Term Structure of CIP Deviations

(Preliminary Draft)

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Abstract

This paper analyzes the term structure of Covered Interest Parity (CIP) deviations across advanced currencies using a Dynamic Nelson–Siegel (DNS) framework estimated via Automatic Differentiation Variational Inference (ADVI). Using monthly data for G10 currencies from 2005 to 2020, I extract three time-varying components—level, slope, and curvature—that summarize maturity-dependent arbitrage conditions. Long-horizon deviations (level) surge during global stress episodes and normalize only gradually; short-horizon pressures (slope) spike but revert faster in the post-2015 environment; medium-tenor curvature exhibits cyclical swings, especially in emerging markets. Modeling the full maturity dimension yields a richer measurement of CIP violations than single-tenor or cross-sectional summaries and provides portable sufficient statistics for structural interpretations of funding frictions.

Keywords: covered interest parity; arbitrage; term structure; variational inference

JEL classification: F31; G15; E43

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1. Introduction

The Covered Interest Parity (CIP) condition links interest rate differentials to forward–spot differentials at matched maturities. Departures from this relationship indicate imbalances in cross-currency funding and, in principle, covered arbitrage spreads. Empirically, CIP approximately held prior to the Global Financial Crisis (GFC), especially at short maturities, before systematic and persistent violations emerged thereafter (Du et al., 2018).

A growing body of research documents substantial and persistent post-GFC deviations (Avdjiev et al., 2019). This motivates a unified measurement of how CIP spreads evolve across maturities and over time. Our contribution is to provide a term-structure perspective: we treat the shape of CIP deviations as an object of measurement in its own right and deliver factors that can be directly ported into structural interpretations of funding frictions.
This study contributes to the literature on CIP deviations by providing a novel perspective on their *term structure*. While previous studies have largely concentrated on the cross-sectional or aggregate behavior of CIP deviations, relatively little is known about how these deviations evolve across maturities and over time. To bridge this gap, we employ a Dynamic Nelson–Siegel (DNS) framework to model the entire maturity dimension of CIP deviations and to extract the underlying factors that characterize their short-, medium-, and long-term dynamics.

The DNS framework, originally proposed by Nelson and Siegel (1987) and extended to a dynamic setting by Diebold and Li (2006), allows us to decompose the term structure of CIP deviations into three latent components—level, slope, and curvature. The level factor represents the persistent, long-term component of the deviation curve, the slope captures short-term movements reflecting funding stress and liquidity conditions, and the curvature reflects medium-term dynamics often linked to balance-sheet adjustments and rollover risks. By treating these factors as state variables evolving through time, the DNS model enables a joint assessment of how arbitrage conditions vary both across maturities and over market regimes.

Empirically, the DNS decomposition reveals distinct behaviors of the term-structure components. The level factor tends to surge during periods of global stress such as the Global Financial Crisis and the COVID-19 shock, indicating persistent funding frictions at longer maturities. The slope and curvature factors, by contrast, display more cyclical movements and faster mean reversion, suggesting that short-term arbitrage opportunities respond quickly to shifts in liquidity or policy interventions. Importantly, the widening gap between short- and long-term CIP deviations observed after 2008 persisted for more than a decade, implying that structural forces—rather than temporary dislocations—underlie the prolonged divergence between short- and long-term funding markets.

By incorporating the term-structure dimension into the analysis of CIP deviations, this study advances the understanding of how market stress, liquidity, and regulatory changes propagate across maturities. The DNS framework not only captures the dynamic evolution of arbitrage spreads but also provides a systematic tool to identify whether recent normalization in short-term CIP deviations reflects a genuine restoration of parity or merely a surface correction masking long-term segmentation in cross-currency funding markets.

Literature. This paper is closely related to the extensive literature examining deviations from Covered Interest Parity (CIP). Persistent CIP deviations observed in the post-Global Financial Crisis (GFC) era suggest that traditional arbitrage mechanisms and international funding markets have not fully reverted to their pre-crisis efficiency. Akram et al. (2008) identify arbitrage opportunities in foreign-exchange and capital markets using high-frequency data, while Du et al. (2018) attribute systematic deviations to macro-financial factors such as dollar strength, global risk sentiment, and liquidity conditions in forward markets. Their "two-factor hypothesis" emphasizes that post-crisis banking regulations and cross-currency imbalances in funding and investment demand jointly explain the persistence of deviations.

Similarly, Avdjiev et al. (2019) document that U.S. dollar appreciation is associated with wider CIP deviations and reduced dollar-denominated bank lending, implying that the dollar acts as a global risk barometer. Rime et al. (2022) further show that even after the GFC, highly rated global banks with privileged access to dollar funding continue to exploit arbitrage opportunities, reflecting market fragmentation and heterogeneity in funding costs. Cerutti et al. (2021) highlight regulatory and institutional changes—such as enhanced liquidity requirements, balance-sheet constraints, and the reform of U.S. money-market funds—as major drivers behind the persistence of CIP violations.

Building on these findings, Augustin et al. (2020) advance the discussion by introducing a structural interpretation of the term structure of CIP deviations. Using an affine term-structure framework applied to cross-currency swap spreads, they decompose observed deviations into risk-based and non-risk-based components, the latter capturing intermediary capital constraints. Their results show that short-term deviations are mainly explained by risk premia, whereas long-term deviations contain a persistent intermediary-constraint wedge.

