ISSN 1229-4640 https://doi.org/10.52595/jas.16.2.57
eISSN 2671-5813

Journal of APEC Studies

www.apecstudies.kr

Global CIP Deviation Factor*

Chul Won Park[a], Jaeho Kim[b†]

[a] *Graduate Student, Department of Economics, Sogang University, South Korea*
[b] *Associate Professor, Department of Economics, Sogang University, South Korea*

Received 14 November 2024 Revised 14 December 2024 Accepted 16 December 2024

ABSTRACT

This paper examines the dynamics of Covered Interest Parity (CIP) deviations in G10 currencies. Using a dynamic factor model, we document the existence of a common global factor structure in CIP deviations across G10 currencies, suggesting these violations are driven by systematic global forces. Our findings reveal that the TED spread, a measure of global funding liquidity, emerged as the dominant factor in explaining CIP deviations during crisis periods through 2017, while the Real Dollar Index showed significant explanatory power during 2013-2017. Notably, we document a recent structural shift where the global CIP factor has become less responsive to traditional predictors, maintaining historically low levels. While substantial CIP deviations were observed during periods of market stress, our analysis suggests the estimated global factor of CIP deviations has maintained historically low levels in recent years.

Keywords: arbitrage, covered interest parity, dynamic factor model, TVP-UC-SV
JEL Classifications: F31, G15, C32

* This work was supported by the Sogang Research Support Grant (Grant #202310032.01).
† *Corresponding Author,* jaehoecon@sogang.ac.kr

I. Introduction

Covered Interest Parity (CIP) postulates that the interest rate differential between two currencies should be equal to the difference between their forward and spot exchange rates. If two currencies deviate from this parity condition, it means the imbalance of the corresponding international currency market and that there exist arbitrage opportunities. Du et al. (2018) empirically demonstrates that CIP held tightly prior to the Global Financial Crisis (GFC). Recent studies such as Avdjiev et al. (2019) have been documenting strong empirical evidence against the aforementioned studies that the significant violation of CIP emerges in the post-GFC period. The CIP violation that have been observed for a long time span strongly call for establishing stylized facts on this phenomenon and for a comprehensive examination on which economic forces derive these anomalies.

This study contributes to the growing literature on the CIP deviation by focusing on the currency and 1 year sovereign bond data of the G10 countries. Firstly, we empirically demonstrate that there exists a common factor structure in the CIP deviations of the G10 countries. This implies that global economic factors play crucial roles for the recent CIP violation. Motivated by this empirical finding, we extract the unobserved common factors from individual countries' CIP deviations by employing a dynamic factor model, which allows for the identification on their shared movements. Secondly, we investigate the relation between the global CIP factor and four important global financial variables that substantially influence the international currency market: Real Dollar Index (RDI), TED Spread, VIX index, and Economic Policy Uncertainty (EPU).

Based on Time-Varying Parameter (TVP) models, we highlight the crucial role of liquidity risk in explaining the dynamics of the global factor in the CIP deviations. The TED spread, defined as the difference between the interest rates on interbank loans (LIBOR) and short-term U.S. government debt (T-bill), is a key indicator of the credit and liquidity risk of the global financial market. Our empirical analysis reveals that the TED spread maintains significant explanatory power for the global factor of CIP deviations both during crisis and non-crisis periods through 2018. While this relationship was particularly strong during the global financial crisis and the 2011 European sovereign debt crisis, where the widening of CIP deviations coincided with rises in the TED spread, the TED spread continued to demonstrate substantial influence even during relatively stable market conditions. This persistent relationship underscores the broader role of funding liquidity conditions in driving CIP deviations beyond just crisis periods. However, since 2018, we observe a structural shift where the influence of the TED spread has notably diminished, likely reflecting changes in market structure including enhanced bank liquidity requirements and the growing role of non-bank financial intermediaries.

Our study is closely related with the large body of the CIP literature. The persistent CIP deviations in the post-GFC era suggests that the traditional mechanisms of arbitrage and the adjustments of the international currency markets may not be operating as efficiently as before. Akram et al. (2008) demonstrates the existence of arbitrage opportunities in FX and capital markets through CIP violations using high-frequency tick data. Du et al. (2018) investigated the macrofinancial determinants of CIP deviations such as U.S. dollar strength, global risk sentiment, and liquidity conditions in the forward exchange market. Specifically, they documented systematic CIP deviations in G10 currencies through their "two-factor hypothesis": costly financial intermediation due to post-crisis banking regulations and international imbalances in funding supply and investment demand across currencies. Avdjiev et al. (2019) documents a significant triangular relationship in global financial markets: they find that US dollar appreciation is associated with wider CIP deviations and decreased dollar-denominated cross-border bank lending, suggesting that the dollar functions as a global risk barometer. Rime et al. (2022) found that in the post-crisis environment, CIP violations exist and exploitable by high-rated global banks with favorable access to USD funding markets and safe foreign currency investment opportunities. These arbitrage opportunities persist due to fragmented USD funding markets and funding cost heterogeneity across banks. Cerutti et al. (2021) highlighted that the breakdown of CIP is associated with multiple factors, including regulatory changes, shifts in bank balance-sheet capacities, divergent monetary policies among major central banks, and specific temporary factors like the reform of U.S. prime money market funds.

Our study differs from the previous studies in that we explicitly focus on extracting and analyzing the common global factor in CIP deviations across G10 currencies. While previous research has primarily focused on bilateral relationships or specific currency pairs, our dynamic factor model approach allows us to identify and quantify the shared movements in CIP deviations across multiple major currencies simultaneously. This approach enables us to investigate whether CIP deviations are driven by systematic global forces rather than country-specific phenomena. Furthermore, our time-varying parameter analysis aims to provide a comprehensive understanding of how these global forces have evolved over different market regimes. By examining the dynamic relationship between the global CIP factor and key macroeconomic variables, we can better understand why the nature and magnitude of CIP deviations have changed over time. This framework allows us to shed new light on how various economic channels affect CIP deviations differently during crisis and non-crisis periods. Finally, our analysis of the recent period contributes to the ongoing debate about whether post-crisis CIP deviations represent a “new normal” in international financial markets. By documenting the evolving relationship between CIP deviations and traditional market predictors, we provide insights into whether the extreme violations observed during crisis periods reflect temporary dislocations or fundamental changes in market structure.

