

Short- and Long-Run Sovereign Risk Uncertainty in U.S. Credit Default Swaps*

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Abstract

This paper decomposes sovereign risk uncertainty in U.S. credit default swap (CDS) spreads into short-run and long-run components. We employ a Bayesian dynamic factor model within a state-space framework to link observed CDS spreads and macro-financial variables to an unobserved latent risk factor. The short-run component, extracted from shorter-maturity CDS spreads, exhibits higher fluctuations and lower persistence, whereas the long-run component, derived from longer-maturity CDS spreads, captures greater persistence. Our empirical findings reveal that long-run uncertainty has a significantly stronger adverse impact on macroeconomic indicators, reducing consumption and industrial production more than short-run uncertainty. Notably, we document a negative relationship between long-run sovereign risk uncertainty and the Economic Policy Uncertainty (EPU) index, suggesting a key distinction between short-term policy volatility and long-term risk expectations. This result indicates that persistent sovereign risk uncertainty does not necessarily amplify short-term policy uncertainty; rather, it may trigger stabilization measures, such as fiscal consolidation or central bank interventions, as policymakers respond to heightened long-term risks. These findings underscore the importance of distinguishing between short-run and long-run sovereign risk uncertainty, offering a novel framework for macroeconomic analysis and financial stability assessment.

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Keywords: Sovereign Risk Uncertainty, Short-Run vs. Long-Run Macroeconomic Shocks, Bayesian Estimation, Kalman Filter, State-Space Models.

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1 Introduction

The uncertainty has become a central focus in economic and financial research due to its critical role in shaping asset prices, investor behavior, and macroeconomic stability. Uncertainty arises from a wide range of sources, including debt crises (Lane, 2012), political instability (Pástor and Veronesi, 2013), trade disruptions (Caldara et al., 2020), financial market volatility (Rigotti and Shannon, 2005), and broader macroeconomic factors such as inflation, unemployment, fiscal policy shifts, and global crises (Bloom et al., 2018; Basu and Bundick, 2017; Caggiano et al., 2014).

To capture these various dimensions of uncertainty, several indices have been developed. The Economic Policy Uncertainty (EPU) index (Baker et al., 2016) quantifies uncertainty arising from policy-related news, while the Trade Policy Uncertainty (TPU) index (Caldara et al., 2020) measures uncertainty in trade agreements and tariffs. Market-implied volatility measures, such as the CBOE Volatility Index (VIX) and its sector-specific counterparts (Gold ETF Volatility and Crude Oil ETF Volatility indices), capture investor expectations of future volatility (Whaley, 2009). More recently, the Climate Change Uncertainty Index (Gavriilidis, 2021) has been introduced to assess environmental risks.¹

While these indices provide valuable insights, they do not explicitly quantify sovereign risk uncertainty – the uncertainty surrounding a government’s ability to meet its debt obligations. Given the increasing prominence of sovereign debt crises and geopolitical tensions – such as the Greek debt crisis beginning in 2009 (Ardagna and Caselli, 2014), the Ukraine war since February 2022, rising tensions between China and Taiwan, and lately, the escalating trade war on tariffs, initially triggered by the Trump administration in 2018 (Fetzer and Schwarz, 2021), further intensified through ongoing trade disputes, and reignited under the new Trump administration in January 2025 – there is a clear need for a dedicated measure that captures market perceptions of sovereign credit risk.

Traditional uncertainty indices, such as the Economic Policy Uncertainty (EPU) index (Baker et al., 2016), are broad in scope, incorporating subjective information from diverse sources, including natural disasters, inflation, and global news. While these measures are useful for capturing short-term fluctuations in policy-related uncertainty, they primarily reflect high-frequency volatility rather than long-term risk expectations. As a result, they may fail to distinguish between transitory uncertainty shocks and persistent structural risks. Furthermore, their reliance on textual analysis and media coverage can lead to lagged responses, making them less effective in capturing real-time market perceptions of sovereign risk across different time horizons.

To address these limitations, we introduce a specialized, market-driven measure that directly links political uncertainty to sovereign risk perceptions based on U.S. credit default swaps (CDS). Specifically, we propose the Sovereign Risk Uncertainty (SRU) index, which we decompose into short-run (sSRU) and long-run (lSRU) components. This distinction allows us to separate immediate, transitory fluctuations in risk from deeper, structural uncertainties that persist over time, providing a more precise assessment of sovereign credit risk embedded in CDS spreads.

CDS spreads quickly reflect economic agents’ uncertainty in financial and economic markets, triggered by unexpected events. However, the impact of these events is not uniform – agents differentiate between temporary shocks that cause short-term market fluctuations and structural risks

¹Although these indices cover a broad range of uncertainty sources, they represent only a subset of the numerous uncertainty measures developed in the literature. Given the vast range of economic and financial uncertainties, it is beyond the scope of this paper to mention them all.

that alter economic fundamentals over the long run. Our starting idea is that the distinction between short-run and long-run uncertainty might be reflected in CDS maturities. For example, shorter maturities (6 months, 1, 2, and 3 years) could primarily capture the latent short-run component, while longer maturities (7, 10, 20, and 30 years) may better reflect persistent, long-run sovereign risk.

Building on this idea, our central hypothesis is that the long-run component of sovereign risk uncertainty exerts a more pronounced adverse effect on macroeconomic variables than short-run uncertainty. Specifically, while short-run uncertainty may generate temporary fluctuations in consumption, production, and asset prices, persistent uncertainty is expected to have a lasting impact on investment decisions, sovereign debt pricing, and financial stability.

Short-run uncertainty captures immediate, high-frequency reactions to geopolitical or macroeconomic events, reflecting temporary volatility and short-lived risk repricing. In contrast, long-run uncertainty arises when an event is perceived as fundamentally altering sovereign creditworthiness, influencing debt sustainability, policy credibility, and long-term investor sentiment. Events such as financial crises, wars, or sustained fiscal imbalances are incorporated differently into expectations – some primarily moving short-term market sentiment, while others reshaping long-term risk assessments.

When uncertainty persists, economic agents discount future outcomes more aggressively, increasing risk premia and demanding higher compensation for long-term exposure. This behavior lowers the present value of long-term returns, discourages investment, and constrains fiscal policy options. As a result, economic decisions made with a long-term perspective – such as investment (Bloom et al., 2007; Beaudry et al., 2001) – often diverge significantly from those driven by short-term considerations, such as consumption (Carroll, 1997). Heightened uncertainty may lead households to increase precautionary savings and reduce consumption, producing contractionary effects in the short run (Kimball, 1990; Basu and Bundick, 2017; Leduc and Liu, 2016).

Our methodological framework employs a Bayesian dynamic factor model within a state-space representation, where observed CDS spreads are linked to an unobserved latent sovereign risk factor and macro-financial variables. The latent state evolves as a first-order autoregressive process, estimated using a Kalman filter for optimal state extraction. The key distinction between the short-run and long-run latent components lies in the persistence parameter, α , which governs the duration of uncertainty effects. Short-run uncertainty exhibits lower persistence, meaning shocks dissipate quickly, reflecting transitory market fluctuations. Conversely, long-run uncertainty is characterized by higher persistence, implying that shocks have enduring effects on sovereign risk perceptions and macro-financial conditions. Our Bayesian estimation framework ensures robust inference by capturing parameter uncertainty and refining the separation of short- and long-run risk dynamics.

The model incorporates exogenous macroeconomic variables, including the industrial production index, personal consumption expenditure, the market value of government debt, and the personal savings rate, allowing us to assess how sovereign risk uncertainty interacts with key economic fundamentals. As a robustness check, we substitute these variables with alternative financial and policy uncertainty measures – specifically, the Economic Policy Uncertainty (EPU) index, the CBOE Volatility Index (VIX), oil prices, the housing price index, and the Dollar Index. The results remain robust to this alternative specification, confirming the stability of our findings across different macro-financial environments.

The latent components are estimated using a Kalman filtering and smoothing procedure which maximizes the likelihood function within the Bayesian framework (Harvey, 1989; RAUCH et al.,

1965). First, we derive prior values for persistence from a preliminary Kalman filter estimation on the principal component of CDS spreads grouped by maturity.² Then, within a fully Bayesian estimation framework as described by Gelman et al. (2013), we estimate short-run and long-run parameters using a random-walk Metropolis-Hastings algorithm with block updates, based on two categories of maturities. Specifically, we estimate α at 0.41 for the short-run component, whereas for the long-run component, it is approximately 0.89, reinforcing the distinction between transitory and persistent sovereign risk.

The estimated parameters are statistically significant, as confirmed by convergence diagnostics proposed by Gelman et al. (2013). The trace plots exhibit stable mixing without evident trends, while the Rhat statistic remains close to 1.00, indicating proper convergence across chains. Additionally, model performance is validated by low root mean square errors (RMSEs) and high correlations between observed CDS spreads and those constructed from the latent components. This strong alignment between the fitted and observed CDS spreads demonstrates that the model effectively captures sovereign risk uncertainty across different maturities, further reinforcing the robustness of our estimation framework.

To evaluate the impact of sovereign risk uncertainty on economic and financial variables, we examine how the two latent components influence key macroeconomic indicators. The empirical analysis reveals that while short-run uncertainty has a modest or mixed effect on consumption, persistent uncertainty—captured by the long-run component—exerts a significantly stronger adverse impact. These findings align with the theoretical framework, which suggests that prolonged uncertainty stemming from structural risks, such as sustained geopolitical tensions or sovereign debt crises, undermines long-term economic confidence, discourages investment, and ultimately depresses consumption.

A similar pattern emerges in the relationship between sovereign risk uncertainty and industrial production (IPI). Consistent with theoretical expectations, short-run uncertainty appears to have a modest or even slightly positive effect on IPI, potentially reflecting temporary adjustments in production schedules or inventory management. In contrast, persistent long-run uncertainty significantly reduces economic output, reinforcing the notion that sustained uncertainty discourages capital formation and disrupts long-term investment planning.

Examining sovereign debt markets, the short-run uncertainty measure exhibits a moderate negative correlation with the market value of treasury debt ($r = -0.3442$), whereas the long-run measure shows a substantially stronger negative correlation ($r = -0.6464$).³ These results suggest that while short-term uncertainty may have a limited or even stimulative effect on debt levels, persistent uncertainty leads to a more pronounced deterioration in sovereign debt valuations, likely due to rising risk premiums and declining investor confidence in long-term fiscal stability. This evidence supports the view that transitory fluctuations and structural risks influence sovereign debt markets in distinct ways.

²The short-run component is identified using CDS spreads with maturities of 6 months, 1 year, 2 years, and 3 years, while the long-run component is derived from 7-year, 10-year, 20-year, and 30-year maturities. To ensure that this classification does not artificially impose structure on our results, we conduct a robustness check where we re-estimate the model using alternative groupings (e.g., including/excluding 5-year CDS spreads and varying short-run cutoffs). The results, reported in Appendix D, show that the estimated persistence parameters remain stable across different classifications, confirming that our decomposition is driven by underlying risk dynamics rather than term structure effects.

³All reported correlation coefficients (r) correspond to the Pearson correlation, which quantifies the linear association between variables.

The analysis of household savings behavior reveals additional contrasts between short-run and long-run uncertainty. Transient uncertainty appears to reduce personal savings, potentially reflecting higher immediate consumption or precautionary savings adjustments, as suggested by [Carroll \(1997\)](#). Conversely, long-run uncertainty is associated with a slight increase in personal savings, though the correlation is relatively weak ($r = -0.2919$) and only marginally significant. These findings suggest that persistent uncertainty may induce a shift toward more cautious financial behavior, albeit to a lesser extent than its effect on consumption and investment.

Turning to policy uncertainty, the results indicate that short-run fluctuations in sovereign risk uncertainty do not have a significant impact on the Economic Policy Uncertainty (EPU) index. However, long-run uncertainty exhibits a negative relationship with policy-related uncertainty, suggesting that prolonged structural risks may influence economic policymaking dynamics. This finding implies that sustained sovereign risk uncertainty does not necessarily translate into heightened short-term policy uncertainty but may instead contribute to a stabilization of policy expectations.

One possible explanation for this negative correlation is the fundamental distinction between what these measures capture. The EPU index reflects policy volatility, which tends to fluctuate with short-term political and economic developments. In contrast, the long-run component of sovereign risk uncertainty reflects expectations about sustained risks, such as concerns over debt sustainability, fiscal imbalances, or long-term economic prospects. If persistent sovereign risk uncertainty prompts governments to implement stabilization policies, such as fiscal consolidation, central bank interventions, or sovereign debt restructuring, these measures may reduce short-term policy uncertainty and dampen fluctuations in the EPU index. Consequently, while expectations about long-run risk remain elevated, the near-term policy environment may appear more stable, leading to the observed negative relationship between long-run uncertainty and EPU.

Finally, the relationship between sovereign risk uncertainty and financial market volatility remains relatively weak. Although the long-run uncertainty measure shows a marginal positive association with the VIX, this effect is statistically insignificant, in line with the findings of [Barrero et al. \(2017\)](#). This suggests that market volatility, as captured by the VIX, is primarily influenced by broader financial and macroeconomic conditions rather than sovereign risk uncertainty alone. Nonetheless, these findings contribute to a more comprehensive understanding of how different dimensions of uncertainty interact with key economic and financial indicators.

The remainder of this paper is organized as follows. Section 2 presents the data, Section 3 introduces the state-space model. Section 4 describes the Bayesian estimation methodology, including the MCMC strategies for the short-run and long-run components. Section 5 presents the results of the bayesian estimation, including convergence diagnostics, posterior estimates, and measures of model fit. Section 6 presents the regression analysis. Finally, Section ?? concludes and discusses implications for sovereign risk analysis.

2 Data Description

This study utilizes U.S. credit default swap (CDS) spreads and a set of macroeconomic and financial variables to analyze sovereign risk uncertainty. The data spans from August 2008 to December 2024, with monthly frequency, ensuring that both short-run and long-run fluctuations in uncertainty are captured. CDS spreads serve as a market-based measure of sovereign credit risk, reflecting investors'

perceptions of the likelihood of a sovereign default. We obtain CDS spreads for multiple maturities - 6 months, 1, 2, and 3 years (short-term maturities) and 7, 10, 20, and 30 years (long-term maturities). We exclude the 5-year CDS spread from our analysis because it does not clearly fall into either the short-run or long-run category. Given its intermediate duration, it may capture elements of both transitory fluctuations and persistent risk, making it ambiguous for the purposes of our decomposition. Figure 1 represent the short run group and CDS and Figure 2 represent the long run, while Appendix A presents the full descriptive statistics of each CDS.