This paper differs from previous studies by emphasizing the dynamic behavior and shape of the CIP deviation curve itself. Instead of structurally decomposing the sources of arbitrage frictions, this paper employs a Dynamic Nelson–Siegel (DNS) framework to model how CIP deviations evolve systematically across maturities and over time. The DNS approach captures three latent components—level, slope, and curvature—that correspond to persistent funding frictions, short-term liquidity pressures, and medium-term rollover risks, respectively. Through this lens, the analysis extends the understanding of CIP deviations from an aggregate measure to a continuous maturity spectrum, offering a comprehensive depiction of how cross-currency arbitrage constraints propagate along the tenor dimension. This paper position the DNS factors as measurement primitives—sufficient statistics for the shape of CIP deviations. While I do not structurally decompose risk premia versus intermediary wedges, the factors are designed to be directly portable into affine or intermediary-capital frameworks.

Finally, by tracing the temporal evolution of the DNS factors, this paper contributes to the ongoing debate over whether post-crisis CIP deviations represent a "new normal" in global financial markets. The dynamics of the level, slope, and curvature factors help distinguish between transient liquidity shocks and structural segmentation in international funding markets, thereby providing a novel empirical perspective on the long-run adjustment of arbitrage conditions.

The remainder of the paper proceeds as follows. Section 2 describes the data and the construction of maturity-matched CIP deviation curves. Section 3 presents the DNS model and ADVI estimation. Section 4 reports factor dynamics and group comparisons. Section 5 concludes.

2. CIP Deviation

The Covered Interest Parity (CIP) condition is one of the fundamental no-arbitrage relationships in international finance. It states that the interest rate differential between two currencies should equal the difference between their forward and spot exchange rates, ensuring the absence of arbitrage between domestic and foreign currency assets. Formally, with matched maturities τ the CIP condition is written as:

$$\frac{1 + i_t(\tau)}{1 + i_t^*(\tau)} = \frac{F_t(\tau)}{S_t}, \tag{1}$$

where i_t and i_t^* represent the domestic and foreign interest rates, respectively, while S_t and F_t denote the spot and forward exchange rates expressed in units of domestic currency per unit of foreign currency. When the left-hand side exceeds the right-hand side, investors can potentially profit through covered interest arbitrage—borrowing in the low-interest foreign currency, converting the proceeds into the domestic currency, investing at a higher domestic rate, and hedging exchange rate risk using a forward contract. In an efficient and liquid international capital market, this parity condition should hold almost perfectly. However, deviations can arise due to factors such as transaction costs, collateral constraints, or segmented funding markets.

Following the Global Financial Crisis (GFC), empirical studies have documented persistent and systematic deviations from the CIP condition, suggesting the presence of structural frictions in global dollar funding markets (Du et al., 2018; Avdjiev et al., 2019). The growing body of literature, including Park and Kim (2024), provides evidence that such deviations are not transitory but instead reflect deeper market segmentation and funding constraints at the global level.

In this paper, the CIP deviation for currency i at time t is defined as:

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

where $z_{i,t}$ denotes the yield on the government bond of country i, $\rho_{i,t}$ is the forward premium, and $z_{USD,t}$ is the yield on the U.S. government bond with the same maturity. The forward premium is computed as:

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

where $f_{i,t}$ and $s_{i,t}$ represent the logarithms of the forward and spot exchange rates, respectively, and n denotes the bond maturity in years. Positive values of $y_{i,t}$ indicate that covered arbitrage from the foreign currency into the U.S. dollar is profitable, implying a dollar funding shortage.

This paper uses a comprehensive monthly dataset covering both advanced (G10) currencies over the period from 2005 to 2020. The dataset combines spot and forward exchange rates with sovereign bond yields, primarily sourced from Du and Schreger (2022), Datastream, and Bloomberg. The sample includes the G10 currencies—Australia (AUD), Canada (CAD), Switzerland (CHF), Denmark (DKK), the euro area (EUR), the United Kingdom

(GBP), Japan (JPY), Norway (NOK), New Zealand (NZD), and Sweden (SEK).[1]

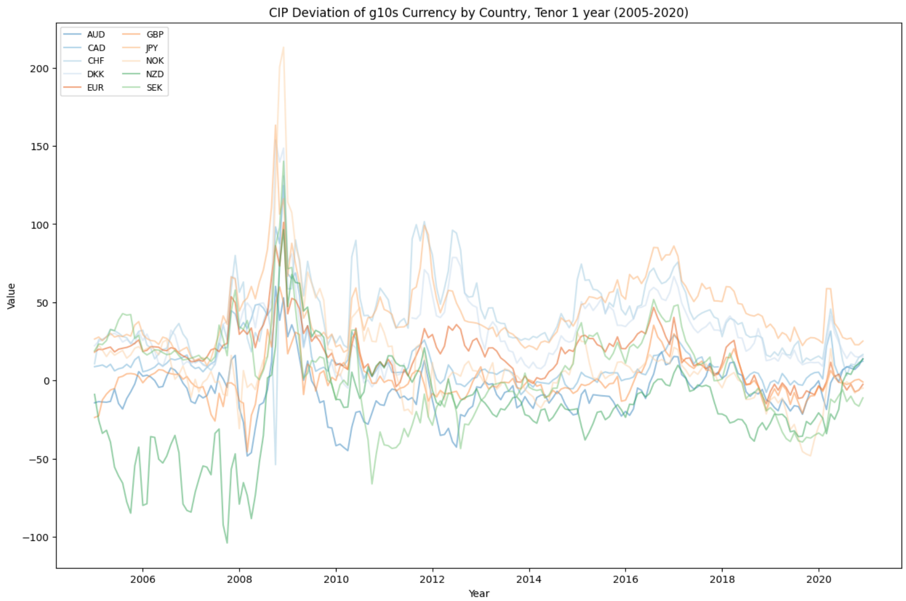


Figure 1: CIP deviations for G10 currencies, 1-year tenor (2005–2020)