The remainder of the paper is structured as follows: Section 2 presents the data used in the study, including CIP, CIP deviations, and other macroeconomic variables. Section 3 discusses the methodology employed, focusing on the Dynamic Factor Model and the TVP Bayesian approach. Section 4 presents the empirical results, encompassing factor analysis, and TVP regression findings. Finally, Section 5 concludes the paper, summarizing the key findings and their implications for understanding the complex dynamics of international finance and their impact on G10 currencies.

II. Empirical Investigation on a Global Factor

1. CIP Deviations

The Covered Interest Parity (CIP), a fundamental no-arbitrage condition in international finance, is expressed as:

$$\frac{1+i_t}{1+i_t^*}=\frac{F_t}{S_t} \tag{1}$$

Where i_t and i_t^* represent the domestic and foreign (net) interest rates, respectively, while S_t and F_t denote the spot and forward exchange rates expressed in terms of the domestic currency per unit of foreign currency. When the left side of the CIP equation exceeds the right side, it suggests the potential for covered interest arbitrage. This arbitrage involves borrowing in the foreign currency at a lower interest rate, converting the funds to the domestic currency, investing at the higher domestic interest rate, and hedging the exchange rate risk with a forward contract. In practice, CIP serves as a barometer for market efficiency. While CIP tends to hold well in liquid and open financial markets, deviations can occur due to factors such as transaction costs, capital controls, and liquidity constraints.

Significant deviations from CIP have been observed particularly since the Global Financial Crisis (GFC), as documented by Avdjiev et al. (2019). In this study, we define the CIP deviation as:

$$y_{i,t}=z_{i,t}-\rho_{i,t}-z_{USD,t} \tag{2}$$

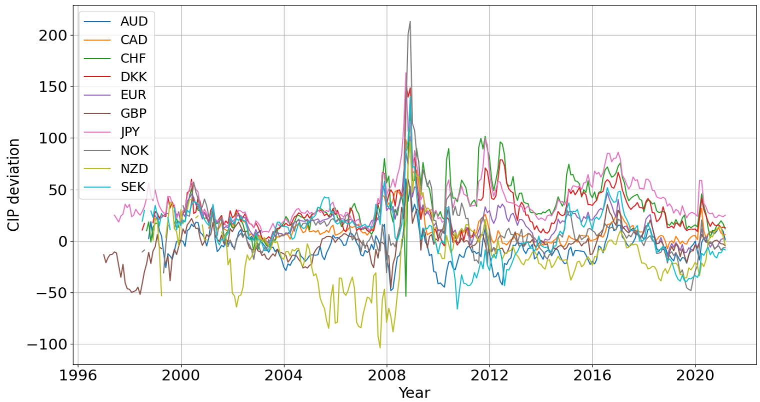
where $y_{i,t}$ is the CIP deviation of currency i at time t, $z_{i,t}$ is the yield on government bonds of country i, $\rho_{i,t}$ is the forward premium, $z_{USD,t}$ is the yield on the U.S. government bond. The forward premium is calculated as follows:

$$\rho_{i,t}=\frac{1}{n}(f_{i,t}-s_{i,t}) \tag{3}$$

Where $f_{i,t}$ is the log of the forward rate and $S_{i,t}$ is the log of the spot exchange rate, n is the common maturity of the foreign and U.S. bonds. This study utilizes a comprehensive monthly dataset measuring deviations from the CIP relation from 2005 to 2020, compiled by Du and Schreger (2022). The bond yields, spot, forward exchange rates of the dataset are obtained from Datastream and Bloomberg. More specifically, in this study, we use 1-year bonds yields, forward, and spot exchange rates for G10 currencies and U.S. dollar from Jan 2006 to 2020: Australia (AUD), Canada (CAD), Switzerland (CHF), Denmark (DKK), Germany (EUR), the United Kingdom (GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), and Sweden (SEK).

Figure 1 presents the CIP deviations for the selected currencies. The CIP deviations display common movements, particularly noticeable around the Global Financial Crisis (GFC) period. These synchronized fluctuations are not only witnessed during the GFC but are also observed in the periods following 2014, which show concurrent rises and falls in CIP deviations. This characteristic of the data supports our statistical analysis for the existence of common factors in the next section.

Figure 1. CIP Deviation for G10 Currency, Tenor 1y (from 2006 or 2020)



Note: Author created based on Du et al. (2018); Government bond CIP deviation data using Bloomberg and Datastream (n.d.).

2. Global CIP Deviation Factor

We adopt the methodology proposed by Bai and Ng (2002) to investigate the presence of a common factor structure in the data. Using Principal Components Analysis (PCA), they recommend selecting the number of factors based on information criteria such as the Bayesian Information Criterion (BIC) and the Panpor Criterion (PC). These criteria evaluate the trade-off between the model's goodness-of-fit and the penalty for overfitting, ensuring an optimal balance between parsimony and explanatory power. The BIC and PC criteria are defined as follows:

$$BIC(k) = \ln\left(\hat{V}(k)\right) + k \times \frac{\ln(NT)}{N+T} \tag{4}$$

$$PC(k) = \ln\left(\hat{V}(k)\right) + k \times \frac{\ln(NT)}{N+T} \tag{5}$$

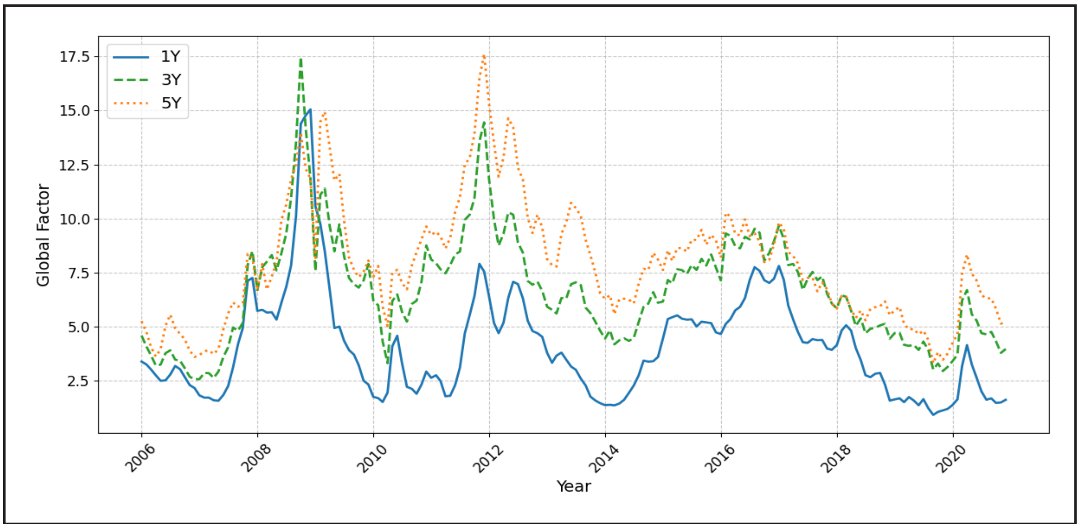
where $\hat{V}(k)$ is the sum of squared residuals from the PCA model with k factors, N represents the number of cross-sectional units, and T denotes the number of time periods. The optimal number of factors is chosen by minimizing the respective information criterion. Using the BIC and PC criteria for k =0,1,2,...,5, we find that the number of latent factors is estimated to be one, which is consistent with our visual inspection in Figure 1. The BIC and PC metrics indicates a global factor influences all the CIP deviations across the G10 countries. For the G10 currencies, our dynamic factor model specification indicates a single common factor structure with no factor lags in the common component equation, suggesting a static form of DFM. The factor evolution follows a first-order autoregressive process, capturing the temporal dynamics of the global factor. The error terms exhibit no serial correlation, as indicated by a zero-order specification in the error structure. Based on the model selection result, we next extract the global factor of the CIP deviations by employing a Dynamic Factor Model (DFM). While PCA is a static dimension reduction model which does not account for serial correlations in the data, the DFM directly models the strong time dependency shown in Figure 1, which improves efficiency in the estimation of the global factor. The DFM for the extraction of the global CIP deviation factor is given as:

$$y_{i,t} = \beta_{0,i} + \beta_{1,i} f_t + \varepsilon_t \tag{6}$$

$$f_t = \lambda_1 f_{t-1} + \lambda_2 f_{t-2} + \cdots + \lambda_P f_{t-P} + e_t \tag{7}$$

where f_t is the latent factor at time t, $\beta_{0,i}$ is the currency-specific intercept term, $\beta_{1,i}$ is the factor loading of currency i, λ_p is the p-th order AR coefficient of the factor, $\varepsilon_{i,t} \sim N(0, \sigma^2_{\varepsilon_i})$ represents the idiosyncratic measurement error and $e_t \sim N(0, \sigma^2_e)$ is the shock to the factor. The DFM is subject to an intrinsic identification issue. Thus, following Bai and Wang (2015), we impose the identification restriction that the factor shock has a unit variance, $\sigma^2_e = 1$ and the sign of the factor loading $\beta_{1,1}$ for series $i = 1$ is positive. Under the restrictions, Bai and Wang (2015) theoretically prove that the latent factor along with all the other model parameters of a dynamic factor model is exactly identified. Then, we apply the Kalman filtering and smoothing algorithms of Durbin and Koopman (2012) for the estimation of the global CIP deviation factor.

Figure 2. Common Factor of CIP Deviation, G10 Currency for Various Tender



Note: Author created based on Du et al. (2018); Government bond CIP deviation data using Bloomberg and Datastream (n.d.).

Figure 2 plots the global CIP deviation factor for different tenors, specifically 1, 3 and 5 years. A closer inspection of the estimated global factors reveals common and notable peaks around the periods of the Global Financial Crisis, 2012, 2017, and 2020. This result provides strong empirical evidence that there are underlying global economic and financial forces impacting the CIP relationship and associated arbitrage trades in international currency markets. Although the factor structure across different tenors suggests interesting term structure patterns,[1] we focus on the 1-year tenor factor for our subsequent analysis. This choice is motivated by our observation that among the three extracted mid-term factors (1, 3, and 5 years), the 3-year and 5-year factors demonstrate highly similar movement patterns and do not provide significantly different results.

Table 1. Explanatory Power of Global Factor for Individual Currencies

Currency	R^2	RMSE	MAE
DKK	0.879	8.245	5.975
JPY	0.811	9.629	7.769
EUR	0.799	7.610	6.306
CAD	0.672	11.890	8.816
NOK	0.669	23.625	17.992
SEK	0.609	21.918	17.254
CHF	0.564	18.908	12.044
GBP	0.530	10.721	8.096
AUD	0.224	13.956	10.544
NZD	0.165	28.446	20.462

Overall Performance Metrics:
Variance Explained: 59.41%,
Overall RMSE: 16.95,
Overall MAE: 11.50

Note: This paper adopts single factor analysis to find global factor for cross-sectional currencies from 2008 to 2018 for G10 countries. The factor extracts 62.3% of variances explained in the G10 currencies and R^2 for each currency suggests that the predictive power of common factor is relatively high and less volatile among currencies. Goodness of fit is evaluated through mean squared errors (RMSE, MAE) and coefficient of determination (R^2).

Table 1 provides empirical support for our analysis of global common factors in CIP deviations across G10 currencies. Our extracted factor explains 59.41% of the total variance in the sample,

1. Another important finding in Figure 1 is that the global CIP deviation factor has a term structure. Although this data pattern is worth investigating, we leave this as future research because it is beyond the scope of this study.

confirming the significant presence of common drivers in international financial markets. This finding validates our factor-based approach and motivates our subsequent analysis of global determinants. The currency-specific results further strengthen our argument, showing particularly strong explanatory power for major currencies, with the global factor capturing 79-88% of the variation in CIP deviations for the Danish Krone (DKK), Japanese Yen (JPY), and Euro (EUR). While most currencies show robust explanatory power, we find notably lower R-squared values only for the Australian Dollar (AUD) and New Zealand Dollar (NZD) at 22.4% and 16.5% respectively, suggesting these currencies may follow somewhat distinct patterns from the main group. This deviation from the overall pattern is limited to these two currencies, with all other G10 currencies showing R-squared values above 50%, further reinforcing the significance of our global factor approach. Collectively, these results not only validate our focus on global common factors but also provide a rich foundation for analyzing how these factors interact with market conditions and policy changes in driving CIP deviations.