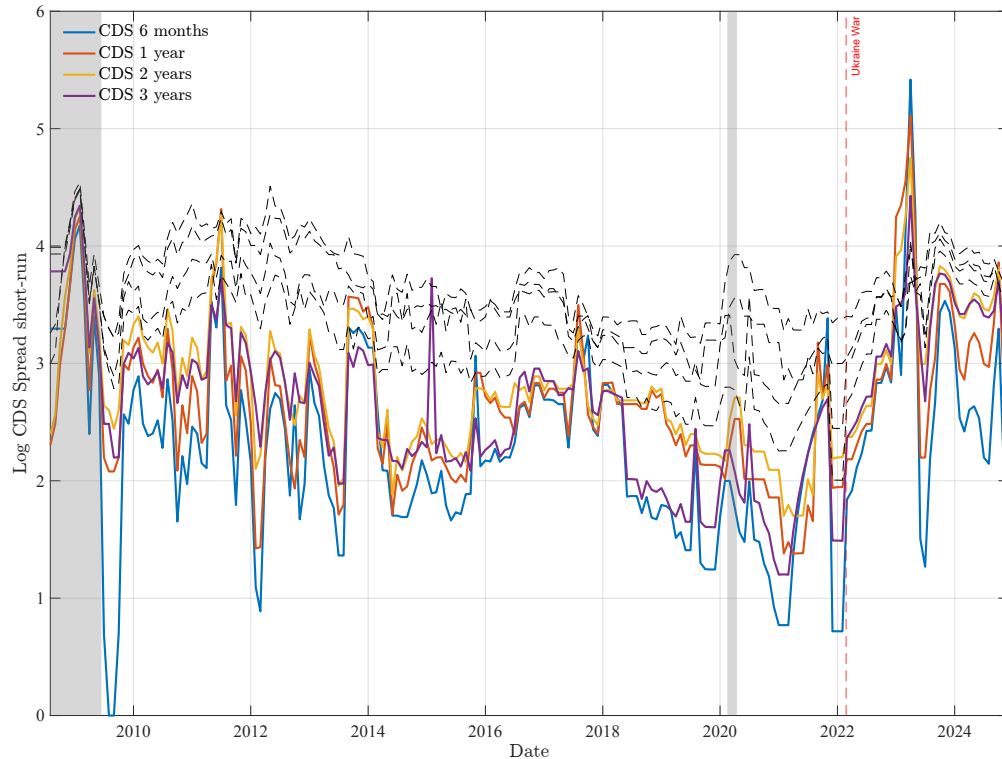


Figure 1: Short-run CDS

Note: The grey shaded regions represent the U.S. recession periods, while the red vertical line represents the starting point of the Russia-Ukraine war.

The data is sourced from [Investing.com](https://www.investing.com), and CDS spreads are expressed in basis points (bps). Given that CDS spreads tend to be right-skewed, we apply a log transformation to normalize their distribution. This transformation ensures that variations in spreads are interpreted in relative rather than absolute terms, improving the statistical properties of our estimation.

To analyze the impact of sovereign risk uncertainty on the broader economy, we include the following macroeconomic and financial variables as exogenous regressors in our state-space model. The Industrial Production Index (IPI) as a measure of real economic activity, capturing fluctuations in aggregate output.⁴ Personal Consumption Expenditure (PCE) that reflects household spending, serving as a proxy for aggregate demand.⁵ Market Value of Marketable Treasury Debt which

⁴Board of Governors of the Federal Reserve System (US), Industrial Production: Total Index [INDPRO], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/INDPRO>, January 14, 2025.

⁵U.S. Bureau of Economic Analysis, Personal Consumption Expenditures [PCE], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/PCE>, January 14, 2025.

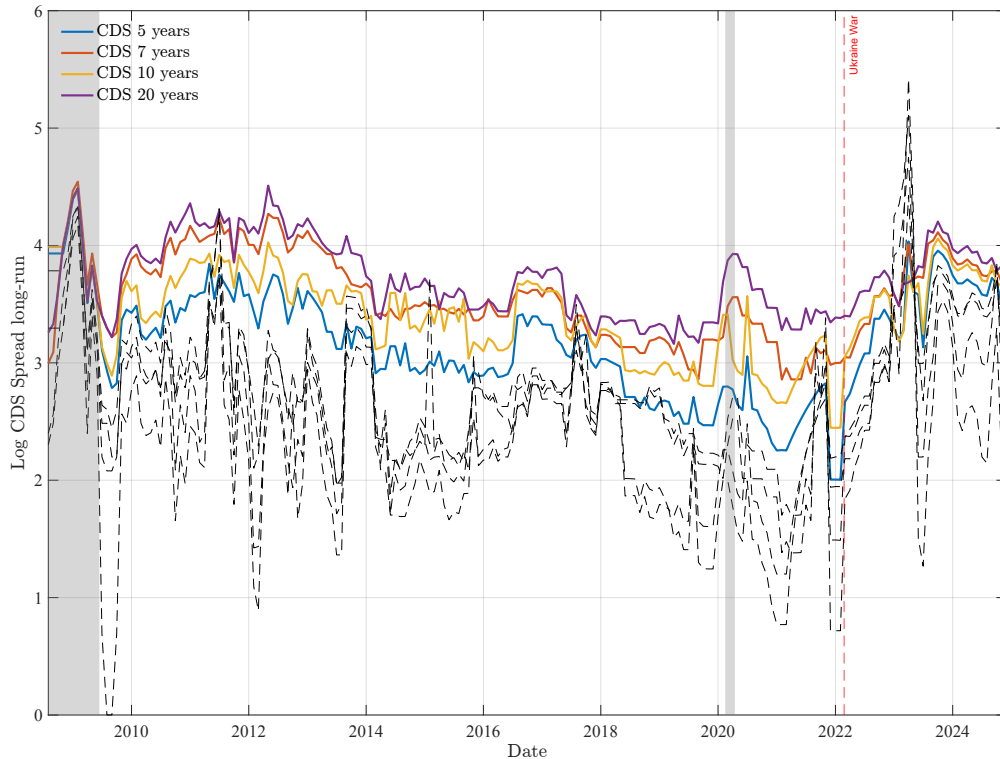


Figure 2: Long-run CDS

Note: The grey shaded regions represent the U.S. recession periods, while the red vertical line represents the starting point of the Russia-Ukraine war.

measures the total outstanding sovereign debt, an indicator of fiscal sustainability⁶. Personal Savings Rate (PSR) that captures household precautionary savings behavior, often influenced by economic uncertainty.⁷ The selection of these variables is dictated by the availability of monthly observations, ensuring consistency in our time-series analysis. The macroeconomic variables are indexed to a base value of 100 in September 2009, marking the official end of the Great Recession in the United States, and are subsequently log-transformed for consistency and comparability.⁸

The measurement equation assumes that macroeconomic variables are exogenous and do not respond to changes in sovereign risk uncertainty. However, to assess potential endogeneity, we conduct a Granger causality test between sovereign risk uncertainty components and key macroeconomic indicators. The results, reported in Appendix B.11, indicate that while short-run uncertainty does not Granger-cause macroeconomic fluctuations, long-run uncertainty exhibits bidirectional causality with sovereign debt pricing and industrial production.

To validate the exogeneity assumption in the measurement equation, we rely on both theoretical and empirical justifications. Theoretically, the selected macroeconomic variables are based on established economic reasoning and prior literature, and they are assumed to be determined

⁶Federal Reserve Bank of Dallas, Market Value of Marketable Treasury Debt [MVMTD027MNFRBDAL], retrieved from FRED, Federal Reserve Bank of St. Louis; , January 14, 2025.

⁷U.S. Bureau of Economic Analysis, Personal Saving Rate [PSAVERT], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/PSAVERT>, January 14, 2025.

⁸All macrovariables are sourced from the [Federal Reserve Bank of St. Louis \(FRED\)](#)

independently of the latent risk factor and measurement error term.

Empirically, we verify exogeneity by examining the residuals from the measurement equation to ensure they are uncorrelated with the exogenous variables. Specifically, we perform diagnostic tests, including Granger causality tests, to confirm that changes in the exogenous variables do not systematically affect the model’s residuals.⁹ Additionally, we assess multicollinearity among explanatory variables using the Variance Inflation Factor (VIF), with results reported in Appendix E. These robustness checks provide further support for the assumption that the exogenous variables are appropriately specified, ensuring the identification and consistent estimation of the model.

To test the robustness of our results, we replace the macroeconomic variables as exogenous regressors in our state-space model with alternative financial and policy-related uncertainty measures, including the Economic Policy Uncertainty (EPU) Index (Baker et al., 2016), newspaper-based measure of policy uncertainty. CBOE Volatility Index (VIX), which captures market-implied expectations of volatility. Oil Prices which represent a key driver of inflation and macroeconomic stability, obtained from the U.S. Energy Information Administration (EIA). Housing Price Index (HPI) that reflects the stability of the real estate sector.¹⁰ Dollar Index (DXY) that measures the relative strength of the U.S. dollar, relevant for assessing global capital flows.¹¹

Our primary estimation follows a benchmark model, which decomposes sovereign risk uncertainty into short-run and long-run components using a state-space model estimated via Bayesian methods. The short-run component is identified using CDS spreads with maturities of 6 months, 1 year, 2 years, and 3 years, while the long-run component is derived from 7-year, 10-year, 20-year, and 30-year maturities. To ensure that this classification does not artificially impose structure on our results, we conduct a robustness check where we re-estimate the model using alternative groupings (e.g., including/excluding 5-year CDS spreads and varying short-run cutoffs). The results, reported in Appendix D, show that the estimated persistence parameters remain stable across different classifications, confirming that our decomposition is driven by underlying risk dynamics rather than term structure effects. The exogenous variables in the benchmark specification include industrial production (IPI), personal consumption expenditure (PCE), treasury debt, and personal savings rate (PSR), allowing us to analyze the relationship between sovereign risk uncertainty and macroeconomic fundamentals.

To assess the robustness of our results, we estimate an alternative specification, modifying the grouping of CDS maturities and replacing macroeconomic variables with financial uncertainty indicators: the VIX, Economic Policy Uncertainty (EPU) index, oil prices, and the Dollar Index. This specification tests whether our findings remain stable under different model assumptions. Table 25 details the two models specifications.

⁹Appendix B.11 presents the estimation results.

¹⁰S&P Dow Jones Indices LLC, S&P CoreLogic Case-Shiller 20-City Composite Home Price Index [SPCS20RSA], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/SPCS20RSA>, February 14, 2025.

¹¹Board of Governors of the Federal Reserve System (US), Nominal Broad U.S. Dollar Index [DTWEXBGS], retrieved from FRED, Federal Reserve Bank of St. Louis; <https://fred.stlouisfed.org/series/DTWEXBGS>, February 14, 2025.

3 Theoretical Model

3.1 State-Space Representation of Sovereign Risk Uncertainty

To estimate sovereign risk uncertainty, we employ a Bayesian dynamic factor model (BDFM) within a state-space framework, where observed credit default swap (CDS) spreads are linked to an unobserved latent sovereign risk factor that evolves dynamically over time. A BDFM is particularly well-suited for this application as it allows for the extraction of time-varying latent risk components while accounting for parameter uncertainty in a probabilistic framework. Unlike structural VAR or DSGE models, which rely on predefined economic relationships, our BDFM leverages data-driven inference, ensuring flexibility in modeling evolving sovereign risk dynamics without imposing restrictive functional forms.

The measurement equation is given by:

$$y_t = \beta N_t + \Gamma x_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, R), \quad (3.1)$$

where y_t represents the vector of observed CDS spreads at time t , N_t denotes the latent sovereign risk factor, and x_t is a vector of macro-financial variables, including industrial production, personal consumption expenditure, government debt, and savings rate. The coefficient matrices β and Γ capture the relationships between CDS spreads, the latent factor, and macroeconomic conditions, while $\varepsilon_t \sim \mathcal{N}(0, R)$ is the measurement error, assumed to be normally distributed with covariance matrix R .

The latent sovereign risk factor follows an autoregressive process defined by the state transition equation:

$$N_t = \alpha N_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q), \quad (3.2)$$

where α is the persistence parameter governing the evolution of N_t , and $\eta_t \sim \mathcal{N}(0, Q)$ is a normally distributed state disturbance term with variance Q .

To distinguish between short-run and long-run sovereign risk uncertainty, we estimate separate persistence parameters for each component, allowing us to differentiate between transient shocks and sustained risks. The persistence parameters (α_{short} and α_{long}) are set as priors based on an initial Principal Component Analysis (PCA) of CDS spreads across different maturities. To assess the robustness of these priors, we conduct a sensitivity analysis by re-estimating the model using alternative prior specifications: (i) weakly informative normal priors centered at 0.5 with standard deviation 0.2, and (ii) hierarchical priors allowing the data to determine the degree of persistence. The results, reported in Appendix C, confirm that our posterior estimates remain stable across different prior choices. The PCA provides a preliminary decomposition, where short-maturity CDS spreads exhibit lower persistence, while long-maturity CDS spreads capture more persistent risk dynamics (Abdi and Williams, 2010). These PCA-derived priors help initialize the Bayesian estimation process.

The Kalman filter iteratively updates estimates of N_t based on new CDS spread observations, capturing the time-varying nature of political and financial uncertainty. The estimated variances of ε_t and η_t are initialized based on prior studies and optimized through maximum likelihood estimation (MLE). The short-run latent component (Short-SRU), derived primarily from short-maturity CDS

spreads, exhibits low persistence ($\alpha_{\text{short}} = 0.41$), meaning shocks dissipate quickly. The long-run latent component (Long-SRU), extracted from long-maturity CDS spreads, exhibits high persistence ($\alpha_{\text{long}} = 0.89$), indicating prolonged effects on sovereign risk perceptions.

The preliminary estimates of short-run and long-run persistence serve as priors in a Bayesian estimation framework. The Kalman filter and Rauch-Tung-Striebel smoother maximize the likelihood function (Harvey, 1989; RAUCH et al., 1965), refining the separation between transitory and persistent uncertainty components. The full estimation methodology, including hyperparameter selection and MCMC convergence diagnostics, is presented in Appendix C.

4 Bayesian methodology estimation

Parameter estimation is carried out using MCMC strategy. We follow Gelman et al. (2013) to estimate the short-run and long-run components via a block-update random-walk Metropolis-Hastings algorithm. We present the details in the subsequent section.

4.1 Bayesian Estimation via MCMC

We adopt a fully Bayesian approach to estimate the unknown parameters

$$\theta = \begin{bmatrix} \alpha \\ \beta \\ \text{vec}(\Gamma) \\ q \\ \text{vech}(R) \end{bmatrix},$$

where $\text{vech}(R)$ denotes the vectorization of the lower triangular part of R (of length $d_R = \frac{n(n+1)}{2}$). The priors used are as follows:

$$\alpha \sim \mathcal{N}(1, 0.5^2), \tag{4.1}$$

$$\beta_i \sim \mathcal{N}(1, 0.5^2), \quad i = 1, \dots, n, \tag{4.2}$$

$$\Gamma_{ij} \sim \mathcal{N}(0, (0.005)^2), \quad i = 1, \dots, n, \quad j = 1, \dots, k, \tag{4.3}$$

$$q \sim \mathcal{N}(\log(0.5), 0.5^2), \quad (\text{so that } Q = \exp(q)), \tag{4.4}$$

$$R \sim \mathcal{IW}(\Psi, \nu), \tag{4.5}$$

with hyper-parameters Ψ (a positive definite $n \times n$ scale matrix) and $\nu > n - 1$ (degrees of freedom). The log-density for the inverse-Wishart prior is, up to an additive constant,

$$\log p(R) \propto -\frac{\nu + n + 1}{2} \log \det(R) - \frac{1}{2} \text{tr}(\Psi R^{-1}). \tag{4.6}$$

A random-walk Metropolis-Hastings algorithm is employed to sample from the joint posterior $p(\theta|y_{1:T})$. At each iteration, a new candidate θ^* is proposed and accepted with probability

$$\min \{1, \exp[\log p(y_{1:T}|\theta^*) + \log p(\theta^*) - \log p(y_{1:T}|\theta) - \log p(\theta)]\}, \tag{4.7}$$

where $p(y_{1:T}|\theta)$ is computed via the Kalman filter described above.

