raftery, 1995; Havranek et al., 2015). If it is less than 0.5, the proxy variable is considered ignorable.

In Figures 4 and 5, we use the case of NZD to illustrate the changing importance of the proxy variables. Specifically, we consider the NZD synthetic specification that yields the most encouraging UIP result in Table 6. The NZD synthetic specification includes, in addition to the interest rate differential variable, eight macro proxy variables for risk premiums, and four US-Global proxy variables for expectational errors. There are $2^{12} = 4,096$ component models in the model space. Based on the DLM-DMA results of these 4,096 component models, we calculate time-varying retrospective inclusion probabilities and use these statistics to infer the shifting importance of these 12 proxy variables.

Figure 4 plots for each proxy variable its time-varying retrospective inclusion probability. All the 12 proxy variables have a retrospective inclusion probability larger than 0.5 for most of the time during the sample period; indicating their relevance in the regression. These retrospective inclusion probabilities vary over time; some display a noticeable 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).

A shift of market perception about the role of the proxy variable can induce a jump in the variable’s importance. Conceivably, the scapegoat theory is likely to apply when there is a high level of uncertainty about the UIP relationship such that market participants can assign a large weight to an observable proxy variable. In the current exercise, the noticeable jumps occurred around the 2007 global financial crisis and the subsequent sovereign debt crisis. These findings are in accordance with the scapegoat theory; market participants are likely to look for a scapegoat when substantial uncertainty makes it challenging to decipher market interactions. The retrospective inclusion probabilities also indicate the (growing) importance of the US global shock variables – a result that is in contrast with the view that the US influence is declining over time.

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27 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.
We do not want to over-interpret these findings because we do not have an explicit theory on how and why these crises generate the observed patterns of changing importance of these proxy variables across exchange rates. Nevertheless, the DLM-DMA results corroborate the scapegoat theory and show the importance of these proxy variables changes over time.

In addition to shifting importance, the proxy variables exhibit time-varying coefficients. Figure 5 shows the time-varying model averaging retrospective coefficient estimates that are given by the weighted sum of retrospective coefficient estimates from component models in the model space with retrospective model probabilities as the weights.\(^{28}\)

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 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 do not appear to match the sharp changes in retrospective inclusion probabilities in Figure 4. That is, the change in the importance does not necessarily imply a specific time-varying pattern of the coefficient estimate.

For the other exchange rates, their synthetic UIP specifications comprise different sets of proxy variables. These proxy variables display patterns of retrospective inclusion probabilities and time-varying model averaging retrospective estimates that are different across currencies. However, when there is a noticeable shift in the importance of a proxy variable, it typically occurs around either around the 2007 global financial crisis or the subsequent sovereign debt crisis. These results are not reported for brevity but are available upon request.

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

6. **Additional Discussions**

In order to work with an operational dimension of model space, we conducted the DLM-DMA analysis with the 27 proxy variables grouped in three categories enlisted in subsections 3.1 to 3.3. In this section, we consider two alternative approaches of reducing the

\(^{28}\) See Appendix B.2 and B.3 for the calculation of time-varying model averaging retrospective coefficient estimate.
dimensionality of model space to obtain a manageable level of computational intensity. The two approaches are Principal Component Analysis (PCA) and Partial Least Squares (PLS). Then, we briefly discuss the results from varying the $\lambda$ parameter that controls the amount of past information used to calculate the time-varying parameters, and carry trade.

6.1 PCA and PLS

The PCA approach is a widely used method in economic studies to reduce the dimensionality of large datasets (Bernanke, 2005 et al.; Caporale and Pittis, 1995; Greenaway-McGregory et al., 2018). For each exchange rate, we apply PCA to each category, and follow the eigenvalue-greater-than-one rule (Kaiser, 1960; Hoyle and Duvall, 2004) to determine the number of common factors in that category. With these selected common factors, the UIP specification includes the interest rate differential and CIP deviation variable, and nine PCA-based common factors for EUR, ten PCA-based common factors for JPY, CHF, NOK, AUD and NZD, and 11 PCA-based common factors for CAD, SEK and GBP. We repeated the DLM-DMA analysis for these specifications with PCA-based common factors and summarized the resulting $\beta$-estimates in Appendix C.3.

A few observations are in order. First, as indicated by the bold figures in Appendix C.3, the UIP specification augmented with PCA-based common factors provides some evidence of a $\beta$-estimate closer to unity, and the improvement differs across currencies. Second, according to the DM statistic, the UIP specification augmented with PCA-based common factors shows a significant reduction in $\beta$-estimate’s MAD in five exchange rates, a significant increase in three exchange rates, and no significant change in one exchange rate. Compared with the results in Table 6, the performance of the UIP specification augmented with PCA-based common factors is better than the synthetic model for the EUR case, but worse for the cases of JPY, CHF, SEK, and NOK. On the average, the use of PCA factors does not yield a $\beta$-estimate closer to one than the synthetic model.