III. Dynamics of the Global CIP Deviation Factor

This section examines four principal elements that may influence the dynamics of the global CIP deviation factor. The four explanatory variables are the Federal Reserve Board's U.S. trade-weighted broad dollar index, the logarithmic changes in the VIX index, Economic Policy Uncertainty index, and the TED spread, which is the difference between the interest rate on short-term U.S. government debt (T-bills) and the interest rate on interbank loans (LIBOR) from 2006 to 2020. We employ a time-varying parameter model to analyze how the relationships between the global CIP deviation factor and the examined economic variables evolve over time.[2]

1. Explanatory Variables

Following Avdjiev et al. (2019) who emphasizes the significant role of the U.S. dollar's strength in the CIP deviation, we consider the U.S. Dollar Index. When the U.S. dollar appreciates, it becomes more expensive for entities such as foreign banks and companies to borrow in dollars through swap markets. The appreciation of U.S. dollar adversely affects the financial positioning of entities outside the U.S., limiting their leverage in securing favorable dollar financing terms. Consequently, the availability of dollar-denominated credit decreases, making it more difficult for market participants to engage in covered interest arbitrage. This could, in turn, exacerbate the CIP deviation, as the premium for acquiring dollars through swap markets increases relative to direct borrowing. This implies that the positive relation between the U.S. Dollar Index and the CIP deviation.

The VIX (CBOE Volatility Index), included in our empirical analysis, is a measure of the expected volatility implied by S&P 500 index options. Commonly referred to as the "fear index", it gauges global risk sentiment. During periods of heightened risk aversion, investors typically reduce

2. We acknowledge that the empirical models do not establish a fundamental causal relationship between the global factor and the explanatory variables. The primary focus of this study is to demonstrate the presence of the global factor in the CIP deviations across different currencies. Investigating the causal relationships for the examined variables is left for future research.

their exposure to risky assets and seek safe-haven investments. This shift in investor behavior leads to a reallocation of balance sheets, with market participants decreasing their holdings of foreign currency-denominated assets in favor of safer domestic assets. Consequently, the availability of foreign currency funding diminishes, complicating efforts to engage in covered interest arbitrage. We examine this economic channel by considering changes in the VIX in our empirical models.

The third explanatory variable is the TED spread, defined as the difference between the three-month LIBOR and the three-month U.S. Treasury bill rate. Previous studies, including those by Baba et al. (2008), Coffey et al. (2009), Ivashina et al. (2015), and Wong and Zhang (2017) have identified credit risk and liquidity risk as significant contributors to deviations from CIP. During financial crises, such as the Global Financial Crisis and the European sovereign debt crisis, the risk premium for unsecured interbank loans escalates markedly. This escalation reflects growing concerns about the creditworthiness of counterparties and the overall stability of the financial system. The TED spread effectively captures changes in the risk premium within the interbank lending market. In this study, we examine whether changes in the TED spread can explain fluctuations in the global CIP deviation factor, thus shedding light on the economic channels influencing the CIP deviations.

The last variable is the U.S. Economic policy uncertainty (EPU) index compiled by Baker et al. (2016). The EPU is constructed by capturing the frequency of newspaper articles containing terms related to economic policy uncertainty. Although EPU has been shown to influence various financial markets such as equity markets (Pastor and Veronesi, 2012; Brogaard and Detzel, 2015) and foreign exchange markets (Krol, 2014; Baker et al., 2016), the relationship between EPU and CIP deviations is an area that requires further investigation. CIP deviations occur when the interest rate parity condition fails to hold, indicating the presence of arbitrage opportunities or market inefficiencies. Du et al. (2018) found that CIP deviations are related to measures of global risk and uncertainty. As EPU is another type of uncertainty, it is plausible that it may contribute to CIP deviations. Uncertainty can cause investors move their funds to safer assets, reducing liquidity in certain markets. This reduced liquidity can prevent arbitrageurs from effectively exploiting CIP deviations, allowing such CIP deviations to persist.

2. Unit-root Test

Before conducting a detailed empirical analysis, we first perform unit root tests to determine whether the variables under examination are stationary or non-stationary. Table 2 presents the results of the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests developed by Dickey and Fuller (1979), Phillips and Perron (1988), and Kwiatkowski et al. (1992), respectively. The null hypothesis of the ADF and PP tests is that the time series process contains a unit root, indicating non-stationarity, while the null hypothesis of the KPSS test is that the time series process is stationary.

The unit root test results reveal different patterns of stationarity across our variables. For RDI and EPU, the test results consistently indicate non-stationarity, with the KPSS test strongly rejecting the null of stationarity at the 1% level (p-values of 0.001 and 0.004, respectively). However, for the global CIP deviation factor (GF), TED, and VIX, the results are less conclusive. These variables exhibit strong persistence in their time series behavior, making it challenging to definitively classify them as either stationary or non-stationary. This is evident in their test statistics lying near the boundary between stationarity and non-stationarity across different tests.

Table 2. P-values for Stationarity and Non-Stationarity Tests

	GF	TED	RDI	VIX	EPU
ADF	0.052*	0.101	0.380	0.058*	0.892
PP	0.234	0.008***	0.466	0.030**	0.169
KPSS	0.272	0.061*	0.001***	0.034**	0.004***

Notes: 1. GF stands for the global CIP deviation factor (1 year Tenor).
2. Significance levels are represented as *p<0.1, **p<0.05, and ***p<0.01.
3. The lag order for the unit root tests is set by the Akaike information criterion (AIC) criterion.