4.2 Estimation Procedure

The overall estimation procedure is summarized as follows:

1. Data Preparation: Load and preprocess the CDS spread data $y_{1:T}$ (taking logs, handling missing values), and assemble the exogenous variable matrix X .
2. Specification: Define the state-space model in Equations Eq. (5.1) and Eq. (??).
3. Prior Specification: Specify the priors for α , β , Γ , q , and R (via its inverse?Wishart prior).
4. MCMC Sampling: Use the Metropolis-Hastings algorithm to sample from the posterior of the full parameter vector θ .
5. Posterior Summaries: Compute posterior-mean estimates $\hat{\theta}$ (e.g., $\hat{\alpha}$, $\hat{\beta}$, $\hat{\Gamma}$, \hat{q} , and \hat{R} , with $\hat{Q} = \exp(\hat{q})$).
6. Filtering and Smoothing: With $\hat{\theta}$ fixed, run the Kalman filter to obtain filtered state estimates $\{N_{t|t}\}_{t=1}^T$ and store the predicted values. Then, apply the Rauch-Tung-Striebel smoother (RAUCH et al., 1965) to obtain the smoothed latent states $\{N_t^s\}_{t=1}^T$.
7. Construction of Fitted CDS: Compute the fitted CDS spreads via

$$\hat{y}_t = \hat{\beta} N_t^s + \hat{\Gamma} x_t, \quad t = 1, \dots, T.$$

8. Inference: Analyze the smoothed latent component N_t^s and the fitted CDS spreads. In our application, the loading vector β allows the latent component to have different impacts on short and long maturities.

The Bayesian approach allows for uncertainty quantification in the estimation of the latent component and the measurement model parameters. In our application, the differences in the elements of β (and potentially Γ) across maturities enable the latent factor N_t to affect short and long maturities differently, which is consistent with empirical observations in the CDS market. The inclusion of a full inverse-Wishart prior on R enables estimation of the entire covariance structure of the measurement noise, thereby capturing potential correlations between the observed CDS spreads.¹²

This methodology is implemented using a custom Metropolis-Hastings MCMC sampler, followed by standard Kalman filtering and RTS smoothing. The resulting smoothed latent states and constructed CDS spreads are used for subsequent inference and model validation.

4.3 Random-Walk Metropolis-Hastings Algorithm with Block Updates

To efficiently sample from the posterior distribution of our model parameters, we employ a random-walk Metropolis-Hastings (MH) algorithm with block updates Gelman et al. (2013). This approach

¹²We use an inverse-Wishart prior for the covariance matrix R due to its conjugacy properties in Bayesian inference, ensuring computational efficiency. However, alternative priors such as the LKJ prior or shrinkage priors (e.g., horseshoe prior) could be explored in future research to further assess robustness.

is particularly advantageous in high-dimensional settings with correlated parameters, as is the case with our state-space model for sovereign risk uncertainty.

4.3.1 Algorithm Overview

At each iteration t of the MH algorithm, a new proposal θ^* is generated by perturbing the current parameter vector $\theta^{(t-1)}$:

$$\theta^* = \theta^{(t-1)} + \epsilon, \quad (4.8)$$

where $\epsilon \sim \mathcal{N}(0, \Sigma)$ is drawn from a multivariate normal distribution with covariance matrix Σ . The proposal θ^* is accepted with probability

$$\alpha = \min \left\{ 1, \frac{\pi(\theta^* | y)}{\pi(\theta^{(t-1)} | y)} \right\}, \quad (4.9)$$

where $\pi(\theta | y)$ denotes the target posterior density given the observed data y .

4.4 Block Updates and Sigmoid Reparameterization

We partition the parameter vector into two blocks. Block 1 contains the parameters governing the latent risk factor, including the unconstrained parameter θ_α , the coefficients β , and the elements of Γ . To ensure the stability of the persistence parameter, we reparameterize α using a sigmoid transformation:

$$\alpha = a + (b - a) \sigma(\theta_\alpha), \quad \sigma(x) = \frac{1}{1 + \exp(-x)}, \quad (4.10)$$

where a and b are the lower and upper bounds for α , respectively. This transformation guarantees that α remains within a stable and plausible range.

Block 2 includes the variance parameters, specifically $q = \log(Q)$ and the vectorized lower-triangular elements of the covariance matrix R . These parameters are updated using a random-walk proposal.

By updating parameters in blocks, we can adaptively tune the proposal distributions to better reflect the posterior geometry, thereby improving mixing and convergence.

4.4.1 Adaptive Tuning of the Proposal Covariance

For each block, the proposal covariance matrix is updated periodically to reflect the empirical covariance of the sampled parameters. Specifically, every certain number iterations the covariance is updated as:

$$\Sigma_{\text{new}} = \text{cov}(\theta_{\text{samples}}) + \delta I, \quad (4.11)$$

where δ is a small positive constant ensuring positive definiteness, and I is the identity matrix. This adaptive strategy helps maintain an optimal acceptance ratio, even in high-dimensional parameter

spaces.

4.4.2 Convergence Diagnostics

Following Gelman et al. (2013) we assess convergence of the benchmark model using standard diagnostics, including trace plots, the Gelman-Rubin statistic (Rhat), and effective sample size (ESS). These measures confirm that the Markov chain has converged to the target posterior distribution and that our parameter estimates are reliable. The benchmark model results are discussed in the following section. Appendix D presents the alternative model results.

5 Bayesian estimation results

The random-walk Metropolis-Hastings algorithm with block updates, enhanced by a sigmoid (logistic) reparameterization for the persistence parameter, provides a robust and efficient method for estimating the parameters of our state-space model (Gelman et al., 2013). By partitioning the parameter vector and adaptively tuning the proposal distributions, our approach effectively navigates the complex posterior landscape, enabling precise inference of both the short-run and long-run components of sovereign risk uncertainty. The benchmark model convergence diagnostics indicate that the estimated parameter vector is well-identified.

The empirical findings are in line with our theoretical formulation. The state-space model in Equations Eq. (3.1) and Eq. (3.2) captures both transient (short-run) and persistent (long-run) components of CDS spreads (Figure 3). The reparameterization of α via θ_α ensures that α remains within the desired bounds, and the different target values for the short-run and long-run groups lead to posterior estimates that conform to theoretical expectations. The improved model fit for the long-run maturities—as indicated by lower RMSE and higher correlation—demonstrates that the persistent component is effectively captured. Figure 4 and 5 show the model fit for each CDS maturity.

As a robustness check, we re-estimate the benchmark model with an alternative grouping of CDS maturities: the short-run group includes 6-month, 1-year, and 2-year maturities, while the long-run group consists of 7-year, 10-year, and 30-year maturities. Additionally, we replace the macroeconomic variables with the VIX, EPU, oil prices, and the Dollar Index as exogenous regressors. The results of the alternative model remain qualitatively similar and are presented in Appendix D.

The results indicate that the model successfully distinguishes between the short-run and long-run dynamics in CDS spreads. The short-run component, with a lower persistence level ($\alpha \approx 0.41$), captures transient shocks and higher volatility, as reflected by higher RMSEs and lower correlations between observed and fitted values as shown in Table 27. Conversely, the long-run component exhibits much higher persistence ($\alpha \approx 0.895$), with lower RMSEs and higher correlations, implying that long-term sovereign risk uncertainty is more stable and persistent. Figure 3 presents the short and long-run estimated latent component.

These findings are consistent with the theoretical model, which posits that sovereign risk uncertainty can be decomposed into components that respond differently to transient shocks (e.g.,

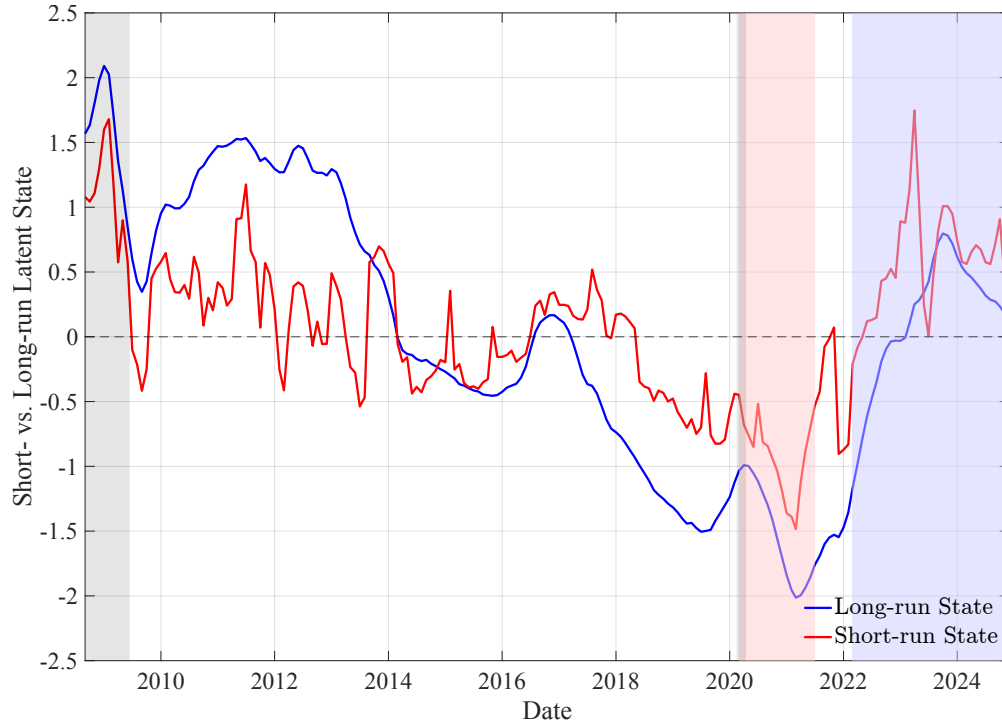


Figure 3: Short- and Long-run Estimated Latent Components

Note: The shaded regions highlight two major geopolitical and economic crises: the COVID-19 pandemic (pink) and the Russia-Ukraine war (magenta). The grey shadow area represent the U.S. recession periods.

political events) and persistent structural factors. In light of recent geopolitical tensions, such as the Ukraine war, marked with an horizontal line in the graphs, this decomposition is particularly valuable as it enables market participants to discount the immediate effects of crises differently from their long-term impact on sovereign credit risk.

5.1 Analysis of Latent Components During Crisis Periods

Figure 3 presents the estimated short-run and long-run latent components of sovereign risk uncertainty. The shaded regions highlight two major geopolitical and economic crises: the COVID-19 pandemic (pink) and the Russia-Ukraine war (magenta). These periods serve as key stress events that allow us to evaluate how sovereign risk uncertainty evolves in response to external shocks.

The short-run and long-run latent components exhibit distinct dynamics, reinforcing the hypothesis that short-run uncertainty reacts sharply to crises, whereas long-run uncertainty adjusts more gradually and persistently. The short-run component shows higher volatility, reflecting immediate market reactions to economic and geopolitical shocks, whereas the long-run component follows a smoother trajectory, capturing the persistent effects of sovereign risk.

The COVID-19 crisis, highlighted in pink, triggered a sharp downward spike in the short-run component around early 2020, reflecting the severe and immediate uncertainty surrounding the pandemic's economic impact. The long-run component also declined but at a more moderate pace, indi-

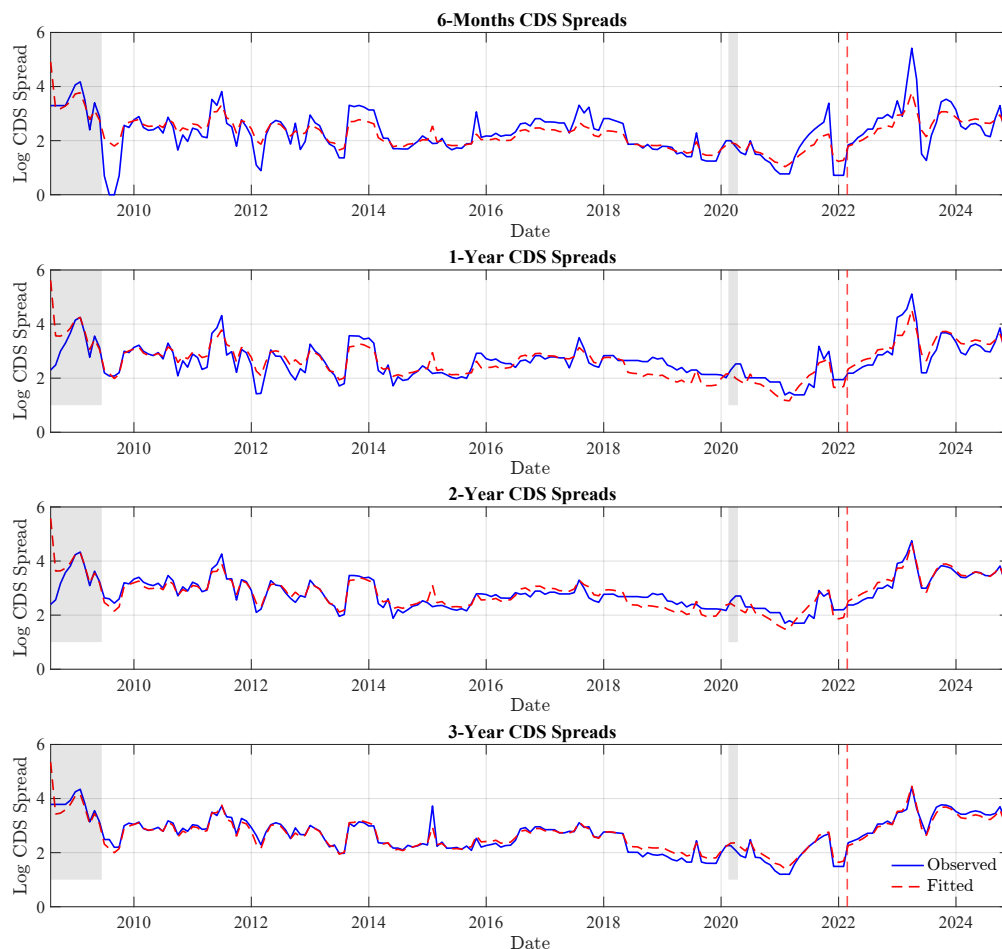


Figure 4: Short-run Observed CDS vs. Constructed CDS

Note: The grey shaded regions represent the U.S. recession periods, while the red vertical line represents the starting point of the Russia-Ukraine war.

cating that while short-term uncertainty was extreme, structural uncertainty surrounding sovereign risk persisted beyond the initial shock. These dynamics suggest that the pandemic caused an abrupt but temporary short-run shock, with the long-run CDS component’s more gradual decline reflecting the influence of policy interventions such as fiscal stimulus and monetary easing, which helped stabilize long-term expectations.