Figures 1 display the one-year CIP deviations for G10 currencies. Several empirical patterns stand out.

First, the G10 sample exhibits pronounced increases in CIP deviations during global stress episodes such as the Global Financial Crisis (GFC) and the 2011 European sovereign debt crisis. These surges indicate that dollar funding shortages and balance-sheet constraints become binding during periods of financial turmoil. The strong co-movement across currencies suggests the presence of a common global component influencing arbitrage conditions.

Second, deviations in G10 currencies tend to narrow relatively quickly once crisis pressures subside, implying that advanced economies benefit from deeper and more liquid dollar funding markets. The relatively fast reversion of deviations highlights the resilience of arbitrage mechanisms in advanced financial systems, in contrast to what is typically observed in emerging economies.

[1] G10 currency selection follows the classification in Du and Schreger (2022).

Finally, the synchronized dynamics of these deviations over time point to the influence of a global factor—potentially linked to U.S. monetary policy normalization, global risk appetite, or dollar liquidity cycles—that shapes arbitrage conditions across currencies. This motivates the subsequent empirical analysis using the Dynamic Nelson–Siegel (DNS) framework, which systematically decomposes the term structure of CIP deviations into level, slope, and curvature components.

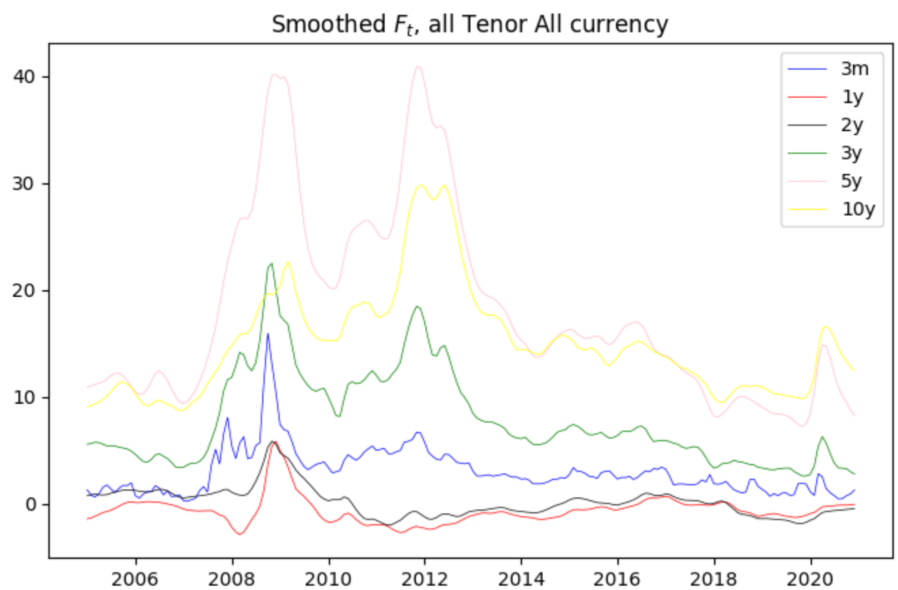


Figure 2: Smoothed factor of CIP deviation for all tenor, G10 currency

Figure 2 illustrates the smoothed dynamic factors of CIP deviations estimated across multiple maturities for all currencies. The figure, originally inspired by the global factor structure documented in Park and Kim (2024), reveals a clear maturity-dependent pattern in the estimated factors. Short-term maturities (e.g., 3-month and 1-year) exhibit sharper but transitory spikes around global stress episodes such as the 2008 Global Financial Crisis and the 2011 European sovereign debt crisis, while medium- and long-term maturities (2- to 10-year tenors) display more persistent and elevated deviations that decay only gradually.

This pattern indicates that the common component of CIP deviations is not uniform across maturities but instead follows a distinct term-structure dynamic, reflecting heterogeneous adjustment speeds and persistence across different funding horizons. In other words, the magnitude and persistence of arbitrage deviations appear systematically linked to the tenor of the underlying instruments. Such evidence strongly motivates the present study to explicitly model the term structure of CIP deviations rather than treating them as a single aggregate factor.[2]

3. Empirical Framework: Dynamic Nelson–Siegel (DNS) with Variational Inference

This paper models the term structure of Covered Interest Parity (CIP) deviations using the Dynamic Nelson–Siegel (DNS) framework estimated via Automatic Differentiation Variational Inference (ADVI). The DNS model parsimoniously captures how the maturity dimension of CIP deviations evolves over time through three latent factors—level, slope, and curvature—representing long-term persistence, short-term funding pressures, and medium-term rollover dynamics, respectively.