The PLS is another approach to reduce the dimensionality of the dataset and has been used in exchange rate studies (Adrian et al., 2011; Fuentes et al., 2015; Kim and Jung, 2018). The approach incorporates information on the correlation with the dependent variable when extracting the latent factors from the explanatory variables. We adopted the leave-one-out cross-validation criterion to determine the number of factors, and obtained six PLS-based factors for EUR, seven PLS-based factors for CHF and CAD, eight PLS-based factors for SEK and NZD, nine PLS-based factors for NOK and 12 PLS-based factors for JPY, GBP and AUD. Then, we repeated the DLM-DMA analysis of the UIP specification that includes the interest
rate differential, the CIP deviation variable, and the PLS-based factors. Appendix C.4 summarizes the resulting $\beta$-estimates.

The results in Appendix C.4 indicate that the presence of PLS-based factors shrinks the distance between the $\beta$-estimate and one for a few exchange rates. However, the extent of improvement appears weaker than that offered by PCA factors or the synthetic model. For instance, according to the DM statistic, the UIP specification augmented with PLS-based factors shows a significant reduction in $\beta$-estimate’s MAD in three exchange rates, a significant increase in two exchange rates, and no significant change in four exchange rates. Compared with the UIP specification augmented with PCA-based factors and the synthetic model considered in subsection 4.3, the inclusion of PLS-based factors does not give a better UIP result in terms of yielding a $\beta$-estimate closer to one.

In sum, compared with synthetic models considered in subsection 4.3, using either the PCA or PLS to reduce the dimensionality does not yield more favorable UIP results.

6.2 The $\lambda$ parameter

As pointed out in subsection 4.1, the results presented in section 4 are generated with the $\lambda$ parameter equals 0.95. Recall that the choice of $\lambda$ 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 $\lambda = 0.96, 0.97, 0.98$ and 0.99.\textsuperscript{29}

We summarize the results of the $\beta$-estimate from synthetic models obtained under different values of $\lambda$ in Appendix C.5. There are a few observations.

First, for a given exchange rate, different values of $\lambda$ give different synthetic models. For example, the synthetic model of JPY includes no proxy variable when $\lambda = 0.95$, but it has different categories of proxy variables for other values of $\lambda$. Different exchange rates exhibit different patterns of changes in the compositions of their synthetic models.

Second, different values of $\lambda$ imply different degrees of improvement of the UIP evidence for different exchange rates. Both the DM and “MAD $\beta$” statistics indicate that, for $\lambda = 0.99$, the $\hat{\beta}^{\text{aug}}_{it}$ from all the nine synthetic UIP models under consideration offers a more favorable evidence for UIP than the corresponding $\hat{\beta}^{\text{biv}}_{it}$. However, the “Mean $\beta$” statistic shows three exchange rates have an average negative $\beta$-estimate; a finding that is at odd with UIP.

\textsuperscript{29} Koop and Korobilis (2012), for example, consider $\lambda = 0.95$ and 0.99 for quarterly data.
Note that the average $\beta$-estimates of JPY and CHF under $\lambda = 0.99$ are further away from the value of one than the corresponding ones under $\lambda = 0.95$.

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 $\lambda$ values. There are complications and caveats in generalizing the implication of deploying these empirical proxy variables to account for the observed UIP failure.

6.3 Carry Trade

The UIP failure; especially the case of a negative $\beta$-estimate, echoes the success of the carry trade strategy, which 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. It is hard to explain carry trade profits with empirical risk factors (Brunnermeier et al., 2008; Burnside, 2012; Menkhoff et al., 2012a).

While our exercise does not directly address carry trade, our findings do not indicate a stable link between the $\beta$-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 $\beta$-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.

7. Concluding Remarks

We attempt to explain UIP failure using 27 empirical proxy variables for CIP deviations, risk premiums and expectational errors. We apply a modified dynamic model averaging procedure to a dynamic linear model to accommodate the shifting importance of explanatory variables as implied by the scapegoat theory and time-varying effect. The behavior of the $\beta$-estimate – the coefficient estimate of the interest rate differential variable in UIP regressions is used to infer the validity and implications of these proxy variables for the UIP relationship.

Our results show that augmenting the canonical bivariate UIP regression with these proxy variables can yield a $\beta$-estimate that is closer to the value of one predicted under UIP. There are, however, qualifications to the improved UIP result. First, while the presence of
proxy variables reduces the deviation of the $\beta$-estimate from one, it does not decrease 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, the importance of these proxy variables and their effects display wide time variability – these non-uniform effects differ across exchange rates. The use of alternative procedures to reduce the dimensionality of the dataset, for instance, does not yield stronger UIP results.

Our empirical results present some data-driven evidence of the scapegoat effect. Specifically, the retrospective inclusion probability measure generated from the modified dynamic model averaging procedure sheds insight on the shifting roles and changing importance of proxy variables over time. There is evidence that the importance of some proxy variables exhibits jumps. Even though the proxy variables that exhibit shifting importance may not be the same across exchange rates, the noticeable changes in importance usually occur around crises when the level of uncertainty is high. The result corroborates the notion that uncertainty is a source of scapegoat effects.

These findings have implications for policymaking and investment decisions. Policymakers and investors should carefully evaluate the role of market sentiment in determining the relevance of determinants of UIP over time and the fickleness of the simple bivariate UIP formulation in formulating policies and investment portfolios that rely on the UIP relationship.