The magenta-shaded region marks the onset of the Russia-Ukraine war in early 2022. Unlike the COVID-19 crisis, this period is characterized by a sharp and prolonged increase in both latent components. The short-run component reacts strongly, signaling immediate market uncertainty following geopolitical escalation. The long-run component also increases, though at a slower pace, suggesting concerns about long-term geopolitical stability, fiscal risks, and broader macroeconomic implications. The war introduced both short-term disruptions and long-term structural risks, which are reflected in both latent components. However, the long-run component’s slower adjustment indicates a more persistent shift in sovereign risk perceptions, likely due to ongoing economic sanctions, geopolitical instability, and uncertainty surrounding global supply chains.

While both crises significantly impacted sovereign risk uncertainty, their effects differed in in-

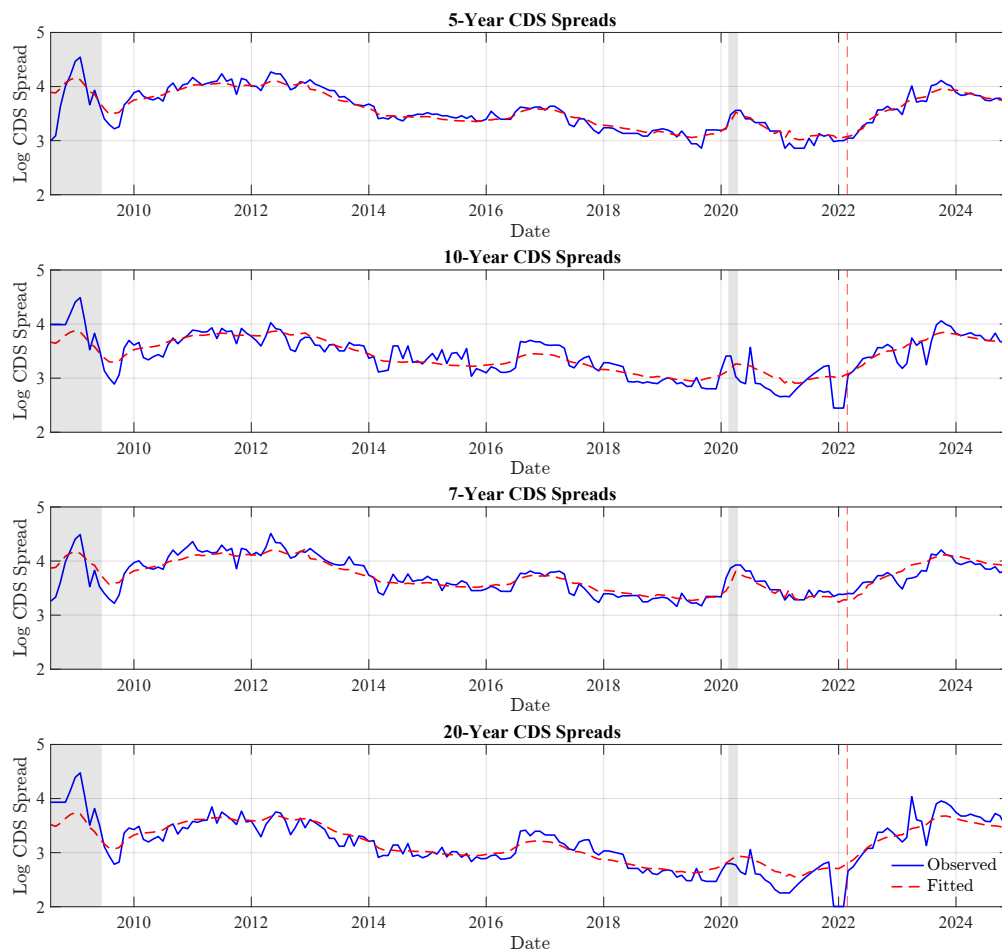


Figure 5: Long-run Observed CDS vs. Constructed CDS

Note: The grey shaded regions represent the U.S. recession periods, while the red vertical line represents the starting point of the Russia-Ukraine war.

tensity and duration. The COVID-19 crisis led to an immediate but temporary shock, reflected in extreme short-run volatility, whereas the war period resulted in a more sustained increase in both components. This suggests that while economic crises such as COVID-19 create abrupt spikes in short-run uncertainty, their impact on long-run uncertainty may be mitigated by policy responses. In contrast, geopolitical conflicts such as the Russia-Ukraine war tend to introduce deeper structural risks that lead to more persistent long-run uncertainty.

Our findings highlight the importance of distinguishing between short-run and long-run uncertainty when assessing sovereign risk and macroeconomic stability. While short-run uncertainty may be mitigated through immediate policy interventions such as central bank actions or fiscal stimulus, long-run uncertainty reflects deeper structural risks that require sustained economic and geopolitical stability to resolve. The crisis periods analyzed confirm that our model effectively captures both transitory and persistent sources of sovereign risk uncertainty, reinforcing its relevance for analyzing the macroeconomic impact of financial and geopolitical shocks.

5.2 Construction of Fitted CDS Spreads

To evaluate the performance of our model, we construct fitted CDS spreads using the estimated parameters and the smoothed latent state. Figure 4 and 5 present the graphical representation. Recall that our measurement equation is given by

$$\mathbf{y}_t = \beta N_t + \Gamma \mathbf{x}_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, R), \quad (5.1)$$

where \mathbf{y}_t is the vector of observed CDS spreads at time t , N_t is the unobserved latent risk factor, \mathbf{x}_t is the vector of exogenous variables, and β and Γ are the parameters linking the latent state and exogenous variables to the observed spreads.

The latent state N_t is estimated by applying the Kalman filter to the state–space model and then refined using the Rauch-Tung-Striebel (RTS) smoother. Denote by \hat{N}_t the smoothed estimate of N_t . The fitted CDS spreads are then constructed by replacing N_t in Equation Eq. (5.1) with \hat{N}_t and disregarding the noise term ε_t :

$$\hat{\mathbf{y}}_t = \beta \hat{N}_t + \Gamma \mathbf{x}_t. \quad (5.2)$$

This process is carried out separately for the short-run and long-run groups, with the estimated parameters reflecting the different dynamic properties of each group. The resulting fitted CDS spreads are then compared with the observed data using metrics such as the root mean square error (RMSE) and the correlation coefficient to assess the model fit.

In our empirical analysis, we observe that the short-run CDS spreads, which capture transient shocks, exhibit higher volatility and larger RMSE values compared to the long-run spreads. In contrast, the long-run fitted CDS spreads display lower RMSEs and higher correlations, indicating that the persistent component of sovereign risk is captured more accurately by our model.

5.3 Posterior Estimates and Convergence Diagnostics

The Bayesian estimation was performed separately for the short-run and long-run components using a block-update random-walk Metropolis-Hastings algorithm. The following posterior estimates were obtained:

For the short-run group we obtained:

$$\alpha = 0.4101,$$

$$\beta = \begin{pmatrix} 0.9338 \\ 1.0863 \\ 1.0426 \\ 1.0427 \end{pmatrix},$$

$$\Gamma = \begin{pmatrix} -0.1376 & 0.2453 & 0.2065 & 0.1742 \\ 0.1019 & 0.1030 & 0.2503 & 0.0816 \\ 0.1258 & 0.1546 & 0.1087 & 0.1764 \\ 0.1373 & 0.2662 & -0.0067 & 0.1350 \end{pmatrix},$$

$$Q = 0.1805,$$

$$R = \begin{pmatrix} 0.2615 & 0.1018 & 0.0183 & -0.0138 \\ 0.1018 & 0.2867 & 0.1861 & -0.0473 \\ 0.0183 & 0.1861 & 0.1512 & -0.0112 \\ -0.0138 & -0.0473 & -0.0112 & 0.0785 \end{pmatrix}.$$

The long-run group estimates are:

$$\alpha = 0.895,$$

$$\beta = \begin{pmatrix} 0.3811 \\ 0.3515 \\ 0.3496 \\ 0.4051 \end{pmatrix},$$

$$\Gamma = \begin{pmatrix} 0.1160 & 0.2083 & 0.1799 & 0.2367 \\ 0.2235 & 0.1018 & 0.1941 & 0.1750 \\ 0.2333 & 0.2364 & 0.1185 & 0.1711 \\ 0.2058 & 0.0769 & 0.0643 & 0.2892 \end{pmatrix},$$

$$Q = 0.0145,$$

$$R = \begin{pmatrix} 0.0173 & 0.0038 & 0.0131 & 0.0029 \\ 0.0038 & 0.0418 & 0.0070 & 0.0373 \\ 0.0131 & 0.0070 & 0.0212 & -0.0031 \\ 0.0029 & 0.0373 & -0.0031 & 0.0477 \end{pmatrix}.$$

Convergence diagnostics for α confirm satisfactory mixing and stability across chains. For the short-run group, the acceptance ratio is 18.46% with an effective sample size (ESS) of 11,854.94, and for the long-run group, the acceptance ratio is 17.02% with an ESS of 10,159.74. In both cases, the potential scale reduction factor (\hat{R}) is close to 1 (1.00 for both groups), indicating that the chains have converged. Additionally, the posterior density plots exhibit smooth unimodal distributions as show in Figure 8, trace plots show well-mixed chains without noticeable trends as show in Figure 6 and autocorrelation plots confirm rapid decay (Figure 7), further supporting convergence.

5.4 Interpretation of the Results

The empirical results confirm that the model successfully differentiates between the short-run and long-run dynamics of sovereign risk uncertainty. The short-run component yields an α of approximately 0.41, indicating that transient shocks dissipate relatively quickly. In contrast, the long-run component has an α of approximately 0.90, reflecting the high persistence associated with long-term sovereign risk.

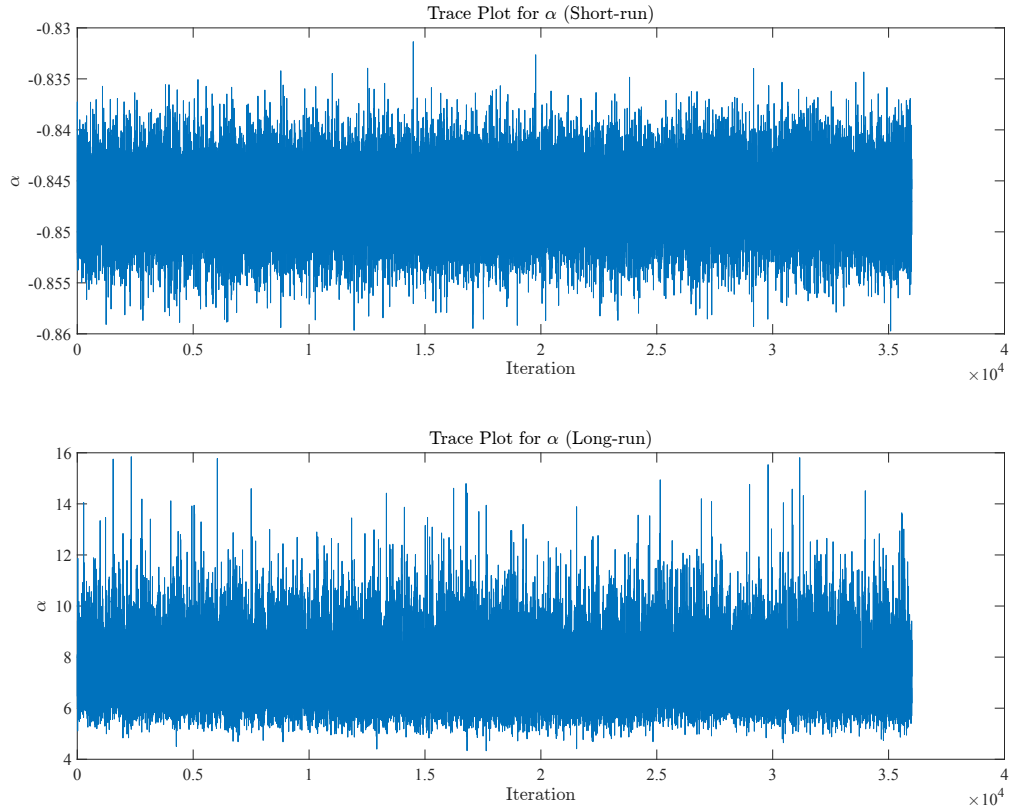


Figure 6: Trace Plot for Short- and Long-run for α

Table 27 shows the short-run CDS spreads show RMSE values ranging from 0.3174 to 0.4434 and correlations between 0.8412 and 0.9611, whereas the long-run CDS spreads exhibit lower RMSEs (from 0.1318 to 0.2020) and high correlations (from 0.8362 to 0.9393). These differences suggest that the model fits the long-run data more closely, consistent with the notion that long-term sovereign risk is smoother and more persistent.

The diagnostic measures show that despite the relatively low acceptance ratios observed for both groups (18.46% for short-run and 17.02% for long-run), the very high ESS values indicate that the MCMC chains are mixing well. The convergence of the chains is further supported by the \hat{R} values, which are equal to or very close to 1.

Overall, the results are in line with our theoretical model. By decomposing sovereign risk uncertainty into short-run and long-run components, the model not only captures the transient shocks and high volatility in the short-run but also the persistent nature of long-term risk. These findings have important implications for risk management and policy-making, especially in the context of geopolitical events that may have differential immediate and long-term effects on sovereign credit risk.

In summary, the estimation results support the theoretical model by clearly distinguishing between short-run and long-run dynamics in CDS spreads. The convergence diagnostics indicate that the MCMC chains have reached stationarity, and the posterior estimates provide evidence that our reparameterization and estimation strategy are well-suited for capturing the inherent uncertainty in both the short and long horizons.