Given these findings, particularly the persistent nature of our key variables, we adopt a modeling approach that explicitly accounts for both non-stationary and stationary components in our subsequent analysis. Specifically, in equations (13), our TVP-UC-SV model decomposes the global factor into a non-stationary trend component τ_t and a stationary cyclical component z_t. This decomposition allows us to capture both the long-run movements through the random walk process of τ_t and the temporary deviations through the stationary z_t process, providing a robust framework for analyzing these highly persistent series.

3. Time-varying Parameter Model With Stochastic Volatility

This section examines the dynamics of CIP deviations using a time-varying parameter unobserved components model with stochastic volatility (TVP-UC-SV)[3]:

$$f_t = \tau_t + z_t \tag{8}$$

$$\tau_t = \tau_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \sigma_\epsilon^2) \tag{9}$$

$$z_t = \sum_{p=1}^{4} \beta'_{p,t} X_{t-p} + e_t, \quad e_t \sim N(0, \sigma_t^2), \quad \sigma_t^2 = \sigma_0^2 \exp(h_t) \tag{10}$$

$$h_t = h_{t-1} + u_{h,t}, \quad u_{h,t} \sim N\left(0, \sigma_h^2\right) \quad (11$$

3. The proposed model can alternatively be interpreted as a Distributed Lag (DL) model with time-varying parameters.

$$\beta_{p,t} = [\beta_{1,p,t}, \beta_{2,p,t}, \beta_{3,p,t} \ \beta_{4,p,t}]' \tag{12}$$

$$\sigma_\epsilon^2 \sim IG\left(\underline{\alpha_\epsilon}, \underline{\delta_\epsilon}\right), \quad \sigma_{k,p}^2 \sim IG\left(\underline{\alpha_{k,p}}, \underline{\delta_{k,p}}\right), \quad \sigma_h^2 \sim IG\left(\underline{\alpha_h}, \underline{\delta_h}\right), \quad \sigma_0^2 \sim IG\left(\underline{\alpha_0}, \underline{\delta_0}\right) \tag{13}$$

where f_t is the global CIP deviation factor, and τ_t and z_t represent the long-run trend and cyclical components of the global CIP deviation factor, respectively. In this model, the vector of detrended and standardized predictors, $X_t = [\widetilde{EPU}_t, \widetilde{RDI}_t, \widetilde{TED}_t, \widetilde{VIX}_t]'$ [4], is hypothesized to explain the future movements of z_t. Therefore, $\beta_{1,p,t}$, $\beta_{2,p,t}$, $\beta_{3,p,t}$, and $\beta_{4,p,t}$ are the coefficients of $\widetilde{EPU}_{t-p}, \widetilde{RDI}_{t-p}, \widetilde{TED}_{t-p}, \widetilde{VIX}_{t-p}$, respectively.

The trend component τ_t is designed to capture the long-run movements of the global CIP deviation factor, given that the unconditional mean of z_t explained by the explanatory variables is restricted to zero.[5] This model allows us to empirically examine how the long-run trend of the global CIP deviation factor evolves over the sample period. The shocks to z_t are modeled with time-varying volatility to allow for the magnitude of the cyclical shocks to change over time, as reflected in the global factor plot in Figure 2. Additionally, contemporaneous values of the explanatory variables are excluded to avoid potential endogeneity issues.

The TVP-UC-SV[6] is estimated by a Bayesian estimation method. We use inverse Gamma distributions as the prior distributions of the following model parameters:

$$\sigma_\epsilon^2 \sim IG\left(\underline{\alpha_\epsilon}, \underline{\delta_\epsilon}\right), \quad \sigma_{k,p}^2 \sim IG\left(\underline{\alpha_{k,p}}, \underline{\delta_{k,p}}\right), \quad \sigma_h^2 \sim IG\left(\underline{\alpha_h}, \underline{\delta_h}\right), \quad \sigma_0^2 \sim IG\left(\underline{\alpha_0}, \underline{\delta_0}\right) \tag{14}$$

where $\underline{\alpha_\epsilon}, \underline{\alpha_{k,p}}, \underline{\alpha_h}, \underline{\alpha_0}$ are the prior shape parameters and $\underline{\delta_\epsilon}, \underline{\delta_{k,p}}, \underline{\delta_h}, \underline{\delta_0}$ are the prior scale parameters of the inverse Gamma distributions. We assume weakly informative priors by setting the scale parameters to be $\underline{\alpha_{k,p}}, \underline{\alpha_h}, \underline{\alpha_0} = 3$. Im and Kim (2022) emphasize that the pile up problem[7] could be an issue in estimation specially when the signal-to-noise ratio of data is close to zero. To avoid the pile-up problem, we assume $\underline{\delta_{k,p}} = 3 * 0.1^2, \underline{\delta_h} = 3 * 0.1^2, \underline{\delta_0} = 3 * 1^2$. we assume an

4. Each variable is de-trended using a third-order polynomial of the time index t. After de-trending, the variables are standardized by subtracting their sample means and dividing by their standard deviations

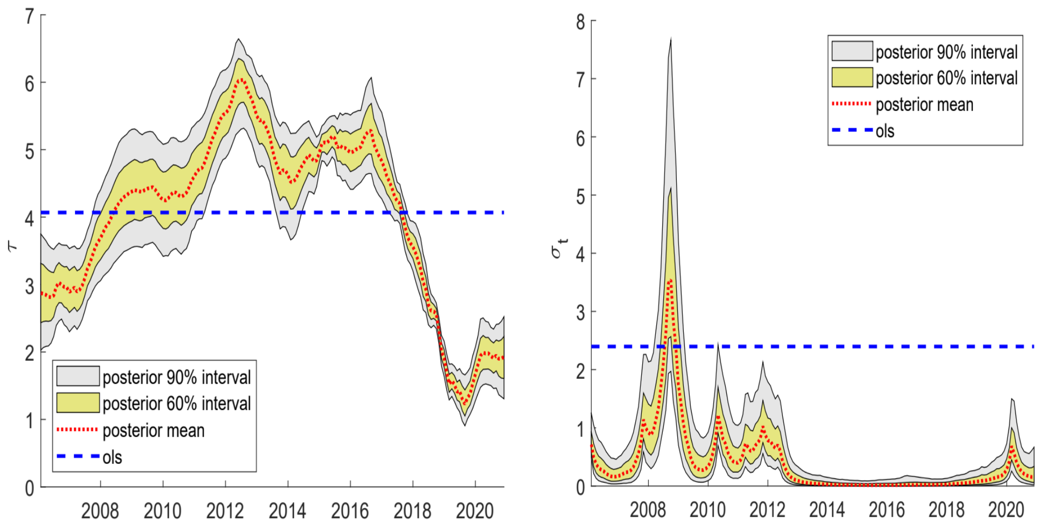
5. Our model specification is flexible enough to accommodate different trend behaviors. If the variance of the random walk intercept term σ_ϵ^2 is zero, the model implies a constant intercept with a stationary cycle. If positive, it allows for a time-varying, non-stationary trend without requiring a pronounced directional trend. Given that the global CIP deviation factor shows no clear upward or downward trend (Figure 2), this specification is more appropriate than including a deterministic time trend.