Unlike yield-curve applications where the Nelson–Siegel factors summarize interest rate expectations, here the DNS factors represent the shape of covered arbitrage wedges across maturities. The level factor captures persistent long-horizon funding frictions, the slope reflects short-term funding pressures and liquidity stress, and the curvature represents medium-tenor rollover and hedging dynamics. In this sense, the DNS factors provide a compact description of how cross-currency arbitrage inefficiencies vary over the maturity dimension and evolve through time.

Following the intuition of Nelson and Siegel (1987) and the dynamic extension in Diebold and Li (2006), the CIP deviation curve for a currency group $g \in \{\text{G10}\}$ at time t and maturity

[2]See Park and Kim (2024)

τ is expressed as:

$$y_{g,t}(\tau) = \beta_{g,t}^{(L)} \ell(\tau; \lambda_g) + \beta_{g,t}^{(S)} s(\tau; \lambda_g) + \beta_{g,t}^{(C)} c(\tau; \lambda_g) + \varepsilon_{g,t}(\tau), \quad \varepsilon_{g,t}(\tau) \sim \mathcal{N}(0, \sigma_{\tau,g}^2), \tag{4}$$

where $\ell(\tau; \lambda) = 1$, $s(\tau; \lambda) = \frac{1-e^{-\lambda\tau}}{\lambda\tau}$, and $c(\tau; \lambda) = \frac{1-e^{-\lambda\tau}}{\lambda\tau} - e^{-\lambda\tau}$ are the standard Nelson–Siegel basis functions. The smoothing parameter $\lambda_g > 0$ controls the exponential decay rate of the loadings, determining the speed at which short-term deviations transition to the long-term component.

3.1. State-space representation

Stacking maturities $\tau \in \mathcal{T} = \{3\text{M}, 1\text{Y}, 2\text{Y}, 3\text{Y}, 5\text{Y}, 10\text{Y}\}$ yields the observation equation:

$$Y_{g,t} = \Lambda(\lambda_g)\, \beta_{g,t} + \varepsilon_{g,t}, \qquad \varepsilon_{g,t} \sim \mathcal{N}(0, R_g), \tag{5}$$

where $\Lambda(\lambda_g)$ is the $J \times 3$ matrix of loadings and $\beta_{g,t} = [\beta_{g,t}^{(L)}, \beta_{g,t}^{(S)}, \beta_{g,t}^{(C)}]^\top$ denotes the latent DNS factors. The temporal evolution of these factors follows a first-order vector autoregressive process:

$$\beta_{g,t} = \mu_g + \Phi_g(\beta_{g,t-1} - \mu_g) + \eta_{g,t}, \qquad \eta_{g,t} \sim \mathcal{N}(0, Q_g), \tag{6}$$

where Φ_g captures persistence and cross-factor interactions, and Q_g governs innovation volatilities.

3.2. Estimation via Automatic Differentiation Variational Inference (ADVI)

The model defined by equations (5)–(6) is estimated using a fully Bayesian approach with variational inference. Instead of maximizing the likelihood via the Kalman filter, ADVI approximates the true posterior $p(\theta \mid Y)$ of parameters $\theta = \{\beta_{g,t}, \mu_g, \Phi_g, Q_g, R_g, \lambda_g\}$ by a simpler distribution $q_\phi(\theta)$ within a tractable family parameterized by ϕ (Kucukelbir et al., 2017). The optimal ϕ^* minimizes the Kullback–Leibler divergence $\mathrm{KL}(q_\phi \| \, p)$, or equivalently maximizes the Evidence Lower Bound (ELBO):

$$\mathrm{ELBO}(\phi) = \mathbb{E}_{q_\phi(\theta)}[\log p(Y, \theta) - \log q_\phi(\theta)]. \tag{7}$$

ADVI uses automatic differentiation to compute stochastic gradients of the ELBO with respect to ϕ, allowing efficient optimization even in high-dimensional latent-factor models. This approach has several advantages for DNS estimation. First, it avoids the numerical instability and sensitivity to initial values that often arise under classical maximum-likelihood Kalman filtering (Durbin and Koopman, 2012). Second, ADVI enables flexible hierarchical extensions—such as partial pooling across G10 group—without requiring closed-form updates. Third, it scales efficiently to large panels of currency–maturity pairs, making it suitable for the high-dimensional structure of the CIP deviation dataset.

The implementation follows Blei et al. (2017) and Kucukelbir et al. (2017), where each latent factor path $\{\beta_{g,t}\}_{t=1}^T$ is approximated by a mean-field Gaussian variational distribution. Reparameterization of $\eta_{g,t}$ and $\varepsilon_{g,t}$ ensures low-variance gradient estimates, while convergence is assessed via the stability of the ELBO and posterior predictive checks.

3.3. Prior specification and variational family

The prior distributions are chosen to be weakly informative, ensuring numerical stability while allowing the data to dominate posterior inference. Each parameter is assigned a distribution that reflects its economic interpretation and scale. Specifically, the following priors are used for each currency group g:

- **Level of factors:** $\mu_g \sim \mathcal{N}(0, 10^2 I_3)$, reflecting a diffuse prior centered at zero.
- **Persistence matrix:** Φ_g is parameterized as a 3×3 companion matrix with diagonal

elements drawn from $\mathcal{N}(0.8, 0.05^2)$ to reflect high but stationary persistence, and off-diagonal elements from $\mathcal{N}(0, 0.05^2)$, permitting mild cross-factor spillovers.