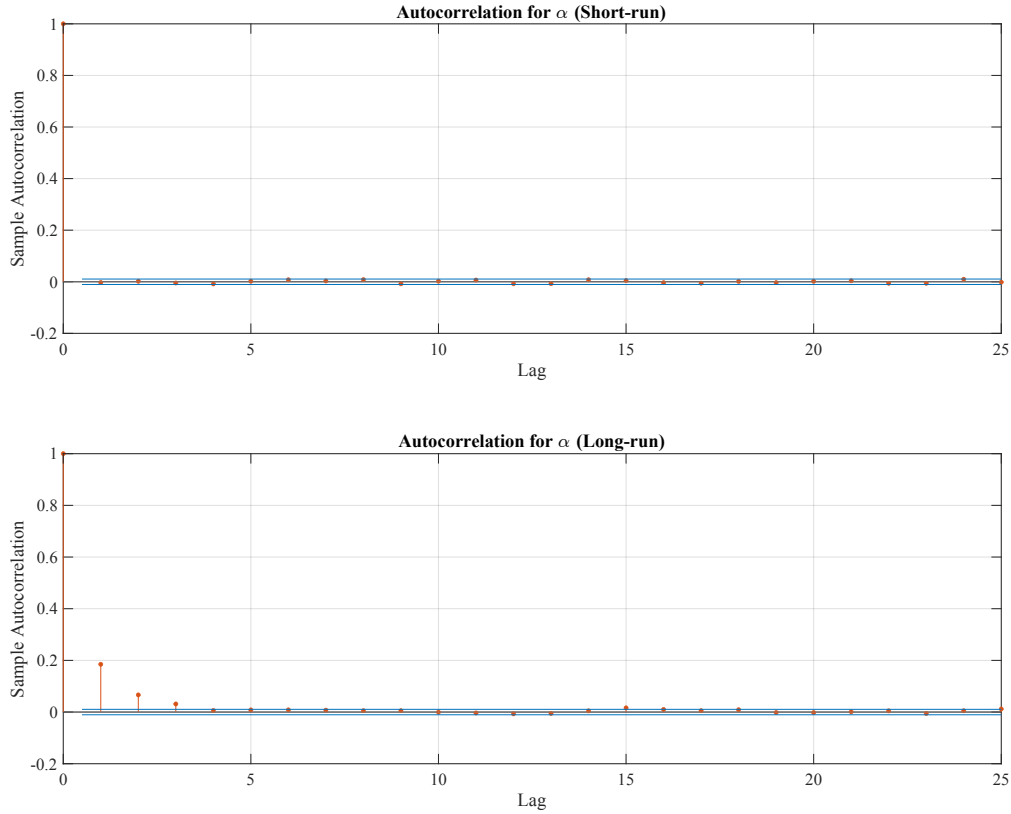


Figure 7: Autocorrelation Functions for Short- and Long-run for α

6 Regression analysis

To assess the economic and financial effects of sovereign risk uncertainty, we estimate a series of regressions using the short-run and long-run latent components as explanatory variables. The dependent variables include key macroeconomic indicators such as personal consumption expenditure, industrial production, government debt, savings, economic policy uncertainty, market volatility (VIX), oil prices, housing prices, and the Dollar Index. The full estimation models and regression tables are presented in Appendix B.

6.0.1 Macroeconomic Effects of Short-Run and Long-Run Uncertainty

Our results suggest that while transient fluctuations in uncertainty have a modest or mixed impact on consumption, persistent uncertainty – captured by the long-run measure – exerts a significantly stronger negative effect on personal consumption expenditure, as shown in Appendix B.1. This finding is consistent with our theoretical framework, which posits that structural uncertainty, such as that arising from sustained geopolitical tensions or sovereign debt crises, depresses consumption by undermining long-term economic confidence and investment decisions.

Similarly, the results reinforce the hypothesis that while short-term uncertainty may have a modest or even positive effect on industrial production, persistent long-run uncertainty is detrimental to economic output as shown in Appendix B.2. This suggests that while short-run fluctuations may

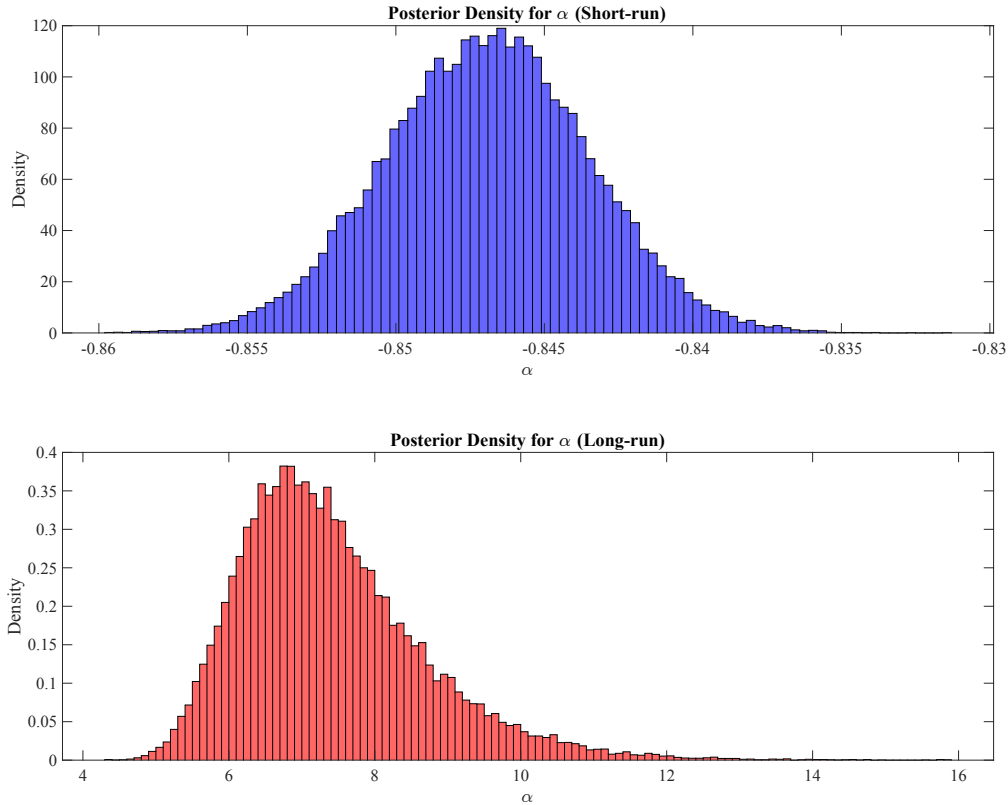


Figure 8: Posterior Densities for Short- and Long-run for α

trigger temporary increases in production due to precautionary adjustments or speculative behavior, prolonged uncertainty weighs on investment, leading to weaker long-term growth prospects.

6.0.2 Impact on Government Debt and Savings Behavior

Appendix B.3 presents the results for the regression analysis for the Treasury Debt. The short-run uncertainty measure exhibits a moderate negative correlation with the log of treasury debt ($r = -0.3442$), whereas the long-run measure displays a stronger negative correlation ($r = -0.6464$). This suggests that while short-run uncertainty may have a stimulative effect on debt levels, possibly due to short-term fiscal expansions or increased borrowing to manage immediate crises, persistent uncertainty exerts a more pronounced negative effect. This is likely due to higher risk premiums and reduced investor confidence in long-term fiscal stability.

Regarding savings behavior, Appendix B.4, the results indicate that transient uncertainties may prompt households to reduce their saving rates, potentially due to increased precautionary consumption. In contrast, the long-run uncertainty index has a positive coefficient, albeit only marginally significant. This suggests that, holding short-run uncertainty constant, an increase in long-run uncertainty may be associated with a slight increase in the personal savings rate. However, given the weaker correlation ($r = -0.2919$) and borderline statistical significance, the evidence for a robust long-run effect on saving behavior remains inconclusive.

6.0.3 Uncertainty and Financial Markets

Turning to financial markets, the results indicate that short-run fluctuations in uncertainty do not substantially influence policy-related uncertainty, while persistent (long-run) uncertainty exerts a discernible negative impact on the EPU index as shown in Appendix B.5. This could reflect a scenario in which prolonged structural uncertainties alter the dynamics of economic policymaking, leading to a perception of reduced policy uncertainty despite underlying sovereign risk.

Appendix B.6 regression analysis suggests a marginal positive relationship between long-run uncertainty and the VIX, though the evidence remains relatively weak. This implies that market volatility, as measured by the VIX, is driven primarily by factors other than sovereign risk uncertainty. Nonetheless, these findings contribute to the broader understanding of how different uncertainty measures interact with financial risk.

In terms of commodity markets presented in Appendix B.7, the long-run uncertainty measure appears to play a more significant role in driving oil prices than short-run uncertainty. While short-run fluctuations may have a limited impact, persistent uncertainty in the sovereign environment is associated with higher oil prices, potentially reflecting higher risk premia or shifts in long-term market sentiment.

6.0.4 Real Estate and Currency Markets

Results of our analysis of housing markets presented in Appendix B.8, suggest that transient uncertainty is associated with speculative or short-term market adjustments, which may initially push housing prices higher. However, sustained long-term uncertainty undermines market confidence and investment, leading to a decline in housing prices. These results align with our theoretical framework, which posits that short-run and long-run risk components have distinct economic implications.

Finally, Appendix B.9 show that the Dollar Index does not appear to be significantly affected by short-run uncertainty, whereas persistent long-run uncertainty exerts a modest positive effect. This could reflect flight-to-quality dynamics, where long-term uncertainty – particularly linked to geopolitical or fiscal challenges – increases demand for the U.S. dollar as a safe-haven asset.

6.0.5 Summary of Regression Analysis Findings

In summary, these regression results highlight the importance of distinguishing between short-run and long-run sovereign risk uncertainty. The findings demonstrate that while short-run uncertainty may generate temporary market adjustments, long-run uncertainty has more persistent and adverse macroeconomic effects. This distinction is critical for understanding the transmission of sovereign risk uncertainty to consumption, production, debt markets, savings, policy uncertainty, and financial assets. The full estimation results are provided in Appendix B.

7 Rolling Window Granger Causality Test

The rolling Granger causality test is employed to capture the time-varying relationship between the short and long-run uncertainty and macroeconomic/financial variables such as the EPU, VIX, oil prices, housing prices, and the Dollar Index. These relationships may shift over time due to external shocks, including wars, elections, or financial crises.

This approach provides three key advantages: i) Capturing Structural Breaks as identifies periods where the causal relationship strengthens, weakens, or disappears altogether, offering insights into how uncertainty evolves in response to major events. ii) Assessing Time-Varying Dynamics as it reveals fluctuations in causality over time, demonstrating that relationships between political uncertainty and macroeconomic indicators are not static. iii) Enhancing Robustness as strengthens the credibility of the results by ensuring that detected causal effects are not driven by a specific time period but persist across different windows.

7.1 Rolling Granger Causality Analysis

To analyze the time-varying relationship between sovereign risk uncertainty and macro-financial variables, we employ a rolling-window Granger causality test. This approach allows us to identify periods where the causal influence of short-run and long-run uncertainty strengthens, weakens, or disappears, reflecting shifts in market dynamics due to major economic or geopolitical events.

7.1.1 Time-Varying Causal Relationships

Figures 17–28 in Appendix B.11 presents the results of the rolling Granger causality test, illustrating the evolving impact of sovereign risk uncertainty on key economic indicators. Several key observations emerge:

Figure 17 and 18 show that causality between short-run sovereign risk uncertainty and industrial production is episodic, strengthening during periods of financial distress (e.g., the 2008–2009 global financial crisis and the COVID-19 pandemic), but weakening during periods of economic stability. Long-run sovereign risk uncertainty exhibits more persistent causality with macroeconomic variables, particularly with personal consumption expenditure, Figure 20 and treasury debt, Figure 24. This suggests that long-term uncertainty has a sustained influence on fiscal and consumption dynamics. Causal effects on the Economic Policy Uncertainty (EPU) index fluctuate, Figure 27 and Figure 28, indicating that sovereign risk uncertainty does not always drive policy uncertainty but does during politically sensitive periods, such as elections and major fiscal policy announcements. Increased causality with oil prices, Figure ??, and the VIX, Figure 26, is evident during Covid-19 and geopolitical shocks, such as the Russia-Ukraine conflict and trade tensions, reinforcing the idea that sovereign risk uncertainty contributes to global market volatility

These results provide strong evidence that the impact of sovereign risk uncertainty is not constant over time but evolves in response to macroeconomic and geopolitical developments. Short-run uncertainty tends to have temporary effects, with causality strengthening only in periods of heightened risk. In contrast, long-run uncertainty appears to exert a more stable and sustained influence on economic and financial variables, consistent with the hypothesis that persistent uncertainty affects investment decisions, debt sustainability, and long-term economic confidence.

Overall, the rolling Granger causality results reinforce the importance of distinguishing between short-run and long-run uncertainty. They highlight the dynamic nature of uncertainty transmission mechanisms and suggest that policymakers and investors should account for these evolving relationships when assessing sovereign risk exposure.

8 Conclusion

This paper develops a Bayesian dynamic factor model within a state-space framework to decompose sovereign risk uncertainty into short-run (Short-SRU) and long-run (Long-SRU) components. By employing a Kalman filter for optimal state estimation and a Bayesian Markov Chain Monte Carlo (MCMC) approach for parameter inference, we extract latent sovereign risk factors from observed credit default swap (CDS) spreads. The integration of random-walk Metropolis-Hastings with block updates and a sigmoid reparameterization for the persistence parameter ensures robust and efficient estimation (Gelman et al., 2013). Convergence diagnostics confirm that the model is well-identified, exhibiting stable posterior distributions, efficient mixing, and \hat{R} values near unity.

By utilizing CDS spreads across different maturities, our model effectively disentangles transitory fluctuations from persistent structural uncertainty. This decomposition provides a granular perspective on the evolution of sovereign risk uncertainty and its broader macroeconomic implications. By explicitly modeling the persistence structure within a state-space setting, we uncover key dynamics in sovereign risk transmission that standard models fail to capture.

Our empirical findings reveal a striking asymmetry in the macroeconomic impact of short-run versus long-run sovereign risk uncertainty. Long-run uncertainty exerts a far more pronounced adverse effect, significantly depressing personal consumption and industrial production, reflecting its deep influence on long-term economic confidence, investment decisions, and fiscal stability. In contrast, short-run uncertainty primarily drives temporary market volatility but has a more limited and sometimes ambiguous effect on macroeconomic fundamentals.

Regression and correlation analyses confirm that persistent uncertainty systematically elevates sovereign risk premiums and induces more cautious financial behavior. Treasury debt markets respond more negatively to long-run uncertainty, likely due to increased borrowing costs, heightened risk aversion, and declining investor confidence in fiscal sustainability. Interestingly, while short-run uncertainty is associated with lower personal savings, long-run uncertainty induces a more defensive financial posture, reinforcing the necessity of distinguishing between these two components.

Robustness checks confirm that these results remain stable across alternative macro-financial indicators, including the Economic Policy Uncertainty (EPU) index, CBOE Volatility Index (VIX), oil prices, housing prices, and the Dollar Index. The consistency of our findings highlights the reliability of our sovereign risk uncertainty decomposition and its adaptability across different economic conditions.

A rolling-window Granger causality test further underscores the time-varying nature of sovereign risk transmission, revealing that geopolitical shocks, financial crises, and major policy shifts can fundamentally reshape the relationship between sovereign risk uncertainty and macro-financial conditions. These findings emphasize the necessity of a dynamic, adaptive modeling approach, as static models fail to capture the evolving nature of uncertainty-driven financial disruptions.

The Covid-19 crisis and the ongoing Russia-Ukraine war serve as crucial case studies validating our model’s ability to disentangle transitory market stress from deeper structural risks. Our decomposition captures how short-run uncertainty dominates the initial phases of crises, while long-run uncertainty emerges as the dominant force affecting sovereign risk pricing, economic activity, and policy responses over extended horizons. These results reinforce the macroeconomic relevance of our framework in real-world crisis scenarios.

A key contribution of this study is the identification of a negative relationship between long-run sovereign risk uncertainty and the Economic Policy Uncertainty (EPU) index. This result underscores a fundamental distinction between the two measures: while EPU captures short-term policy volatility, the long-run sovereign risk uncertainty component reflects expectations about sustained risks. Our analysis suggests that persistent sovereign risk uncertainty does not necessarily heighten short-term policy uncertainty; rather, it may induce government stabilization measures, such as fiscal consolidation, central bank interventions, or sovereign debt restructuring, which help to reduce immediate policy volatility. This distinction is critical, as it highlights how long-run uncertainty shapes macroeconomic expectations and policy responses rather than short-term fluctuations.