While our exercise offers some data-driven indirect evidence of the scapegoat effect, we do not have explanations on the variability of the shift pattern in importance and these proxy variables across individual exchange rates. Further analysis on the factors underlying the observed scapegoat effect is warranted.

Undeniably, our exercise is mainly an empirical one that highlights non-uniform effects displayed by UIP regressions. It is beyond the scope of the current study to assess the extent to which these empirical proxy variables capture the effects of the unobserved factors that are relevant for the UIP discussion, the conditions under which these proxy variables are good empirical proxy variables, and the factors that determine their importance in different historical periods. Conceivably, shifting roles and time-varying effects of proxy variables for unobservable factors due to market perception variations can contribute to the difficulty of rectifying the empirical UIP failure. The exchange-rate-specific results present additional challenges of developing a general explanation for the observed UIP failure. Nonetheless, an empirical model for explaining UIP failure is likely to be one that allows for variables to display non-uniform effects due to changing importance and time-varying coefficients.
References


### Table 1. Bivariate UIP Regression: Different Sample Periods

<table>
<thead>
<tr>
<th>Periods</th>
<th>Coef</th>
<th>JPY</th>
<th>CHF</th>
<th>EUR</th>
<th>CAD</th>
<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
</tr>
</thead>
<tbody>
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<td></td>
<td>Mean ((\bar{\alpha}))</td>
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<td>-0.318</td>
<td>-0.090</td>
<td>0.096</td>
<td>0.187</td>
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<td>(0.522)</td>
<td>(0.468)</td>
<td>(0.553)</td>
<td>(0.783)</td>
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<td>0.679**</td>
<td>-2.759</td>
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<td>-0.763</td>
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<td>(1.359)</td>
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<td>(1.007)</td>
<td>(1.424)</td>
<td>(1.363)</td>
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<td>-0.916</td>
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<td>(1.935)</td>
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<td>(0.500)</td>
<td>(2.721)</td>
<td>(2.224)</td>
<td>(1.722)</td>
<td>(1.633)</td>
<td>(2.635)</td>
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<td>Mean ((\bar{\alpha}))</td>
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<td>-0.605</td>
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<td>-0.032</td>
<td>-0.160</td>
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<td>0.189</td>
<td>0.312</td>
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<td>-0.929</td>
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<td>(0.595)</td>
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<td>(0.783)</td>
<td>(0.739)</td>
<td>(1.109)</td>
<td>(1.373)</td>
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<tr>
<td></td>
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<td>-4.530***</td>
<td>-4.505***</td>
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<td>-3.883***</td>
<td>-1.779</td>
<td>-1.548*</td>
<td>-5.086***</td>
<td>-3.847***</td>
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<td>(1.989)</td>
<td>(1.839)</td>
<td>(1.647)</td>
<td>(2.545)</td>
<td>(1.349)</td>
<td>(1.786)</td>
<td>(1.341)</td>
<td>(2.405)</td>
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<td>0.118</td>
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<th>AUD</th>
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<tbody>
<tr>
<td>2007Q3-2018Q4</td>
<td>Mean ((\bar{\alpha}))</td>
<td>-0.223</td>
<td>-0.236</td>
<td>-0.058</td>
<td>0.069</td>
<td>0.008</td>
<td>0.047</td>
<td>0.275</td>
<td>0.627</td>
<td>0.609</td>
</tr>
<tr>
<td></td>
<td>(\alpha)</td>
<td>1.632</td>
<td>0.396</td>
<td>0.701</td>
<td>0.421</td>
<td>0.721</td>
<td>0.747</td>
<td>-0.145</td>
<td>0.528</td>
<td>-3.487*</td>
</tr>
<tr>
<td></td>
<td>(1.169)</td>
<td>(1.054)</td>
<td>(0.796)</td>
<td>(0.851)</td>
<td>(0.990)</td>
<td>(0.750)</td>
<td>(1.093)</td>
<td>(1.498)</td>
<td>(2.358)</td>
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<tr>
<td>Adj.R2</td>
<td>0.077</td>
<td>0.003</td>
<td>0.020</td>
<td>-0.005</td>
<td>-0.005</td>
<td>0.061</td>
<td>0.019</td>
<td>-0.023</td>
<td>0.085</td>
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</table>

Notes: The Table reports the OLS results of the regression \[ y_t = \alpha + \beta y_{t-1} + \eta_t \] \[ y_t = s_t - s_{t-1} \] and \[ \bar{\eta}_t = \bar{s}_{t-1} - \bar{s}_{t-1} \]. Heteroskedasticity and autocorrelation consistent standard errors are in parentheses. *, **, *** indicate the rejection of \(\alpha = 0\) or \(\beta = 1\) at the 10%, 5% or 1% level. The row of “Mean (\(\bar{\alpha}\))” 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