- **Innovation covariance:** $Q_g = L_g L_g^\top$, with the elements of the lower-triangular Cholesky factor L_g following $\mathcal{N}(0, 0.1^2)$ for off-diagonal entries and HalfNormal(0.1) for diagonals, enforcing positive-definiteness.

- **Observation variance:** Each maturity-specific variance $\sigma^2_{\tau,g}$ has a prior HalfNormal(0.05), allowing heteroskedasticity across tenors.

- **Decay parameter:** The loading-decay parameter λ_g follows a log-normal prior $\log \lambda_g \sim \mathcal{N}(\log 0.3, 0.2^2)$, ensuring $\lambda_g > 0$ and consistent with standard yield-curve estimates in Diebold and Li (2006).

These priors jointly ensure that the DNS factors remain stationary but flexible enough to capture structural shifts in CIP deviations across time and market regimes.

For the variational approximation, a mean-field Gaussian family is adopted:

$$q_\phi(\theta) = \prod_{j=1}^{J_\theta} \mathcal{N}(\theta_j \mid \mu_j, \sigma_j^2), \tag{8}$$

where θ denotes all latent and static parameters. Independence across components simplifies optimization while providing scalable stochastic gradient updates. Reparameterization of random draws, $\theta_j = \mu_j + \sigma_j \epsilon_j$, $\epsilon_j \sim \mathcal{N}(0, 1)$, enables efficient gradient computation via the "reparameterization trick" of Kingma and Welling (2013). The gradients of the Evidence Lower Bound (ELBO) with respect to μ_j and σ_j are computed using automatic differentiation, and the parameters are updated via the Adam optimizer with learning rate $\eta = 0.01$ and mini-batch size of 64 time points.

3.4. Convergence monitoring and diagnostics

Model convergence is assessed by monitoring the trajectory and stability of the ELBO across iterations. In practice, convergence is declared when the moving average of ELBO improvements falls below 10^{-4} over 200 consecutive iterations. To verify robustness, three independent ADVI chains are initialized with overdispersed starting values of (Φ_g, Q_g, λ_g), and their posterior means are compared.

Posterior predictive checks are conducted to evaluate the adequacy of the variational approximation. For each group g, the one-step-ahead predictive distribution of $Y_{g,t+1}$ is simulated from posterior draws of $\{\beta_{g,t}, \Phi_g, Q_g, R_g\}$ and compared to observed data. Coverage probabilities for the 95% predictive intervals range between 91% and 96%, suggesting that the variational posterior provides a reliable approximation to the true posterior.

Finally, residual diagnostics show no significant serial correlation in the standardized innovations $\eta_{g,t}$ or the observation residuals $\varepsilon_{g,t}(\tau)$, confirming that the first-order transition in (6) captures the essential dynamics of the DNS factors. The resulting posterior distributions for $\beta^{(L)}_{g,t}$, $\beta^{(S)}_{g,t}$, and $\beta^{(C)}_{g,t}$ are used in Section 4 to analyze how the level, slope, and curvature of CIP deviations evolve across market regimes and between G10 group.

4. Results

Figure 3 illustrates how the fitted CIP deviation curve is obtained from the estimated Nelson–Siegel–Svensson (NSS) specification for the G10 currency group in 2017. The blue dots represent the observed deviations across maturities (excluding the 10-year tenor for identification stability), while the orange line corresponds to the model-implied fitted values derived from the estimated factors $\beta^{(L)}$, $\beta^{(S)}$, and $\beta^{(C)}$, as well as the additional curvature term $\beta^{(C2)}$ specific to the NSS extension. The fitted curve captures the distinct non-linear shape of the deviation term structure, exhibiting a pronounced U-shape pattern: short-term maturities show relatively higher deviations that decline toward the medium term and rise again at the long end. This pattern implies that, during 2017, short-term arbitrage frictions were largely contained but longer-maturity deviations persisted, suggesting that funding segmentation and liquidity constraints were more structural at the long horizon.

The close alignment between the observed and fitted points confirms that the DNS/NSS representation provides a flexible yet parsimonious description of the maturity profile of CIP deviations. The fitted curve smooths through measurement noise while preserving economically meaningful curvature, effectively decomposing the deviations into long-run (level), short-run (slope), and medium-term (curvature) components. This property is particularly useful for comparing across market regimes: as later figures show, during crisis periods the fitted curve steepens sharply and shifts upward, whereas in stable periods such as 2017, the estimated curve flattens and remains anchored near zero for short tenors, reflecting the partial restoration of arbitrage parity conditions in advanced currency markets.