6. Note that the proposed model can be considered as a Distributed-Lag model with time varying parameter and volatility by treating τ_t as an intercept term.

7. The pile-up problem is the problem that a variance parameter is estimated to be exactly zero although its true value is not zero. This problem is pervasive in ARMA, unobserved components, and time-varying parameter models.

informative prior to limit excessive volatility in the long-run trend of the global CIP deviation factor. Specifically, we set $\underline{\alpha_\epsilon}$ to 30 and $\underline{\delta_\epsilon}$ to 30*0.03^2. This choice implies that the prior mean of σ_ε^2 is approximately 0.03^2. As a result, for a one-month period, the trend is expected to move by 0.03 with roughly 60% probability and by 0.06 with approximately 90% probability. The Particle MCMC algorithm is applied to the Baeysian estimation because our proposed model involves the non-linearity in the stochastic volatility process.

Figure 3. Long-run Trend and Time Varying Volatility

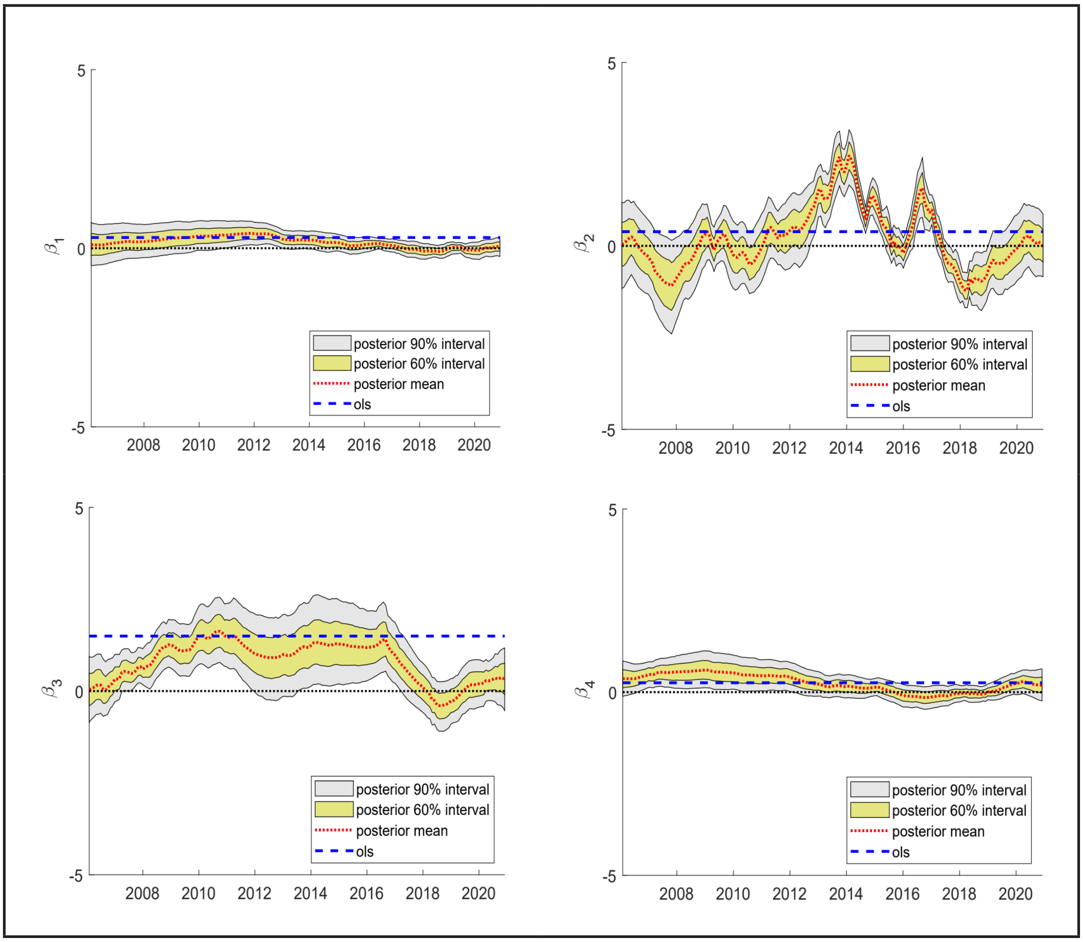


Note: Author created based on Du et al. (2018); Government bond CIP deviation data using Bloomberg and Datastream (n.d.).

The left panel of Figure. 3 displays the posterior distribution of the time trend of the global factor along with the corresponding OLS estimate of a static DL model with constant model parameters. The long-run trend of the global factor indicates that the CIP deviation has gradually yet substantially diminished since 2012. This implication is starkly differ from the OLS estimate for the constant long-run trend. Consequently, the long-run trend τ_t has remained historically low in recent years.

The right panel of Figure 3 shows the posterior distribution for the stochastic volatility of the cyclical component z_t. The time-varying volatility exhibits increases during the two financial stress periods around 2008 and 2011. This implies that the volatility of CIP deviations tends to expand significantly during times of financial stress. Notably, the variance of the factor innovation is estimated to be substantially smaller in the our TVP-UC-SV model than the static DL model over the entire sample period.