<table>
<thead>
<tr>
<th>Coef</th>
<th>JPY</th>
<th>CHF</th>
<th>EUR</th>
<th>CAD</th>
<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
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<tbody>
<tr>
<td>Mean</td>
<td>-0.593</td>
<td>-0.649</td>
<td>0.093</td>
<td>-0.008</td>
<td>0.147</td>
<td>-0.037</td>
<td>0.020</td>
<td>0.496</td>
<td>-0.850</td>
</tr>
<tr>
<td>Mean se</td>
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<td>1.544</td>
<td>1.035</td>
<td>0.625</td>
<td>1.151</td>
<td>1.098</td>
<td>1.208</td>
<td>1.644</td>
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<tr>
<td>MAD</td>
<td>0.127</td>
<td>0.698</td>
<td>0.445</td>
<td>0.291</td>
<td>0.373</td>
<td>0.345</td>
<td>0.400</td>
<td>0.645</td>
<td>1.534</td>
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<tr>
<td>Mean</td>
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<td>-0.403</td>
<td>1.870</td>
<td>0.867</td>
<td>0.393</td>
<td>1.602</td>
<td>1.124</td>
<td>-1.513</td>
<td>1.066</td>
</tr>
<tr>
<td>Mean se</td>
<td>2.559</td>
<td>2.947</td>
<td>3.502</td>
<td>2.600</td>
<td>2.237</td>
<td>2.848</td>
<td>2.299</td>
<td>2.744</td>
<td>2.861</td>
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<tr>
<td>MAD</td>
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<td>1.416</td>
<td>1.402</td>
<td>0.718</td>
<td>0.997</td>
<td>1.082</td>
<td>2.513</td>
<td>2.290</td>
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</table>

Notes: The Table reports the DLM estimation results of the regression \( y_t = \alpha + \beta x_t + \epsilon_t \). The rows “Mean \( \alpha \)” and “Mean se \( \alpha \)” give the average value of retrospective intercept estimates \( \{\hat{\alpha}_t\}_{t,T} \) and of their standard errors, the row “MAD \( \alpha \)” the mean absolute deviation of \( \hat{\alpha}_t \)-estimates from 0, the rows “Mean \( \beta \)” and “Mean se \( \beta \)” the average value of retrospective of \( \beta \)-estimates \( \{\hat{\beta}_t\}_{t,T} \) and of their standard errors, and the row “MAD \( \beta \)” is the mean absolute deviation of \( \beta \)-estimates from 1. See the text for details.

Table 3. Summary of \( \beta \)-estimates: UIP Regressions Augmented with the Proxy variables for CIP deviations

<table>
<thead>
<tr>
<th>Coef</th>
<th>JPY</th>
<th>CHF</th>
<th>EUR</th>
<th>CAD</th>
<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
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</thead>
<tbody>
<tr>
<td>Mean ( \beta )</td>
<td>-0.468</td>
<td>-0.039</td>
<td>1.719</td>
<td>1.430</td>
<td>0.304</td>
<td>2.072</td>
<td>1.348</td>
<td>-1.307</td>
<td>1.170</td>
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<tr>
<td>MAD ( \beta )</td>
<td>1.773</td>
<td>1.071</td>
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<td>1.596</td>
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<td>1.072</td>
<td>1.155</td>
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<td>2.442</td>
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<td>-0.322</td>
<td>-1.033</td>
<td>4.800***</td>
<td>-1.923*</td>
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Notes: Summary of \( \beta \)-estimates from the regression \( y_t = x_t'\theta_t + \epsilon_t; x_t = (1, \nu_t, CIPd_{-t})' \) is presented. The rows “Mean \( \beta \)” and “MAD \( \beta \)” give the average value of retrospective of \( \beta \)-estimates and the mean absolute deviation of \( \beta \)-estimates from 1. Numbers in the squared brackets under “Mean \( \beta \)” and “MAD \( \beta \)” are, respectively, \(|\Sigma (\hat{\beta}_t - 1)/\Sigma (\hat{\beta}_t - 1)| / |\Sigma (\hat{\beta}_t - 1)| \) and \(|\Sigma (\hat{\beta}_t - 1)| / |\Sigma (\hat{\beta}_t - 1)| \), and those in bold have a value less one. The row “DM” gives the DM statistics of the null hypothesis of \( E((\hat{\beta}_t - 1) - |\beta_t - 1|) = 0 \). *, **, *** indicate significance at the 10%, 5% and 1% level. See the text for details.
<table>
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<td>-1.240</td>
<td>1.425</td>
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Notes: Summary of $\beta$-estimates from the regression $y_t = x_t'\theta + \varepsilon_t$; $x_t = (1, \delta_i, \delta_{P_t})'$ is presented. The first column lists the categories of proxy variables for risk premiums included in the augmented UIP regression specifications. “Macro” refers to the category comprises eight proxy variables that are related to the relative macroeconomic environment, “US-Global” the category comprises five proxy variables for risks in the US financial markets and the global foreign exchange market, and “Country” the category comprises two country-specific proxy variables 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 Proxy variables of Expectational Errors

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Notes: Summary of $\beta$-estimates from the regression $y_t = x_t^\prime \theta + \epsilon_t; \ x_t = (1, \sqrt{V_t}, E\hat{R})^\prime$ is presented. The first column lists the categories of proxy variables for expectational errors included in the augmented UIP regression specifications. “Macro” refers to the category comprises four proxy variables for macro shocks, “US-Global” the category comprises four proxy variables 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 Proxy variables

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Panel B

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Notes: Panel A presents the summary of β-estimates from synthetic UIP regressions with selected categories of proxy variables for CIP deviations (CIP_{t-1}), risk premiums (r\hat{P}_{t-1}), and expectational errors (E\hat{\epsilon}_t). Panel B presents, for each exchange rate, the specific categories of proxy variables in the synthetic UIP regression. See the notes to the previous tables.
Figure 1. $\beta$-estimates from the Bivariate DLM UIP Specification

Notes: The solid line gives the $\beta$-estimate from the bivariate DLM regression $y_t = \alpha + \beta b_{tT} + \epsilon_t$. The gray area represents the 95% credible region. The dash horizon line is the unity horizon line.