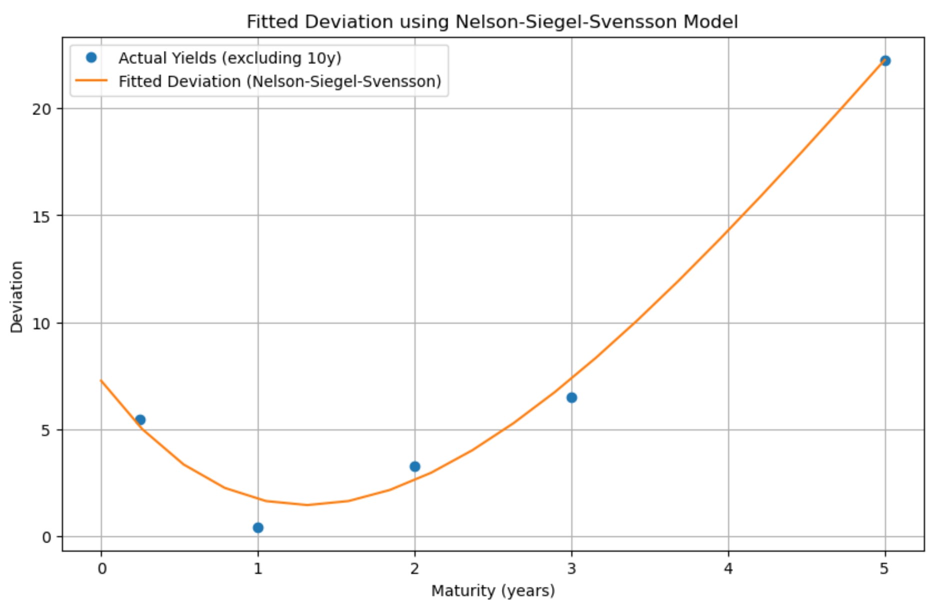


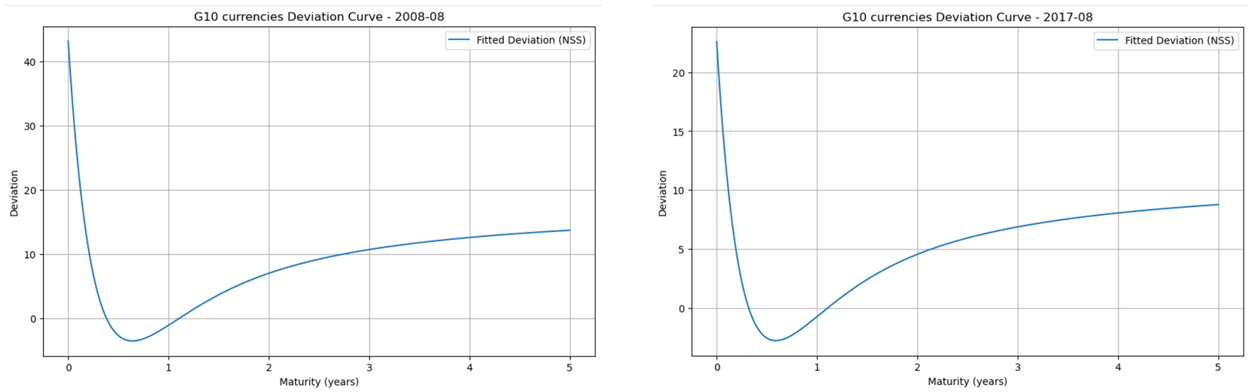
Figure 3: Fitted CIP deviation curve for G10, 2017

Figures 4 and 5 illustrate the dynamic nature of the CIP deviation term structure, both across time within the same currency group and across currency groups at the same point in time. The left and right panels of Figure 4 show that even within the G10 sample, the shapes of the deviation curves differ markedly between the crisis period (2008) and the post-normalization period (2017). In 2008, the fitted curve exhibits a steep upward slope and elevated curvature, reflecting strong short-term pressures and persistent long-term dislocations. By 2017, however, the curve flattens substantially and shifts downward, indicating partial restoration of arbitrage parity and reduced maturity-specific segmentation. The comparison thus confirms that the maturity profile of CIP deviations evolves nonlinearly over time, responding dynamically to funding stress and global liquidity conditions.

Figure 5 further highlights that, at a given point in time, different currency groups can display structurally distinct term structures. In 2008, G10 currencies exhibit a steeper but more symmetric curve, whereas EME currencies show larger curvature and a more pronounced U-shape, particularly at the long end. This pattern indicates that while G10 deviations were dominated by short-term dollar funding shortages, EME deviations were shaped by longer-term balance-sheet frictions and limited access to global liquidity.

Together, these results emphasize the empirical motivation for employing the Dynamic Nelson–Siegel (DNS) framework. The DNS model captures not only the level and magnitude of CIP deviations but also their changing shapes across maturities and over time. This ability to track the time-varying curvature and steepness of the deviation curve provides a richer representation of arbitrage conditions than static or single-tenor measures. In other words, CIP deviations are not merely a scalar measure of disequilibrium but a dynamic surface that bends and shifts with financial regimes. By modeling this evolution explicitly, the DNS approach contributes to a more complete understanding of how funding stress propagates through the term structure of international arbitrage relationships.