Our findings emphasize the importance of distinguishing between short-run and long-run uncertainty when assessing sovereign risk and macroeconomic stability. While short-run uncertainty can often be mitigated through immediate policy interventions such as central bank actions or fiscal stimulus, long-run uncertainty reflects deeper structural risks that require sustained economic and geopolitical stability. The two crisis periods analyzed—the Covid-19 pandemic and the Russia-Ukraine war—confirm that our model effectively captures both transitory and persistent sources of sovereign risk uncertainty, reinforcing its relevance for macroeconomic and financial analysis.

These results have important implications for policymakers, investors, and researchers. Understanding the differential impact of short-run and long-run uncertainty is essential for designing effective fiscal and monetary policies that mitigate sovereign risk. Additionally, financial market participants can use these insights to assess sovereign credit risk more accurately and adjust portfolio strategies accordingly.

Overall, this study contributes to the growing literature on uncertainty and macroeconomic stability by providing a structured framework to quantify and analyze sovereign risk uncertainty. Future research may extend this approach to other countries, incorporate additional macro-financial variables, or refine the estimation technique to account for nonlinearities in the sovereign risk transmission mechanism.

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A Summary Statistics of CDS Spreads

Tables 26 and 27 report the summary statistics for the short-run and long-run CDS spreads, respectively. For each maturity, we present the observed mean, the fitted mean (obtained via Kalman filter estimation), the root mean square error (RMSE), and the correlation between the observed and fitted values.

Table 1: Short-run CDS Summary Statistics

Maturity	Observed Mean	Fitted Mean	RMSE	Correlation
6-Months	2.2879	2.2167	0.4434	0.8412
1-Year	2.6485	2.6064	0.3993	0.8082
2-Years	2.8260	2.8097	0.3174	0.8582
3-Years	2.6686	2.6768	0.1852	0.9611

Table 2: Long-run CDS Summary Statistics

Maturity	Observed Mean	Fitted Mean	RMSE	Correlation
10-Years	3.5667	3.5669	0.1318	0.9393
7-Years	3.4111	3.4244	0.1938	0.8738
20-Years	3.7188	3.7166	0.1415	0.9009
30-Years	3.1664	3.1728	0.2020	0.9159

B Regression Analysis

B.1 Personal Consumption Expenditure and Sovereign Risk Uncertainty

We estimate a linear regression model to assess the impact of sovereign risk uncertainty on the Personal Consumption Expenditure. The model is specified as follows:

$$\text{PerCons} = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.1})$$

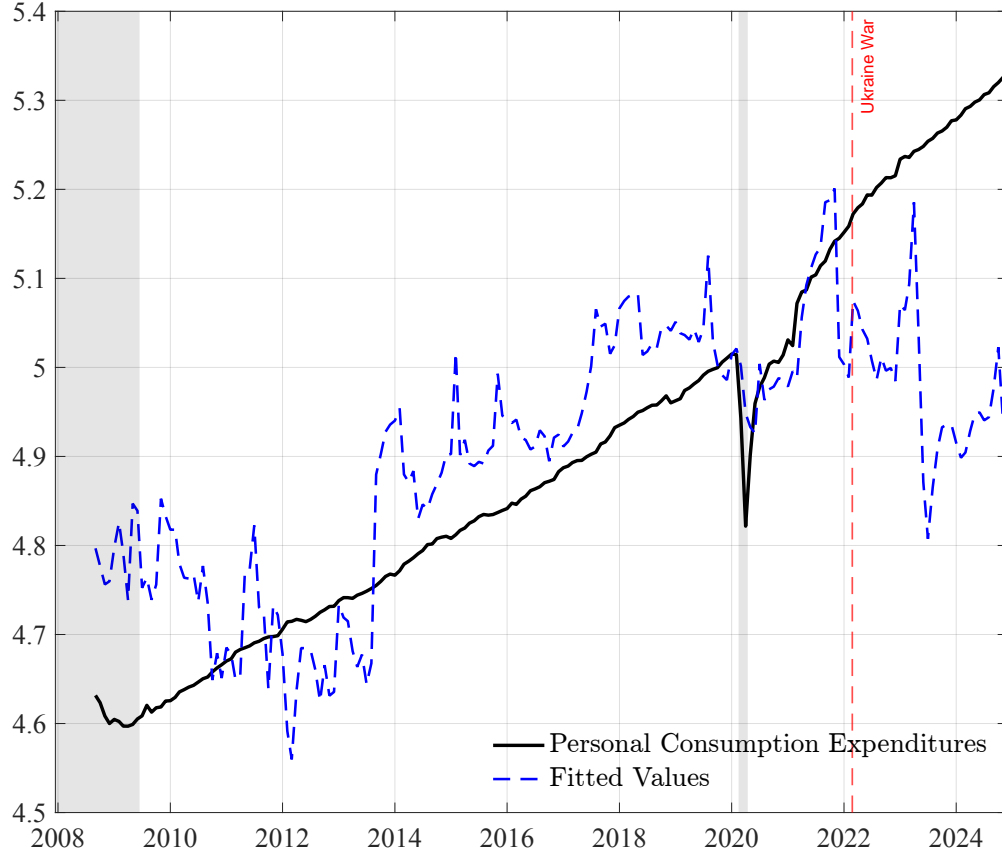
where PerCons denotes the log of Personal Consumption Expenditure, and the predictors Short run Sovereign Risk Uncertainty Index (sSRU) and Long run Sovereign Risk Uncertainty Index (lSRU) represent the short-run and long-run components of sovereign risk uncertainty, respectively.

Table 3 presents the estimated coefficients along with their standard errors, t-statistics, and p-values. The model is estimated using 197 observations, yielding a root mean squared error (RMSE) of 0.159, an R^2 of 0.443, and an adjusted R^2 of 0.437. The overall model is highly significant (F-statistic = 77.2, p-value = 2.19×10^{-25}).

We further examine the relationship between the uncertainty measures and consumption by computing Pearson correlation coefficients between the log of Personal consumption and each uncertainty index. The correlation between the log of Personal Consumption Expenditure and the short-run uncertainty index is -0.1187 , indicating a weak negative association. In contrast, the

Table 3: Regression Results: log of Personal Consumption Expenditure on Sovereign Risk Uncertainty

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	4.8889	0.0115	424.68	6.09×10^{-290}
sSRU	0.1975	0.0264	7.48	2.58×10^{-12}
ISRU	-0.1948	0.0159	-12.23	7.46×10^{-26}

**Figure 9:** Personal Consumption Expenditure fitted values

correlation with the long-run uncertainty index is -0.5317 , suggesting a much stronger negative relationship.

The regression analysis shows that, holding other factors constant, short-run uncertainty is associated with a positive coefficient (0.1975), while long-run uncertainty is associated with a negative coefficient (-0.1948). Although the short-run component sSRU exhibits a weak negative correlation with log of Personal Consumption Expenditure ($r = -0.1187$), the long-run component ISRU shows a considerably stronger negative correlation ($r = -0.5317$).

These findings suggest that while transient fluctuations in uncertainty may have a modest or mixed impact on consumption, persistent uncertainty – as captured by the long-run measure – has a more pronounced adverse effect on personal consumption. This is consistent with our theoretical framework, which posits that prolonged or structural uncertainty (e.g., stemming from sustained geopolitical tensions or debt crises) can significantly depress consumption, likely due to its impact

on long-term economic confidence and investment decisions.

B.2 Industrial Production and Sovereign Risk Uncertainty

We estimate a linear regression model to assess the relationship between the Industrial Production Index (IPI) and two measures of sovereign risk uncertainty: the short-run and long-run components. The model is specified as

$$\text{IndProdIdx} = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{ISRU} + \varepsilon, \quad (\text{B.2})$$

where: IndProdIdx is the Industrial Production Index, sSRU represents the short-run uncertainty measure, ISRU represents the long-run uncertainty measure, and ε is the error term.

Table 4 summarizes the estimated regression coefficients.

Table 4: Regression Results: IndProdIdx on sSRU and ISRU

Variable	Estimate	SE	t-Statistic	p-Value
(Intercept)	4.5882	0.0031	1477.2	0
sSRU	0.0278	0.0071	3.9048	0.00013
ISRU	-0.0349	0.0043	-8.1212	5.26×10^{-14}

We further investigate the bivariate associations between the Industrial Production Index and the uncertainty measures. The Pearson correlation coefficient between sSRU and IPI is -0.1851 , indicating a weak negative relationship. In contrast, the correlation between ISRU and IPI is -0.4718 , which suggests a stronger inverse relationship between long-run uncertainty and industrial production.

The regression results suggest that the two uncertainty measures have distinct effects on industrial production. The positive coefficient for sSRU implies that, holding long-run uncertainty constant, an increase in short-run uncertainty is associated with a slight increase in the Industrial Production Index. This might reflect short-term fluctuations that do not have a lasting adverse impact on production. Conversely, the negative coefficient for ISRU indicates that higher levels of persistent (long-run) uncertainty are associated with lower industrial production, consistent with the notion that sustained uncertainty dampens economic activity. The stronger negative correlation between ISRU and IPI ($r = -0.4718$) further supports this interpretation.

Overall, these findings reinforce our theoretical framework by demonstrating that while short-term uncertainty may have a modest or even positive effect on industrial production, persistent long-run uncertainty is significantly detrimental to economic output.

B.3 Empirical Analysis: Market Value of Treasury Debt

In this section, we examine the relationship between the logarithm of the marketable treasury debt (denoted as $\log(\text{TreasDebt})$) and the two components of sovereign risk uncertainty: the short-run

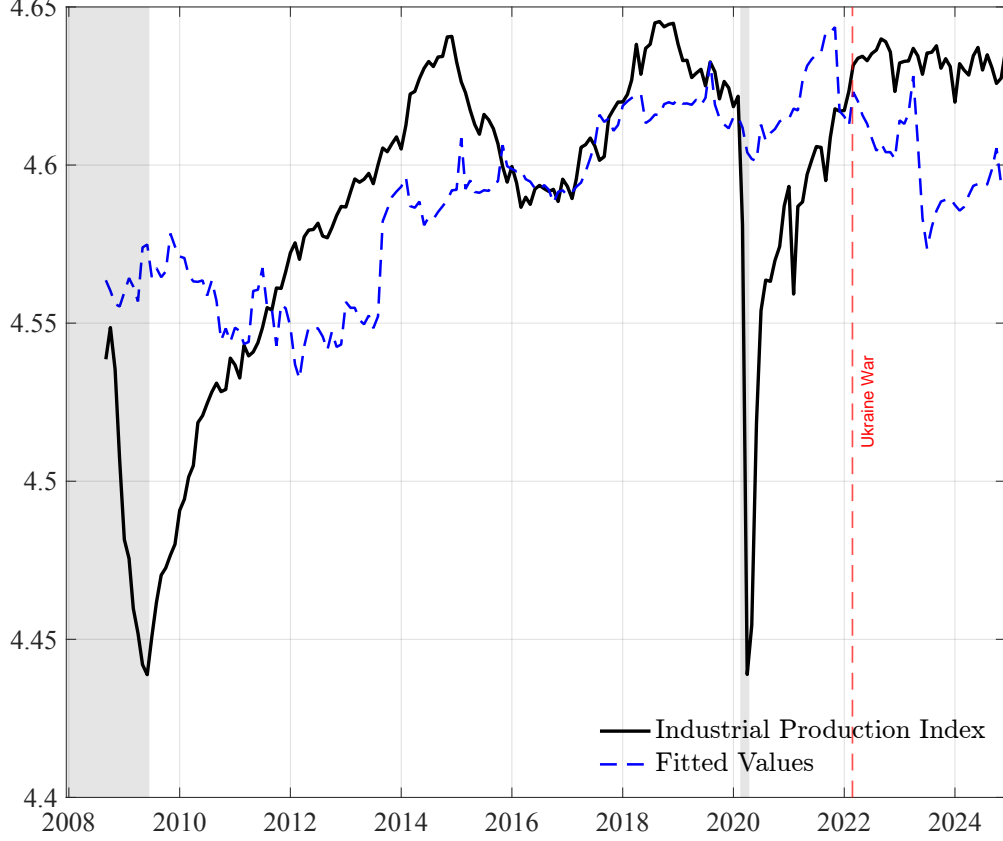


Figure 10: Industrial Production Index fitted values

and long-run indices. The model is specified as

$$\log(\text{TreasDebt}) = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.3})$$

where TreasDebt is the market value of marketable treasury debt, sSRU and lSRU are the short-run and long-run uncertainty measures, respectively, and ε is an error term.

Table 5 reports the estimated regression coefficients from the linear model in Equation Eq. (B.3). The estimation is based on 197 observations, with 194 degrees of freedom. The model yields a root mean squared error (RMSE) of 0.293, an R^2 of 0.455 (adjusted $R^2 = 0.449$), and a highly significant overall F-statistic ($F(2, 194) = 80.9$, $p = 2.78 \times 10^{-26}$).

Table 5: Regression Results for $\log(\text{TreasDebt})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	5.3277	0.02121	251.19	8.82×10^{-246}
sSRU	0.17665	0.048678	3.629	0.0003639
lSRU	-0.32124	0.029364	-10.94	5.25×10^{-22}

To further understand the bivariate relationships, we compute the Pearson correlation coeffi-

icients between the uncertainty measures and $\log(\text{TreasDebt})$.

Table 6 shows the correlation matrix for the short-run component, while Table 7 displays the correlation matrix for the long-run component.

Table 6: Correlation Matrix: ShortRunIndex and $\log(\text{TreasDebt})$

	ShortRunIndex	$\log(\text{TreasDebt})$
ShortRunIndex	1.0000	-0.3442
$\log(\text{TreasDebt})$	-0.3442	1.0000

Table 7: Correlation Matrix: LongRunIndex and $\log(\text{TreasDebt})$

	LongRunIndex	$\log(\text{TreasDebt})$
LongRunIndex	1.0000	-0.6464
$\log(\text{TreasDebt})$	-0.6464	1.0000

The regression analysis (Table 5) reveals that the short-run and long-run uncertainty measures have statistically significant and opposite effects on the market value of treasury debt. Specifically, the positive coefficient on sSRU (0.17665) suggests that an increase in short-run uncertainty is associated with an increase in $\log(\text{TreasDebt})$. Conversely, the negative coefficient on lSRU (-0.32124) indicates that higher persistent (long-run) uncertainty is associated with lower $\log(\text{TreasDebt})$.

The correlation analysis corroborates these findings. The short-run uncertainty measure exhibits a moderate negative correlation with $\log(\text{TreasDebt})$ ($r = -0.3442$), while the long-run measure displays a stronger negative correlation ($r = -0.6464$). This implies that while short-run uncertainty might have a modest, perhaps even stimulative effect on debt levels, persistent uncertainty exerts a more pronounced negative influence, potentially reflecting increased risk premiums or reduced market confidence in long-term fiscal stability.