Figure 2. The Empirical Density Distributions of $|\tilde{\beta}_{b_{tT}} - 1|$ and $|\tilde{\beta}_{b_{tT}} - 1|$

Note: For each exchange rate, the empirical density distributions of absolute deviations of $\beta$-estimates from one are plotted. The solid curve is for $|\tilde{\beta}_{b_{tT}} - 1|$ based on $\beta$-estimates from the synthetic UIP regression reported in Table 6, and the dash curve is for $|\tilde{\beta}_{b_{tT}} - 1|$ from the corresponding bivariate UIP regression in Table 2.
Figure 3. $\beta$-estimates from Bivariate and Synthetic UIP Regressions

Notes: For each exchange rate, the solid and dash curve lines trace $\beta$-estimates ($\hat{\beta}_{\text{syn}}^{\text{aug}}$) from the synthetic UIP specification in Table 6 and $\beta$-estimates ($\hat{\beta}_{\text{biv}}^{\text{biv}}$) from the corresponding bivariate UIP regression in Table 2. The grey area gives the 95% credible region of $\hat{\beta}_{\text{syn}}^{\text{aug}}$. The horizontal dash line is the unity line.
Figure 4. Retrospective Inclusion Probabilities of Proxy variables: the NZD Synthetic Model

Notes: For each proxy variables, 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: the NZD Synthetic Model

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

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 \( t \), \( \ln() \) is the log operator, and “\( \Delta \)” is the first-difference operator. It is expressed in percentage term.

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

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

**Proxy variables for Risk Premiums, \( rP_{r, t} \)**
(3)–(8) Cross-country differences of (a) inflation rates: \( \Delta \ln(CPI_{t, i}) - \Delta \ln(CPI_t) \), (b) interest rate changes: \( \Delta (1+i_{t-1})^{1/4} - \Delta (1+i_{t, -1})^{1/4} \), (c) money supply growth rates: \( \Delta \ln(M_{r, t}) - \Delta \ln(M_{i, t}) \), (d) output growth rates: \( \Delta \ln(GDP_{r, t}) - \Delta \ln(GDP_t) \), (e) productivity growth rates: \( \Delta \ln(GDP_{r, t} / labor_{r, t}) - \Delta \ln(GDP_t / labor_t) \), and (f) changes of unemployment rates: \( \Delta Uem_{r, t} - \Delta Uem_t \); where \( CPI \) is the CPI, \( M \) is the money supply, \( GDP \) is the GDP, \( labor \) is the number of employed persons, and \( Uem \) 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.
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.

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

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

The global realized upside and downside semi-variances are constructed from the averages of the corresponding semi-variances of individual exchange rate series:

$$m_i^{-1} \sum_{j=1}^{n} \{ (R_{i,j+1/n_j} - R_{i,j/n_j})^2 I(R_{i,j+1/n_j} > 0) \}^{-1/2}$$

and

$$m_i^{-1} \sum_{j=1}^{n} \{ (R_{i,j+1/n_j} - R_{i,j/n_j})^2 I(R_{i,j+1/n_j} \leq 0) \}^{-1/2},$$

where $m_i$ is the number of available currencies at time $t$, $R_{i,j/n_j} = \ln(S_{i,j/n_j} / S_{i,(j-1)/n_j}) - [(1+i_{j+1/n_j})^{1/4} - (1+i_{j/n_j})^{1/4}] / n_j$, $S_{i,j/n_j}$ is the $i$-th exchange rate observed on day $j/n_j$, $n_j$ is the number of observations between time $t$ to $t+1$, and $I(.)$ is an indicator function. They are expressed in percentage term.

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

Lagged exchange rate changes: $\Delta \ln(S_{i,t}^*)$ expressed in percentage term.

Shocks to the cross-country differences of (a) inflation rates: $\Delta \ln(CPI_{i,t}) - \Delta \ln(CPI_{i,t}^*)$, where $\hat{\bar{x}}$ is the cyclical component of $\bar{X}$ obtained by detrending it with the HP filter with a parameter of 1600, (b) money supply growth rates: $\Delta \ln(M_{i,t}) - \Delta \ln(M_{i,t}^*)$, and (c) output gaps: $\hat{y}_i - \hat{y}_i^*$, where $\hat{y}_i$ and $\hat{y}_i^*$ are HP filter generated output gaps in the home country and in the US respectively. They are expressed in percentage term.

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

Contemporaneous VIX index and Contemporaneous TED spread.