Figure 4. Timr-varying Coefficient $\beta_{\mathrm{k,t}}$ of EPU, RDI, TED, VIX



Note: Author created based on Du et al. (2018); Government bond CIP deviation data using Bloomberg and Datastream (n.d.).

The long-run cumulative effect of each explanatory variable on the global CIP deviation factor is measured by $\beta_{k,t} = \sum_{p=1}^{4} \beta_{k,p,t}$ for k = 1,2,3,4. The upper right panel β_3 of Figure 4 illustrates the time-varying long-run relationship between the global factor and the RDI, an indicator of the real value of the U.S. dollar, calculated on a trade-weighted basis. Since fluctuations in the dollar's value directly influence international capital flows, examining its relationship with CIP deviations is both important and meaningful.

Our analysis reveals dynamics in this relationship over different market regimes. Prior to 2012, we observe a mild negative relationship between the two variables, though this relationship is not statistically significant as the 90% posterior interval includes 0. The relationship strengthened notably during 2013-2017, when the U.S. Dollar Index appreciated by approximately 25%. During this period, we observe significantly positive RDI coefficients ranging from 1.5 to 2.0, providing empirical evidence that dollar strength amplified CIP deviations. A closer examination of the relationship between actual RDI levels and estimated coefficients reveals that during the 2013-2017 period, approximately 80% of the times when RDI recorded its highest levels (above the 75th percentile) coincided with significantly positive RDI coefficients. Notably, from mid-2015 to late 2016, when RDI reached its peak levels, the RDI coefficients also maintained their highest values (1.8-2.0). This provides direct evidence of substantial concordance between periods of real dollar strength and high RDI coefficient levels.

However, the transmission mechanism from dollar strength to CIP deviations is not uniform across our sample period. Particularly during the crisis period of 2008-2012, we observe negative RDI coefficients despite dollar appreciation. These negative coefficients likely reflect the dominance of other factors - particularly funding liquidity constraints and market stress - which may have overshadowed the traditional relationship between dollar strength and CIP deviations. This suggests that the impact of dollar strength on CIP deviations is conditional on broader market conditions and their interaction with other financial factors, underscoring the importance of considering the full market context when analyzing the dollar's role in CIP deviations.

The TED spread is a key indicator of interbank credit risk and funding market liquidity. This variable is defined as the difference between the interest rates on interbank loans (LIBOR) and short-term U.S. government debt (T-bill), and it is known to be sensitive to global financial market conditions. The lower left panel (β_3) of Figure 4 illustrates the time-varying long-run relationship between the global factor and the TED spread. Our analysis reveals a strong positive relationship between the TED spread and CIP deviations that persisted well beyond crisis periods. While this relationship was particularly pronounced during the 2008 Global Financial Crisis and the 2011 European Sovereign Debt Crisis, the TED spread maintained significant explanatory power through 2018, even during relatively stable market conditions. This persistent influence suggests that funding liquidity conditions, as captured by the TED spread, play a broader role in CIP deviations beyond just crisis periods. The diminishing influence of the TED spread after 2018 likely reflects several structural changes in international financial markets. First, the implementation of Basel III regulations has led to more stringent liquidity requirements for banks, potentially reducing their reliance on short-term wholesale funding markets that the TED spread traditionally captured. Second, the increased role of non-bank financial intermediaries in cross-border lending may have reduced the significance of traditional interbank funding metrics. Third, central banks' enhanced liquidity provision frameworks and more coordinated international responses to market stress may have decreased the importance of conventional funding stress indicators. These changes suggest a transformation in how funding conditions affect CIP deviations, rather than simply indicating improved market functioning.

We also examine the roles of the VIX and EPU indices as determinants of CIP deviations in our model. Overall, their effects on the CIP deviations are much smaller in magnitude compared to the dollar index and Ted spread. The Economic Policy Uncertainty (EPU) index measures uncertainty related to economic policy by tracking the frequency of relevant keywords in major newspaper articles. This index specifically targets policy-related risks, setting it apart from financial risk indicators like the VIX. The TVP regression result, shown in the upper left panel of Figure 4, indicates that the EPU index generally have no significant relationship with CIP deviations throughout most of the sample period.

The VIX index is a key indicator of market volatility and investor risk aversion. It reflects the implied volatility of S&P 500 index options over the next 30 days and typically increases when market uncertainty rises. Our findings, presented in the lower right panel of Figure 4, show that the VIX index generally maintained a positive relationship with CIP deviations, except during the period from 2014 to 2018. However, its impact has diminished in recent years, particularly after 2020.

From the empirical analyses in this section, it can be concluded that the TED Spread was the most significant factor in explaining fluctuations in CIP deviations during the two financial crises and the period thereafter, up until 2017. The RDI was an important determinant of CIP deviations from 2013 to 2017. In contrast, the EPU and VIX indices have been relatively less influential in explaining CIP deviations. However, in recent years, the global CIP deviation factor has not been responsive to any of the predictors, with its level and volatility remaining historically low. Although the empirical results are neither fully comprehensive nor definitive, they collectively suggest that CIP deviations are not as pronounced as those observed during the late 2000s and mid-2010s.

IV. Conclusion

This paper investigates the dynamics of Covered Interest Parity (CIP) deviations in G10 currencies during the post-Global Financial Crisis period, making several contributions to the literature. First, using a dynamic factor model, we document the existence of a common global factor structure in CIP deviations across G10 currencies. This finding suggests that systematic global forces, rather than currency-specific factors, may be the primary drivers of these violations.

Second, our time-varying parameter analysis reveals significant temporal variation in the relationships between the global CIP factor and key macroeconomic variables. Notably, we find that the TED spread, a measure of funding liquidity, emerged as the dominant factor in explaining CIP deviations during crisis periods. The TED spread maintained significant explanatory power not only during crisis periods but also through relatively stable market conditions until 2018, highlighting the broader role of funding liquidity conditions in CIP dynamics.

Third, we find dynamics between the Real Dollar Index and CIP deviations. During 2013-2017, approximately 80% of periods with high dollar strength coincided with significantly positive RDI coefficients, though this relationship varied notably across different market conditions. However, traditional market sentiment indicators such as the Economic Policy Uncertainty index and VIX demonstrated relatively limited influence on CIP deviations throughout our sample period.