The empirical evidence suggests that transient fluctuations and persistent structural risks affect the market value of treasury debt in distinctly different ways, consistent with our theoretical framework.

B.4 Empirical Analysis: Personal Saving Rate and Sovereign Risk Uncertainty

We estimate the following linear regression model to investigate the effect of sovereign risk uncertainty on personal saving rates. Specifically, we model the logarithm of the personal saving rate (PerSavR) as a function of the short-run and long-run uncertainty measures:

$$\text{PerSavR} = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \tag{B.4}$$

where PerSavR is the log of the personal saving rate, sSRU and lSRU represent the short-run and long-run components of sovereign risk uncertainty, and ε is the error term.

Table 8 presents the estimated regression coefficients. The model is based on 197 observations

(with 194 degrees of freedom) and yields a root mean squared error (RMSE) of 0.323. The coefficient on sSRU is highly significant (-0.37139 (SE = 0.05368, $t = -6.9193$, $p = 6.44 \times 10^{-11}$)), indicating that higher short-run uncertainty is associated with lower personal saving rates. The coefficient on lSRU is significant at 7% (0.060261 (SE = 0.03238, $t = 1.8611$, $p = 0.06424$)), suggesting a marginally positive effect.

Table 8: Regression Results for $\log(P_Sav_R)$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	4.6243	0.02339	197.73	1.07×10^{-225}
ShortRunIndex	-0.37139	0.05368	-6.9193	6.44×10^{-11}
LongRunIndex	0.060261	0.03238	1.8611	0.064238

We also compute the Pearson correlation coefficients between the uncertainty measures and $\log(P_Sav_R)$. Table 9 shows the correlations: the correlation between sSRU and $\log(P_Sav_R)$ is -0.5032 , indicating a moderate negative association. The correlation between lSRU and $\log(P_Sav_R)$ is -0.2919 , suggesting a weaker negative relationship.

Table 9: Correlation Matrix for Personal Saving Rate and Uncertainty Indices

	Uncertainty	$\log(P_Sav_R)$
ShortRunIndex	1.0000	-0.5032
$\log(P_Sav_R)$	-0.5032	1.0000
LongRunIndex	1.0000	-0.2919
$\log(P_Sav_R)$	-0.2919	1.0000

The regression results indicate that short-run uncertainty has a statistically significant negative impact on the personal saving rate. Specifically, a one-unit increase in the short-run uncertainty index is associated with a decrease of approximately 0.37 units in $\log(P_Sav_R)$, ceteris paribus. This suggests that transient uncertainties may prompt households to reduce their saving behavior, possibly due to increased immediate consumption or precautionary savings adjustments.

In contrast, the long-run uncertainty index has a positive coefficient, albeit only marginally significant. This implies that, holding short-run uncertainty constant, an increase in long-run uncertainty might be associated with a slight increase in the personal saving rate. However, given the weaker correlation (-0.2919) and borderline statistical significance, the evidence for a robust long-run effect on saving behavior is less clear.

Overall, these findings show that while transient shocks (captured by the short-run index) appear to reduce personal savings, persistent uncertainty might induce more cautious behavior, albeit to a lesser extent.

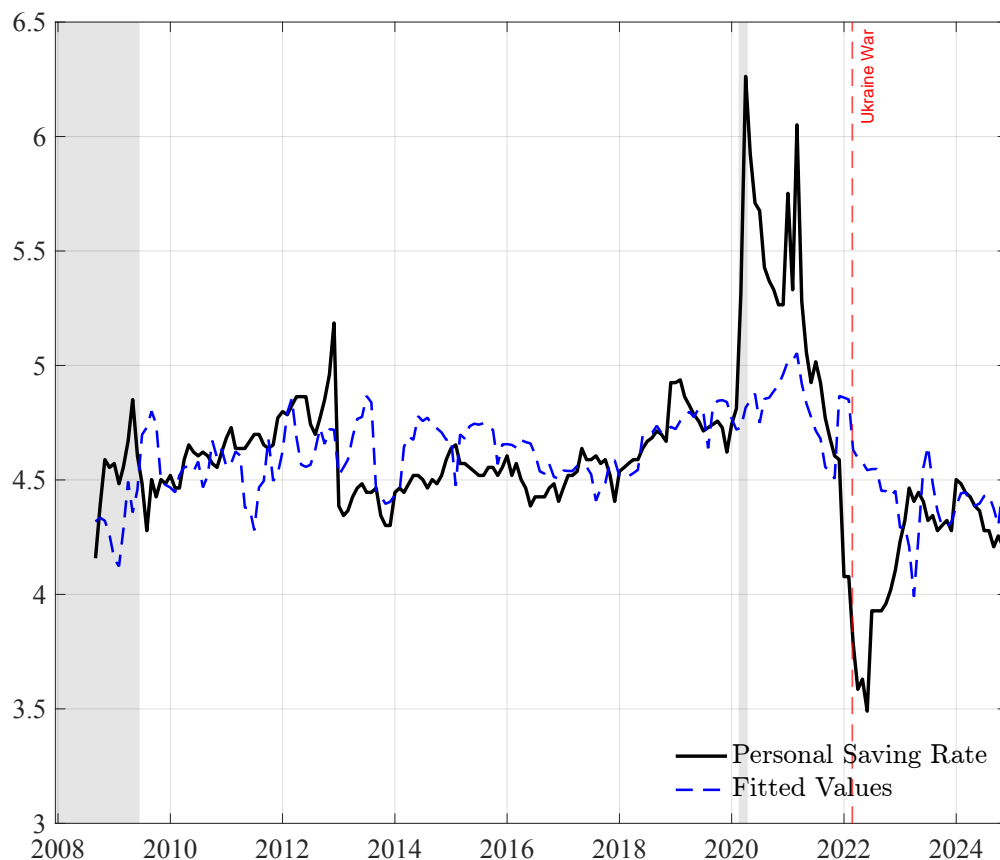


Figure 11: Personal Saving Rate fitted values

B.5 Empirical Analysis: Economic Policy Uncertainty

To examine the relationship between Economic Policy Uncertainty (EPU) and the sovereign risk uncertainty components, we estimate the following linear regression model:

$$\text{EPU} = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.5})$$

where $\text{EPU} = \log(\text{EPU index})$ is the log of the Economic Policy Uncertainty index, and sSRU and lSRU are the measures of short-run and long-run sovereign risk uncertainty, respectively.

Table 10 displays the estimated coefficients from the model in Equation Eq. (B.5). The regression is based on 197 observations (with 194 degrees of freedom) and produces a root mean squared error of 0.0681, an R^2 of 0.057 (adjusted $R^2 = 0.0473$), and an overall F-statistic of 5.86 (p-value = 0.00338).

Table 10: Regression Results for $\log(\text{EPU})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	1.6079	0.00493	325.91	1.14×10^{-267}
sSRU	0.0006627	0.01132	0.05853	0.95339
lSRU	-0.016161	0.00683	-2.3661	0.01896

The results indicate that the intercept is highly significant. The coefficient on sSRU is positive but statistically insignificant ($p = 0.9534$), whereas the coefficient on lSRU is negative and statistically significant ($p = 0.0190$).

We further assess the bivariate relationships between the EPU index and the uncertainty measures. Table 11 presents the correlation between sSRU and the EPU index, while Table 12 presents the correlation for lSRU.

Table 11: Correlation Between ShortRunIndex and $\log(\text{EPU})$

ShortRunIndex	$\log(\text{EPU})$
1.0000	-0.1818
-0.1818	1.0000

Table 12: Correlation Between LongRunIndex and $\log(\text{EPU})$

LongRunIndex	$\log(\text{EPU})$
1.0000	-0.2442
-0.2442	1.0000

The regression analysis indicates that the short-run component of sovereign risk uncertainty does not have a statistically significant effect on economic policy uncertainty, as evidenced by the small and insignificant coefficient on sSRU. In contrast, the long-run uncertainty measure has a significant negative coefficient, suggesting that higher persistent uncertainty is associated with lower levels of economic policy uncertainty. This negative relationship is further supported by the correlation analysis, where the correlation between lSRU and $\log(\text{EPU})$ is -0.2442 , compared to -0.1818 for the short-run component.

These findings imply that while transient (short-run) fluctuations in uncertainty may not substantially influence policy-related uncertainty, persistent (long-run) uncertainty appears to exert a discernible negative impact on the EPU index. The negative effect could reflect a scenario in which long-term, structural uncertainties alter the dynamics of economic policymaking, leading to a perception of reduced policy uncertainty despite underlying sovereign risk.

B.6 Empirical Analysis: Relationship between Uncertainty and the VIX

To investigate how our measures of sovereign risk uncertainty relate to market volatility, we estimate a linear regression model where the dependent variable is the logarithm of the CBOE Volatility Index (VIX). The model is specified as follows:

$$\log(\text{VIX}) = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \tag{B.6}$$

where $\log(\text{VIX})$ represents the logarithm of the VIX, sSRU and lSRU denote the short-run and long-run components of sovereign risk uncertainty, respectively, and ε is an error term.

Table 13 shows the estimated coefficients from the regression model in Equation Eq. (B.6). The estimation is based on 197 observations with 194 degrees of freedom. The root mean squared error

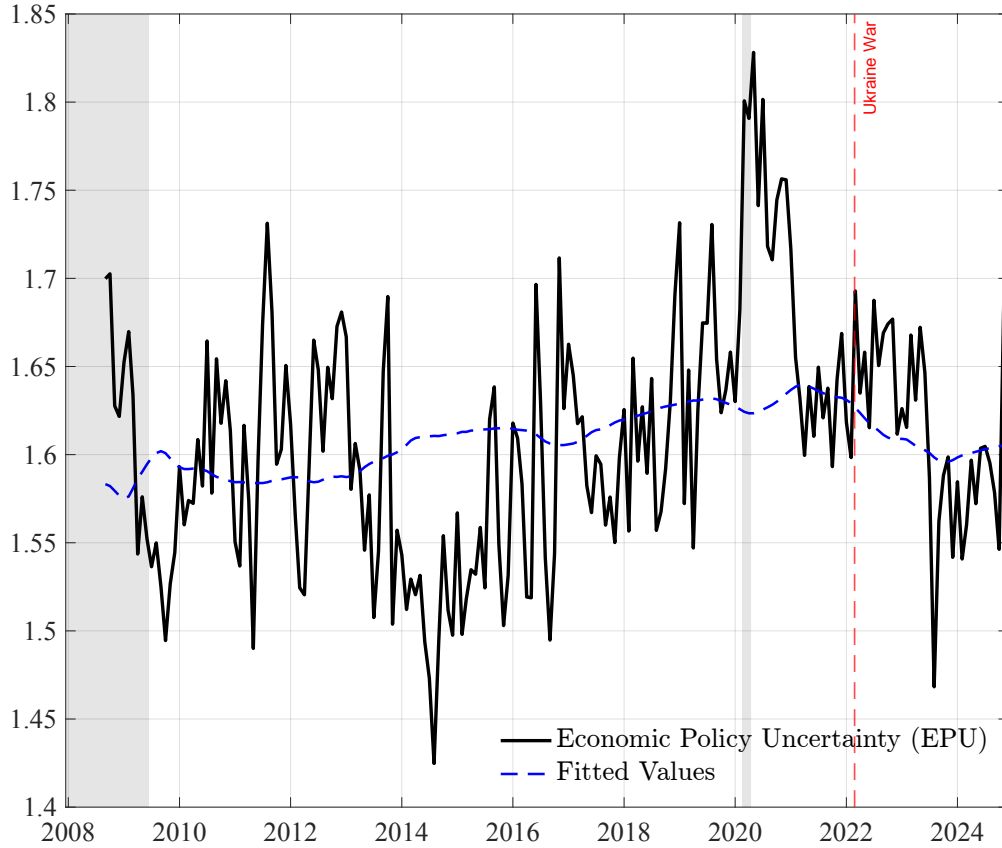


Figure 12: EPU fitted values

is 0.361, and the model explains approximately 3% of the variation in $\log(\text{VIX})$ ($R^2 = 0.0291$). The overall model is marginally significant (F-statistic = 2.91, $p = 0.057$).

Table 13: Regression Results for $\log(\text{VIX})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	2.9262	0.026144	111.93	3.43×10^{-178}
sSRU	-0.023833	0.060002	-0.39721	0.69165
lSRU	0.068986	0.036195	1.906	0.05813

We further analyze the bivariate relationships by computing Pearson correlation coefficients between the uncertainty measures and the log-transformed VIX. Tables 14 and 15 present these correlation matrices.

The regression analysis in Table 13 indicates that the short-run uncertainty measure has a negative but statistically insignificant effect on the VIX, with a coefficient of -0.0238 ($p = 0.69165$). In contrast, the long-run uncertainty measure has a positive coefficient of 0.0690, which is marginally significant ($p = 0.05813$). However, the overall model explains only about 3% of the variation in $\log(\text{VIX})$ (i.e., $R^2 = 0.0291$).

The correlation analysis further supports these findings. The correlation between $\log(\text{VIX})$ and sSRU is weak ($r = 0.1045$), while the correlation with lSRU is slightly stronger ($r = 0.1683$). These

Table 14: Correlation between ShortRunIndex and $\log(\text{VIX})$

Variable	Correlation
ShortRunIndex	1.0000
$\log(\text{VIX})$	0.1045

Table 15: Correlation between LongRunIndex and $\log(\text{VIX})$

Variable	Correlation
LongRunIndex	1.0000
$\log(\text{VIX})$	0.1683

low correlations, along with the modest explanatory power of the regression model, suggest that the VIX is likely influenced by additional factors beyond the sovereign risk uncertainty measures captured by our model.