The global realized upside and downside jumps are the averages of the corresponding jumps of individual exchange rates given by:

$$m_i^{-1} \sum_{j=1}^{n} \{ (QJPP_{i,j} - QJPP_{i,j-1}^*) \}^{-1/2}$$

and

$$m_i^{-1} \sum_{j=1}^{n} \{ QJPN_{i,j} - QJPN_{i,j-1}^* \}^{-1/2},$$

where $QJPP_{i,j} = \sum_{j=1}^{n} (R_{i,j+1/n_j} - R_{i,j/n_j})^2 I(R_{i,j+1/n_j} > 0) - \frac{\pi^{-1}}{4} \sum_{j=1}^{n} | R_{i,j+1/n_j} - R_{i,j/n_j} |$.

and $QJPN_{i,j} = \sum_{j=1}^{n} (R_{i,j+1/n_j} - R_{i,j/n_j})^2 I(R_{i,j+1/n_j} \leq 0) - \frac{\pi^{-1}}{4} \sum_{j=1}^{n} | R_{i,j+1/n_j} - R_{i,j/n_j} |$. They are expressed in percentage term.

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 adopt the subscript “\( k \)” to (7) and (8) for the \( k \)-th model in the model space:

\[
\begin{align*}
    y_t &= x_t' \theta_{t,k} + e_{t,k} + \epsilon_t \sim N(0, \Sigma_{t,k}), \\
    \theta_{t,k} &= \theta_{t-1,k} + \delta_{t,k} \sim N(0, W_{t,k}).
\end{align*}
\]  

(B.1.1)  

(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 \( Y_{t-1} = \{y_1, y_2, ..., y_{t-1}\} \) and the parameter vector \( \theta \) estimate at time \( t-1 \) derived from information from time 1 to \( t-1 \) follows:

\[
\begin{align*}
    \theta_{t-1,k} | Y_{t-1} &\sim N(\hat{\theta}_{t-1,k}, \Sigma_{t-1,k}), \\
    \hat{\theta}_{t-1,k} &= \hat{\theta}_{t-1,k} + \lambda^{-1} (\hat{\Sigma}_{t-1,k} - \Sigma_{t-1,k}) \hat{\epsilon}_{t-1,k}, \\
    \hat{\epsilon}_{t-1,k} &= \hat{\epsilon}_{t-1,k} + \lambda^{-1} (\hat{\Sigma}_{t-1,k} - \Sigma_{t-1,k}) \hat{\epsilon}_{t-1,k}.
\end{align*}
\]

(B.1.3)

(B.1.4)

(B.1.5)

The estimate \( \hat{\Sigma}_{t-1,k} \) is obtained via the exponentially weighted moving average (EWMA) setup; \( \hat{\epsilon}_{t-1,k} = \lambda \hat{\epsilon}_{t-1,k} + (1-\lambda)\hat{\epsilon}_{t-1,k} \) (Koop and Korobilis, 2012).

The distribution of \( \theta_{t,k} | Y_{t-1} \) and \( \theta_{t,k} | Y_t \) (B.1.4, B.1.3), the Bayes’ theorem implies

\[
\begin{align*}
    \theta_{t,k} | Y_t &\sim N(\hat{\theta}_{t,k}, \Sigma_{t,k}), \\
    \hat{\theta}_{t,k} &= \hat{\theta}_{t-1,k} + \lambda^{-1} (\hat{\Sigma}_{t-1,k} - \Sigma_{t-1,k}) \hat{\epsilon}_{t-1,k}, \\
    \hat{\epsilon}_{t-1,k} &= \hat{\epsilon}_{t-1,k} + \lambda^{-1} (\hat{\Sigma}_{t-1,k} - \Sigma_{t-1,k}) \hat{\epsilon}_{t-1,k}.
\end{align*}
\]

(B.1.6)  

(B.1.7)

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 \( \theta_{t,k} \) and \( y_{t,k} \) for \( t=1,2,...,T \), \( k=1,2,...,K \), and a given \( \lambda \) value. Let \( L_k \) be the event that the \( k \)-th model is the true model at time \( t \).

Let \( \pi_{t-1,k} = P(L_k = k | F_{t-1}) \) 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 \( F_{t-1} \) includes the retrospective likelihood of all \( K \) models at time \( t-1 \). Assume the time \( t \)
predicted model probability $\pi_{t_{-1}, t} = P(L = k | F_{t_{-1}})$ follows a Markov process given by the KxK transition matrix $Q_{t_{-1}} = [q_{t_{-1}, k}]$, where $q_{t_{-1}, k} = P(L = k | F_{t_{-1}}, L_{t+1} = \ell)$. Thus,

$$\pi_{t_{-1}, t} = \sum_{t_{-1}} P(L = k | F_{t_{-1}}, q_{t_{-1}, k}).$$

(B.2.1)

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

$$\pi_{t_{-1}, t} = \left[(\pi_{t_{-1}, t_{-1}})^{\gamma} + c\right]\left[\sum_{t_{-1}} \pi_{t_{-1}, t_{-1}}\right]^{-1},$$

(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),

$$\pi_{t_{-1}, t} = \sum_{t_{-1}} \pi_{t_{-1}, t_{-1}}(\pi_{t_{-1}, t_{-1}})^{\gamma} + c,$$