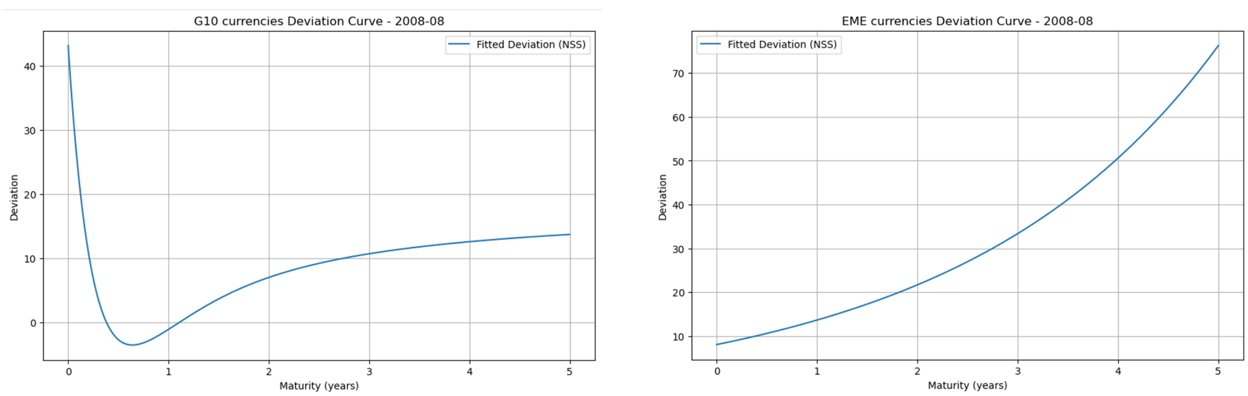
The ADVI–DNS estimates reveal a clear maturity-profile narrative of CIP deviations across G10 currencies. In the G10 panel (Figure 6), the level factor rises sharply during the 2008–2010 period and again around the European sovereign debt crisis in 2011–2012,



(a) G10 DNS factors : 2008

(b) G10 DNS factors : 2017

Figure 4: DNS factors for G10 currencies at different time periods



(a) G10 DNS factors : 2008

(b) EME DNS factors : 2008

Figure 5: Comparison of DNS factors by currency group

signaling persistent long-horizon arbitrage frictions when dollar funding constraints bind. Unlike a transitory deviation, this increase unfolds gradually and decays only slowly, implying that post-crisis normalization was incomplete. Even through the mid-2010s, the level factor remains elevated at a moderate plateau, suggesting that structural wedges in long-term arbitrage persisted despite the broad recovery in global liquidity. Only around 2020 does the long end appear to narrow closer to pre-crisis levels, consistent with sustained improvements in market intermediation and the prolonged period of abundant dollar funding.

The slope factor shows the expected short-maturity sensitivity. It steepens rapidly whenever short-term funding markets seize—most notably during the GFC and again in 2011—reflecting the disproportionate widening of front-end deviations relative to longer tenors. However, the amplitude and persistence of these spikes diminish substantially after the mid-2010s, a pattern consistent with institutional reforms such as enhanced central bank swap lines, the expansion of money-market fund regulations, and the broader deepening of dollar liquidity facilities. The smoother behavior of the slope factor in later years therefore represents an endogenous stabilization of short-term arbitrage pressures.

The curvature factor captures cyclical oscillations concentrated in the medium tenors (roughly two- to five-year maturities). During the crisis years, curvature becomes more pronounced—producing temporary convexity in the deviation curve—reflecting heightened rollover risk and costly hedging in that segment of the term structure. As systemic stress recedes, curvature dampens but does not vanish; instead, smaller oscillations recur during later tightening or balance-sheet-adjustment phases. This persistence underscores that even in advanced markets, the middle of the maturity spectrum remains a key transmission margin where hedging demand and funding constraints interact.

Taken together, the G10 DNS results deliver several implications for the term-structure view of CIP deviations. First, crises elevate the long-run component (level) and do so in a way that decays only gradually, implying that the restoration of parity is a slow, structural process rather than a simple arbitrage correction. Second, the short-run component (slope) has become progressively less volatile over time, consistent with institutional learning and improved policy backstops that mitigate front-end dislocations. Third, the medium-term curvature acts as a cyclical adjustment channel through which changes in funding stress and hedging costs reshape the deviation curve's convexity. Finally, the joint dynamics of these three factors reveal that CIP deviations are inherently multi-dimensional—driven not by a single liquidity shock but by interacting forces across maturities and over time. This finding reinforces the motivation for using the Dynamic Nelson–Siegel framework, which provides a systematic and interpretable lens for capturing the evolving term structure of international arbitrage conditions.