Perhaps most notably, our analysis documents that the estimated global factor of CIP deviations has become less responsive to traditional predictors since 2018, maintaining historically low levels of both magnitude and volatility. This pattern in the global factor suggests changes in the structure of international financial markets compared to the period of significant anomalies observed during the late 2000s and mid-2010s.

These findings have potential implications for both policymakers and market participants. For policymakers, our results suggest the importance of monitoring global funding conditions and dollar dynamics when assessing potential stress in international financial markets. The decreased responsiveness of the estimated global factor to traditional predictors in recent years might reflect structural changes in international financial markets, including evolving funding mechanisms and regulatory environments. For market participants, our findings suggest that while the global factor has maintained historically low levels in recent years, the potential for CIP deviations during periods of market stress continues to warrant attention, particularly given the complex interaction between dollar dynamics and funding conditions we document.

The findings of this study also have significant implications for APEC economies and their financial systems. As APEC economies are highly integrated into global financial markets, deviations from Covered Interest Parity (CIP) can reflect underlying vulnerabilities in their financial systems, particularly during periods of global financial stress. The documented global factors influencing CIP deviations, such as the TED spread and the Real Dollar Index, highlight the critical role of funding liquidity and currency strength. For APEC economies, these factors emphasize the importance of robust liquidity management and the need for policies that mitigate exposure to global financial volatilities.

Future research could explore several promising directions. Our analysis documents notable differences in CIP deviations across different tenors, suggesting the existence of a term structure in the global CIP factor. A comprehensive investigation of this term structure, particularly focusing on how different maturities respond to market stress and regulatory changes, could enhance our understanding of cross-currency funding markets. Also, extending our analysis to emerging market currencies could provide a more comprehensive understanding of global financial market integration and efficiency. Finally, examining the role of post-crisis regulatory changes in the recent normalization of CIP deviations could help inform future policy decisions.

References

Akram, Q. F., Rime, D., & Sarno, L. (2008), Arbitrage in the foreign exchange market: Turning on the microscope, *Journal of International Economics*, *76*(2), 237-253.

Avdjiev, S., Du, W., Koch, C., & Shin, H. S. (2019), The dollar, bank leverage, and deviations from covered interest parity, *American Economic Review: Insights*, *1*(2), 193-208.

Baba, N., Packer, F., & Nagano, T. (2008), The spillover of money market turbulence to FX swap and cross-currency swap markets, *BIS Quarterly Review, March*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1517684

Bai, J., & Ng, S. (2002), Determining the number of factors in approximate factor models, *Econometrica*, *70*(1), 191-221.

Bai, J., & Wang, P. (2015), Identification and Bayesian estimation of dynamic factor models, *Journal of Business & Economic Statistics*, *33*(2), 221-240.

Baker, S. R., Bloom, N., & Davis, S. J. (2016), Measuring economic policy uncertainty, *The Quarterly Journal of Economics*, *131*(4), 1593-1636.

Brogaard, J., & Detzel, A. (2015), The asset-pricing implications of government economic policy uncertainty, *Management Science*, *61*(1), 3-18.

Cerutti, E. M., Obstfeld, M., & Zhou, H. (2021), Covered interest parity deviations: Macrofinancial determinants, *Journal of International Economics*, *130*(c), 103447.

Coffey, N., Hrung, W. B., & Sarkar, A. (2009), *Capital constraints, counterparty risk, and deviations from covered interest rate parity* (FRB of New York Staff Report, 393), FRB. https://www.newyorkfed.org/medialibrary/media/research/staff_reports/sr393.pdf

Dickey, D. A., & Fuller, W. A. (1979), Distribution of the estimators for autoregressive time series with a unit root, *Journal of the American Statistical Association*, *74*(366a), 427-431.

Du, W., & Schreger, J. (2022), CIP deviations, the dollar, and frictions in international capital markets, *Handbook of International Economics*, *6*, 147-197.

Du, W., Im, J., & Schreger, J. (2018), The U.S. treasury premium, *Journal of International Economics, 112*, 167-181.

Du, W., Tepper, A., & Verdelhan, A. (2018), Deviations from covered interest rate parity, *The Journal of Finance*, *73*(3), 915-957.

Durbin, J., & Koopman, S. J. (2012), *Time series analysis by state space methods* (2nd ed.), Oxford Academic. https://doi.org/10.1093/acprof:oso/9780199641178.001.0001

Ghorbel, A., Loukil, S., & Bahloul, W. (2022), Connectedness between cryptocurrencies, gold and stock markets in the presence of the covid-19 pandemic, *European Journal of Management and Business Economics*, *33*(1), 87-103.

Ivashina, V., Scharfstein, D. S., & Stein, J. C. (2015), Dollar funding and the lending behavior of global banks, *The Quarterly Journal of Economics*, *130*(3), 1241-1281.

Kim, C. J., & Kim, J. (2022), Trend-cycle decompositions of real GDP revisited: Classical and Bayesian perspectives on an unsolved puzzle, *Macroeconomic Dynamics*, 26(2), 394-418.

Krol, R. (2014). Economic policy uncertainty and exchange rate volatility, *International Finance*, *17*(2), 241-256.

Kwiatkowski, D., Phillips, P. C. B., Schmidt, P., & Shin, Y. (1992), Testing the null hypothesis of stationarity against the alternative of a unit root: How sure are we that economic time series have a unit root?, *Journal of Econometrics*, *54*(1-3), 159-178.

Pastor, L., & Veronesi, P. (2012), Uncertainty about government policy and stock prices, *The Journal of Finance*, *67*(4), 1219-1264.

Phillips, P. C. B., & Perron, P. (1988), Testing for a unit root in time series regression, *Biometrika*, *75*(2), 335-346.

Rime, D., Schrimpf, A., & Syrstad, O. (2022), Covered interest parity arbitrage, *The Review of Financial Studies*, *35*(11), 5185-5227.

Wong, C. Y., & Zhang, H. (2017), Corporate environmental policy, disclosure and cash flow sensitivities, *The British Accounting Review*, *49*, 372-384.