(B.2.3)

where $\pi_{t_{-1}, t_{-1}}$ is the retrospective likelihood value of the $i$-th model at time $t$.\(^{30}\)

The model probability $\pi_{t_{-1}, t}$ 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)

$$\pi_{t_{-1}, t} = \sum_{t_{-1}} \pi_{t_{-1}, t_{-1}}(\pi_{t_{-1}, t_{-1}})^{\gamma} + c,$$

(B.2.4)

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

**B.3 Parameter Averaging**

The retrospective model averaging estimates of $y_i$ and parameters are given by $\hat{y}_{i}^{DMA} = \sum_{i = 1}^{K} \pi_{i, t} \hat{y}_{i, t}$, and $\hat{\theta}_{j, t}^{DMA} = \sum_{i = 1}^{K} \pi_{i, t} \hat{\theta}_{j, t}$, where $\pi_{i, t}$ is the retrospective model probability (B.2.4). The $i$-th parameter’s retrospective inclusion probability is $RIP_{i}^{DMA}(\theta) = \sum_{i = 1}^{K} \pi_{i, t} I_{i}(\theta)$ for all $i$, where $I_{i}(\theta)$ is the indicator function that equals 1 if $\theta$ is included in the $k$-th model.

The variance of the retrospective parameter $\hat{\theta}_{j, t}$ is $\sum_{i = 1}^{K} \pi_{i, t} \left[\text{var}(\hat{\theta}_{j, t}) + \hat{\theta}_{j, t}^{2} \right] - \left(\hat{\theta}_{j, t}^{DMA} \right)^{2}$.

**B.4 Initial Values in the Estimation**

<table>
<thead>
<tr>
<th>Category</th>
<th>Parameters</th>
<th>Initial Values</th>
</tr>
</thead>
<tbody>
<tr>
<td>DMA setup</td>
<td>$\tau$ in DMA</td>
<td>0.99</td>
</tr>
<tr>
<td></td>
<td>$\kappa$ for EWMA</td>
<td>0.98</td>
</tr>
<tr>
<td></td>
<td>$V_0$ for EWMA</td>
<td>variance of OLS residuals</td>
</tr>
<tr>
<td></td>
<td>$\Sigma_{0, k}$ for all $k$</td>
<td>diagonal elements are $\text{var}(y)/\text{var}(x)^{#}$, non-diagonal elements are 0</td>
</tr>
<tr>
<td></td>
<td>$\pi_{0, k}$ for all $k$</td>
<td>$1/K$</td>
</tr>
<tr>
<td></td>
<td>$c$</td>
<td>0.001/K</td>
</tr>
<tr>
<td>UIP setup</td>
<td>$\alpha_0$, intercept</td>
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</tr>
<tr>
<td></td>
<td>$\beta_0$ of $V_{i}$</td>
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</tr>
<tr>
<td></td>
<td>$\theta_{i, 0}$ of $CiP_{d_{i}}$</td>
<td>1</td>
</tr>
<tr>
<td></td>
<td>$\theta_{i, 0}$'s for $R\hat{P}<em>{i}$ and $E\hat{R}</em>{i}$</td>
<td>0</td>
</tr>
</tbody>
</table>

Notes: \(^{\#}\) “y” is the LHS variable, “$x_i$” is the RHS variable in the $k$-th model.

**B.5 Derivation of (B.2.4).**

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

$$\pi_{t_{-1}, t} = P(L = k | F_{t}) = \sum_{t_{-1}} P(L = k | F_{t}, L_{t+1} = \ell)P(L_{t+1} = \ell | F_{t}).$$

(B.5.1)

As discussed, (B.2.3) is based on retrospective distributions. For the typical DMA based on “forecasts,” (B.2.3) is modified to $\pi_{t_{-1}, t} = P(L = k | F_{t}) = \pi_{t_{-1}, t} \hat{f}_{i} (y_{i} | Y_{t_{-1}})\left[\sum_{t_{-1}} \pi_{t_{-1}, t} \hat{f}_{i} (y_{i} | Y_{t_{-1}})\right]^{-1}$, where the likelihood value is based on (B.1.4).
The Bayes’ theorem implies,
\[ P(L_t = k \mid F_t, L_{t+1} = \ell) = P(L_t = k \mid F_t, L_{t+1} = k, L_{t+1} = \ell)\]
\[ = P(L_t = k \mid F_t, L_{t+1} = \ell)P(F_t \mid F_{t+1} = k, L_{t+1} = \ell)(P(F_{t+1} \mid F_t, L_{t+1} = \ell))^{-1} \]
\[ = P(L_t = k \mid F_t)P(L_{t+1} = \ell \mid F_t) = [P(L_{t+1} = \ell \mid F_t)]^{-1} \]
\[ = \pi_{t+1,k}q_{t+1,k}(\pi_{t+1,k})^{-1}. \]  
where (B.5.2) follows from \( F_{t+1} = \{F_t, \ldots, F_1\} \), \( F_t \) and \( F_{t+1} \) are independent of the state of \( L_t \), and, thus, the two terms \( P(F_{t+1} \mid \cdot) \) cancel out, (B.5.3) follows from the Bayes’ theorem.