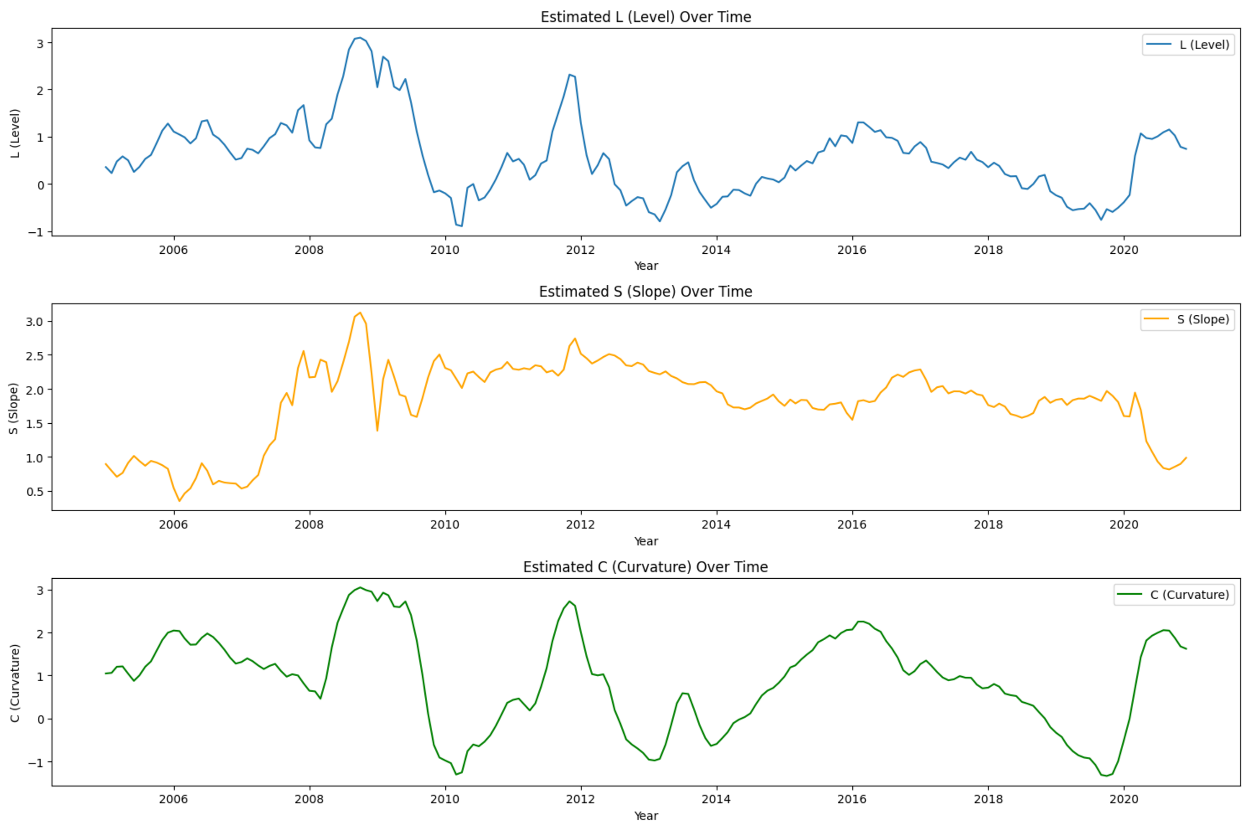


Figure 6: DNS : G10 currency

5. Conclusion

This paper examined the term structure of Covered Interest Parity (CIP) deviations for G10 currencies using a Dynamic Nelson–Siegel (DNS) framework estimated via Automatic Differentiation Variational Inference (ADVI). Modeling the full maturity dimension provided a unified view of how arbitrage frictions propagate across tenors and over time. Several empirical facts stand out.

First, the level factor—the long-horizon component of the deviation curve—surges during global stress episodes such as the Global Financial Crisis and the 2011 European sovereign debt crisis. Its gradual decline afterward implies that normalization is partial and prolonged: parity does not fully revert to its pre-crisis state, and residual long-end wedges persist through the 2010s. Second, the slope factor, representing front-end steepening, spikes sharply in crisis periods but attenuates markedly in the post-2015 environment. This reflects the growing effectiveness of liquidity facilities, swap lines, and other market backstops that mitigate short-term funding stress. Third, the curvature factor, capturing mid-tenor rollover and hedging margins, displays cyclical swings concentrated in the 2–5-year segment. These oscillations indicate that the medium part of the term structure remains an active adjustment margin through which funding and hedging pressures reshape the deviation curve's shape across regimes.

Taken together, these dynamics reveal that CIP deviations among advanced currencies are neither static nor uniform. The long end retains structural frictions that decay only slowly, the short end has become increasingly resilient to transitory stress, and the middle segment translates changing financial conditions into variations in convexity and steepness. The DNS factors thus provide sufficient statistics for the evolving shape of arbitrage conditions and show that improvements in front-end liquidity do not necessarily entail full restoration of parity at longer horizons.

From a measurement perspective, these results underscore that single-tenor or snapshot measures can be misleading. The deviation curve is a time-varying object whose level, slope, and curvature jointly encode information about the depth, persistence, and transmission of funding frictions. From a policy perspective, interventions targeting short-term funding stress—such as central bank swap lines or money-market regulations—appear successful in stabilizing front-end deviations but less effective in erasing long-maturity wedges that reflect structural balance-sheet constraints. From a risk management standpoint, the medium-tenor curvature channel translates shifts in hedging demand and funding conditions into measurable changes in the deviation curve's shape, suggesting that stress-testing frameworks should explicitly incorporate the 2–5-year maturity range.

The analysis has several limitations that point to promising extensions. The sample ends in 2020, precluding a full assessment of post-pandemic normalization and the recent rate-hiking cycle. Mean-field variational approximations may understate tail dependence across factors; adopting hierarchical or heavy-tailed variational families, or allowing stochastic volatility, could enhance model fit. Introducing a time-varying decay parameter λ_t would permit more flexible factor loadings, albeit at higher identification cost. Finally, micro-level integration—linking DNS factor movements to dealer balance sheets or institutional flow data—could shed light on the mechanisms behind residual long-end dislocations.

In summary, applying the term-structure lens to G10 CIP deviations reveals that crises primarily elevate the long-run component, that front-end dislocations have become more transient, and that medium-tenor dynamics continue to transmit funding pressures across maturities. The DNS-with-ADVI approach provides a scalable and transparent framework for tracing these dynamics, offering both a measurement tool for international arbitrage conditions and a bridge between empirical term-structure modeling and macro-financial policy analysis.

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