Substituting (B.5.4) into (B.5.1), we obtain (B.2.4):
\[ \pi_{t+k} = P(L_t = k \mid F_t) = \pi_{t+k} \sum_{i=1}^{K} q_{i,k}(\pi_{t+1,k})^{-1}. \]

The retrospective model probability depends on the transition matrix \( Q = [q_{i,k}] \). 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 \( q_{i,k} \)’s are the same for \( k = 1, 2, \ldots, K \), and then, \( q_{i,k} = \pi_{i+1,k} \), and \( \pi_{i+1,k} = \pi_{i,k} \). 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-currency basis is used as the proxy variables 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 $|\hat{\beta}_{t,T}^{\text{aug}} - 1|$ in Different Augmented UIP Regressions for EUR

Notes: The solid line is the density distribution of $|\hat{\beta}_{t,T}^{\text{aug}} - 1|$ in different augmented UIP regressions, and the dash line is the density distribution of $|\hat{\beta}_{t,T}^{\text{biv}} - 1|$.
### C.3. Summary of $\beta$-estimates: UIP Regressions Augmented with PCA-Based Factors

<table>
<thead>
<tr>
<th></th>
<th>JPY</th>
<th>CHF</th>
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<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
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<tbody>
<tr>
<td>Mean $\beta$</td>
<td>-2.325</td>
<td>-0.737</td>
<td>1.052</td>
<td>1.317</td>
<td>0.064</td>
<td>1.301</td>
<td>0.067</td>
<td>-0.925</td>
<td>1.062</td>
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<td></td>
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<td>[0.501]</td>
<td>[7.506]</td>
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<tr>
<td>MAD $\beta$</td>
<td>3.325</td>
<td>1.737</td>
<td>0.424</td>
<td>0.370</td>
<td>0.936</td>
<td>0.419</td>
<td>1.290</td>
<td>1.926</td>
<td>0.906</td>
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<tr>
<td>DM</td>
<td>-6.415***</td>
<td>-4.070***</td>
<td>6.415***</td>
<td>6.320***</td>
<td>-1.824*</td>
<td>1.694*</td>
<td>-0.727</td>
<td>2.321**</td>
<td>4.090***</td>
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</table>

Notes: The PCA factors are extracted for each proxy category, and the number of PCA-factors is determined by the eigenvalue-greater-than-one rule. See the notes to Table 3

### C.4 Summary of $\beta$-estimates: UIP Regressions Augmented with PLS-Based Factors

<table>
<thead>
<tr>
<th></th>
<th>JPY</th>
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<th>EUR</th>
<th>CAD</th>
<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean $\beta$</td>
<td>-1.470</td>
<td>0.026</td>
<td>2.239</td>
<td>1.242</td>
<td>-0.119</td>
<td>1.296</td>
<td>-0.079</td>
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<td>[0.694]</td>
<td>[1.424]</td>
<td>[1.813]</td>
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<td>[0.491]</td>
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<td>[0.876]</td>
<td>[21.684]</td>
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<tr>
<td>MAD $\beta$</td>
<td>2.470</td>
<td>1.022</td>
<td>1.244</td>
<td>1.015</td>
<td>0.936</td>
<td>0.419</td>
<td>1.290</td>
<td>2.200</td>
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<td>[1.557]</td>
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<td>-0.032</td>
<td>-0.488</td>
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Notes: The PLS-based factors are extracted from 26 proxies of risk premiums ($\hat{r}_{RP}^t$) and expectational errors ($\hat{E}_R^t$), and the number of PLS-based factors is determined by the leave-one-out cross validation criterion. See the notes to Table 3

### C.5 Results of Synthetic UIP Models: Different $\lambda$ values

#### Panel A

<table>
<thead>
<tr>
<th>$\lambda$</th>
<th>Estimator</th>
<th>JPY</th>
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<th>EUR</th>
<th>CAD</th>
<th>SEK</th>
<th>GBP</th>
<th>NOK</th>
<th>AUD</th>
<th>NZD</th>
</tr>
</thead>
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<tr>
<td>0.96</td>
<td>Mean $\beta$</td>
<td>-0.214</td>
<td>0.625</td>
<td>-0.355</td>
<td>-0.173</td>
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<td>1.333</td>
<td>0.404</td>
<td>-0.054</td>
<td>0.490</td>
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<tr>
<td></td>
<td></td>
<td>[1.005]</td>
<td>[0.253]</td>
<td>[3.657]</td>
<td>[2.693]</td>
<td>[0.342]</td>
<td>[1.000]</td>
<td>[36.641]</td>
<td>[0.407]</td>
<td>[1.161]</td>
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<tr>
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<td>MAD $\beta$</td>
<td>1.284</td>
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<td>0.596</td>
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<td>[1.000]</td>
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<td>1.708*</td>
<td>8.002***</td>
<td>3.604***</td>
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Panel B

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Notes: Panel A presents, for a given λ value, the summary of β-estimates from synthetic UIP regressions with selected categories of empirical proxy variables for CIP deviations (\(\hat{CIP}_d\)), risk premiums (\(\hat{RP}_t\)), and expectational errors (\(\hat{ER}_t\)). Panel B presents, for each currency and λ value, the specific categories of empirical proxy variables 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.