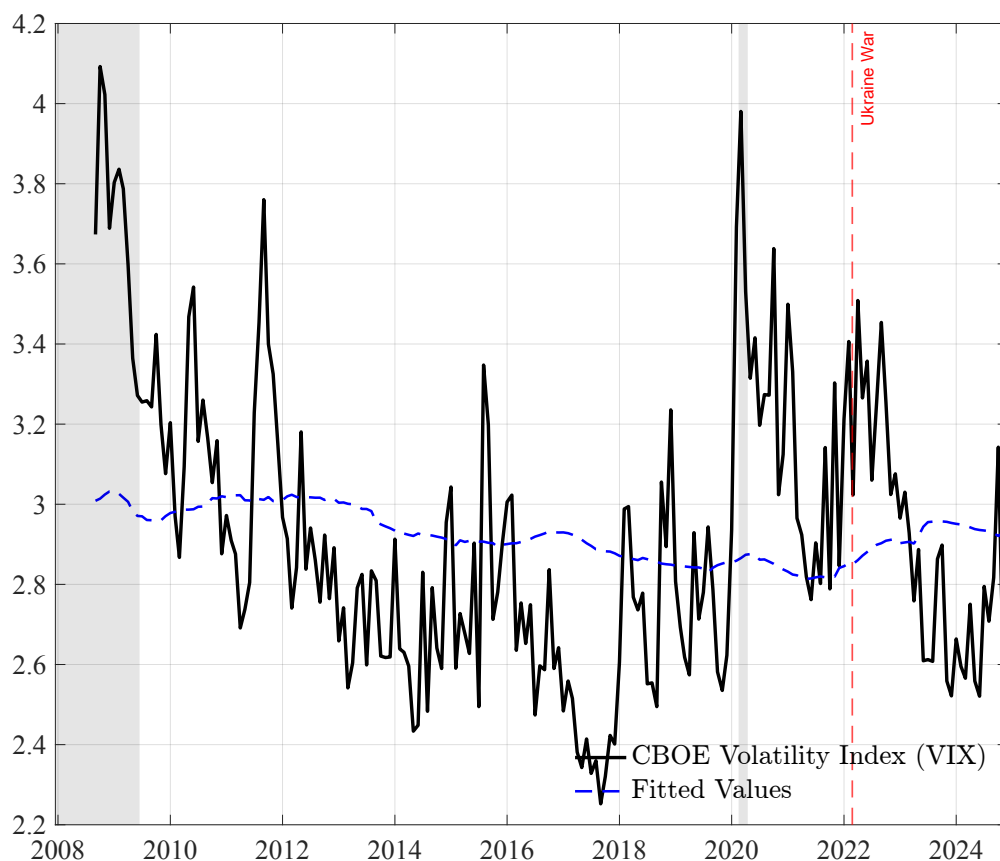


Figure 13: VIX fitted values

In summary, while our analysis shows a marginal positive relationship between long-run uncertainty and the VIX, the evidence is relatively weak. This implies that market volatility, as measured by the VIX, is driven primarily by factors other than the sovereign risk uncertainty captured by the short-run and long-run indices. Nonetheless, these findings contribute to the broader understanding of how various uncertainty measures relate to different aspects of market risk.

B.7 Empirical Analysis: Oil Prices and Sovereign Risk Uncertainty

We investigate the relationship between oil prices and sovereign risk uncertainty by estimating a linear regression model. The dependent variable is the natural logarithm of oil prices, and the independent variables are the short-run and long-run uncertainty indices. The model is specified as

$$\log(\text{OilPrice}) = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.7})$$

where $\log(\text{OilPrice})$ is the logarithm of the oil price, sSRU and lSRU are the measures of short-run and long-run sovereign risk uncertainty, respectively, ε is the error term.

Table 16 reports the estimated coefficients for the model in Equation Eq. (B.7). The regression is based on 197 observations (with 194 degrees of freedom), yielding a root mean squared error (RMSE) of 0.296, an R^2 of 0.188, and an adjusted R^2 of 0.179. The overall model is statistically significant (F-statistic = 22.4, $p = 1.72 \times 10^{-9}$).

Table 16: Regression Results for $\log(\text{OilPrice})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	4.2232	0.021455	196.84	2.55×10^{-225}
sSRU	-0.024529	0.04924	-0.4982	0.61894
lSRU	0.1455	0.029703	4.8984	2.03×10^{-6}

To further explore the relationships, we compute the Pearson correlation coefficients between the uncertainty indices and the logarithm of oil prices. Table 17 presents the correlation between sSRU and $\log(\text{OilPrice})$, and Table 18 shows the correlation between lSRU and $\log(\text{OilPrice})$.

Table 17: Correlation between ShortRunIndex and $\log(\text{OilPrice})$

Variable	Correlation
sSRU	1.0000
$\log(\text{OilPrice})$	0.2956

Table 18: Correlation between LongRunIndex and $\log(\text{OilPrice})$

Variable	Correlation
lSRU	1.0000
$\log(\text{OilPrice})$	0.4322

The regression results (Table 16) reveal that the estimated intercept is 4.2232, which is highly significant. The coefficient for sSRU is -0.02453 and is not statistically significant ($p = 0.61894$). This suggests that short-run uncertainty does not have a significant impact on oil prices. Conversely, the coefficient on lSRU is positive (0.1455) and statistically significant ($p = 2.03 \times 10^{-6}$), indicating that higher long-run uncertainty is associated with higher oil prices.

The correlation analysis supports these findings. The short-run uncertainty measure has a

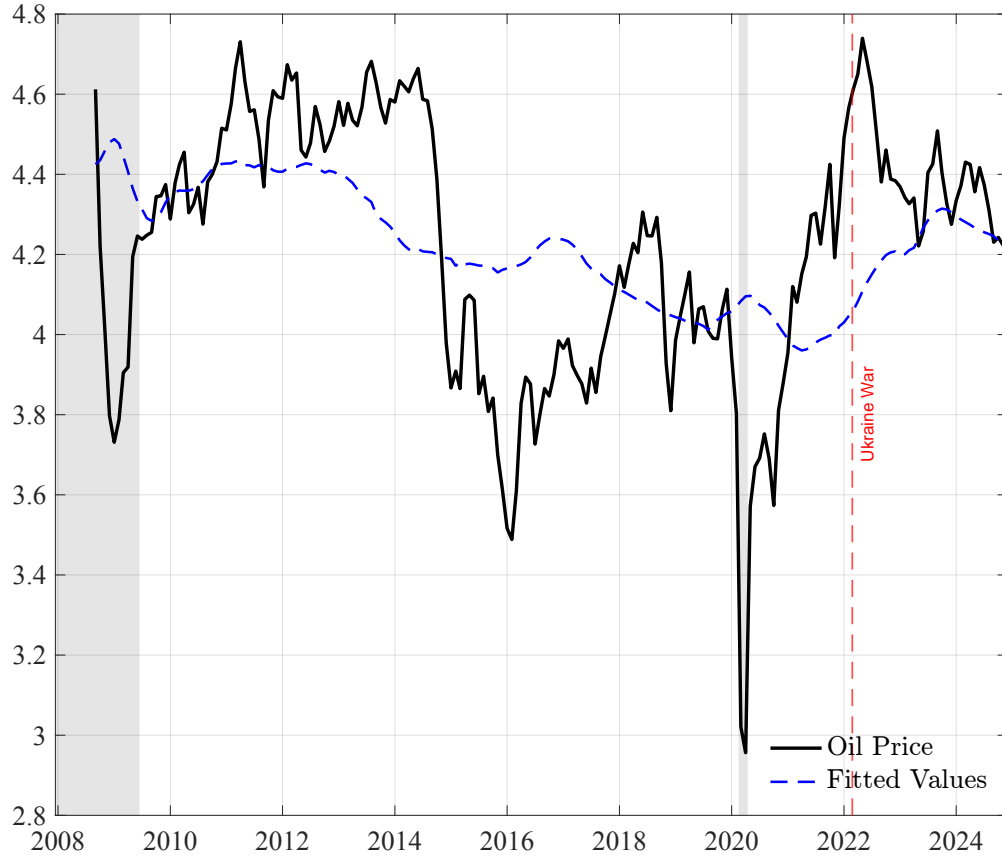


Figure 14: Oil Prices fitted values

moderate positive correlation ($r = 0.2956$) with $\log(\text{OilPrice})$, whereas the long-run uncertainty measure shows a stronger positive correlation ($r = 0.4322$) with $\log(\text{OilPrice})$.

These results suggest that persistent (long-run) uncertainty plays a more important role in driving oil prices than transient (short-run) uncertainty. In practical terms, while short-run fluctuations may have limited impact, sustained uncertainty in the sovereign environment may lead to increased oil prices, potentially reflecting higher risk premia or shifts in market sentiment over the long term.

B.8 Empirical Analysis: Housing Prices and Sovereign Risk Uncertainty

To examine the impact of sovereign risk uncertainty on housing prices, we estimate a linear regression model where the dependent variable is the logarithm of the housing price and the independent variables are the short-run and long-run uncertainty indices. The model is specified as

$$\text{HousePrice} = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.8})$$

where $\text{HousePrice} = \log(\text{SP_house_p})$ is the log of the observed housing prices, sSRU and lSRU denote the short-run and long-run sovereign risk uncertainty indices, respectively, ε is the error term.

Table 19 summarizes the estimated regression coefficients from the model in Equation Eq. (B.8). The estimation is based on 196 observations (with 193 degrees of freedom). The model yields a root mean squared error (RMSE) of 0.197, an R^2 of 0.492, and an adjusted R^2 of 0.487. The overall model is statistically significant with an F-statistic of 93.5 (p-value = 4.14×10^{-29}).

Table 19: Regression Results for $\log(\text{SP_house_p})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	5.2488	0.01429	367.29	1.61×10^{-276}
sSRU	0.28777	0.03277	8.7822	8.61×10^{-16}
lSRU	-0.26787	0.01975	-13.56	7.33×10^{-30}

We compute the Pearson correlation coefficients between the uncertainty indices and the logarithm of housing prices. Table 20 shows the correlation between the short-run uncertainty index and housing prices, while Table 21 shows the correlation for the long-run uncertainty index.

Table 20: Correlation between ShortRunIndex and $\log(\text{SP_house_p})$

Variable	Correlation
ShortRunIndex	1.0000
$\log(\text{SP_house_p})$	-0.0893

Table 21: Correlation between LongRunIndex and $\log(\text{SP_house_p})$

Variable	Correlation
LongRunIndex	1.0000
$\log(\text{SP_house_p})$	-0.5376

The regression results in Table 19 indicate that the model explains nearly 49.2% of the variation in the log of housing prices. The intercept is estimated at 5.2488 and is highly statistically significant. Notably, the coefficient for sSRU is positive (0.28777) and statistically significant, suggesting that an increase in short-run uncertainty is associated with an increase in housing prices. In contrast, the coefficient for lSRU is negative (-0.26787) and statistically significant, indicating that higher persistent uncertainty is associated with lower housing prices.

The correlation analysis provides additional insight. The short-run uncertainty index is only weakly correlated with housing prices ($r = -0.0893$), while the long-run uncertainty index is strongly negatively correlated with housing prices ($r = -0.5376$). This contrast implies that while short-run fluctuations may have a relatively modest relationship with housing prices, persistent (long-run) uncertainty exerts a more pronounced negative impact.

These findings suggest that transient uncertainty may be associated with speculative or short-term market adjustments that tend to push housing prices higher. On the other hand, sustained long-term uncertainty likely undermines market confidence and investment, leading to a decline in housing prices. Such differentiated effects are consistent with our theoretical framework, which posits that short-run and long-run risk components have distinct economic implications.

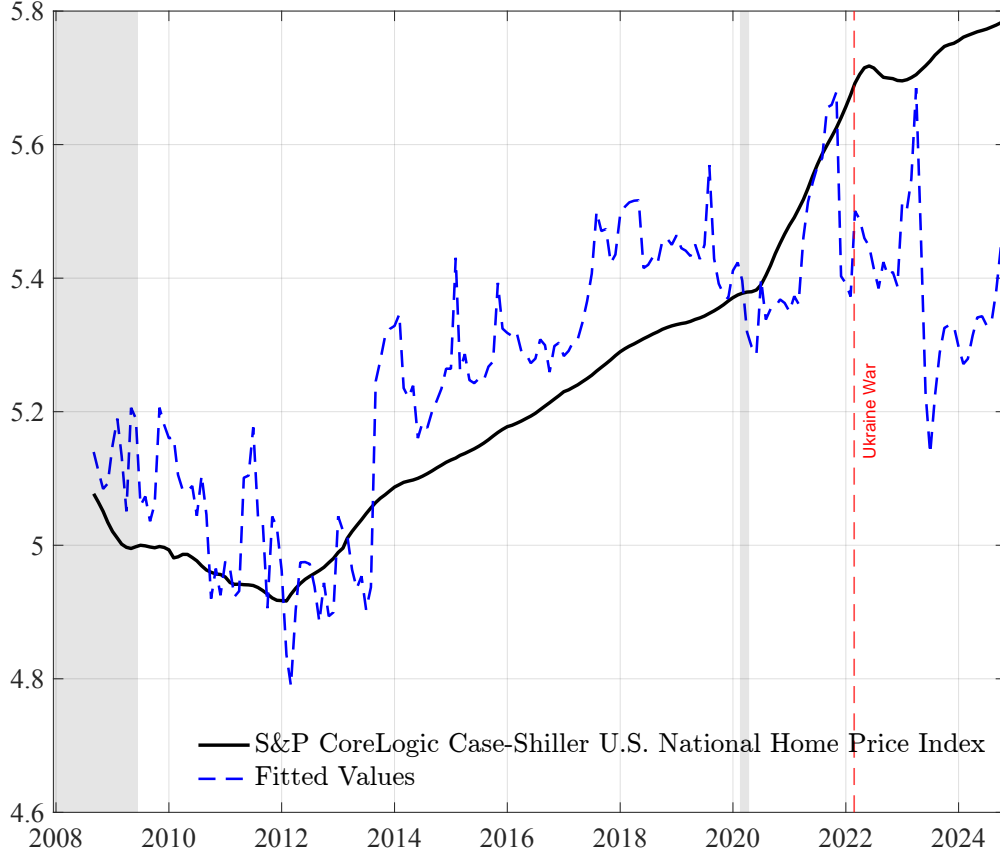


Figure 15: Huosing Prices fitted values

B.9 Empirical Analysis: Dollar Index and Sovereign Risk Uncertainty

We estimate a linear regression model to investigate the relationship between the logarithm of the U.S. Dollar Index and the two components of sovereign risk uncertainty. The model is specified as

$$\log(\text{DollarIdx}) = \beta_0 + \beta_1 \text{sSRU} + \beta_2 \text{lSRU} + \varepsilon, \quad (\text{B.9})$$

where $\log(\text{DollarIdx})$ is the log-transformed Dollar Index, sSRU and lSRU represent the short-run and long-run components of sovereign risk uncertainty, respectively, and ε is the error term.

Table 22 summarizes the estimated coefficients from the model in Equation Eq. (B.9). The regression uses 197 observations (with 194 degrees of freedom) and produces a root mean squared error (RMSE) of 0.0777, an R^2 of 0.467, and an adjusted R^2 of 0.462. The overall F-statistic is 85.1 with a p -value of 2.92×10^{-27} .

We also computed the Pearson correlation coefficients between the uncertainty indices and $\log(\text{DollarIdx})$. The results are summarized in Tables 23 and 24.

The regression analysis (Table 22) indicates that the intercept is highly significant. The coefficient on sSRU is -0.02383 and is not statistically significant ($p = 0.69165$), suggesting that transient

Table 22: Regression Results for $\log(\text{DollarIdx})$

Variable	Estimate	SE	t-Statistic	p-Value
Intercept	2.9262	0.026144	111.93	3.43×10^{-178}
sSRU	-0.02383	0.060002	-0.3972	0.69165
SRU	0.06899	0.036195	1.9060	0.05813

Table 23: Correlation between ShortRunIndex and $\log(\text{DollarIdx})$

Variable	Correlation
sSRU	1.0000
$\log(\text{DollarIdx})$	0.1045

uncertainty has little effect on the Dollar Index. In contrast, the coefficient on ISRU is positive (0.06899) and marginally significant ($p = 0.05813$), implying that higher persistent uncertainty is associated with a modest increase in the log-transformed Dollar Index.

The correlation analysis supports these findings: the correlation between sSRU and $\log(\text{DollarIdx})$ is weak ($r = 0.1045$), while that between sSRU and $\log(\text{DollarIdx})$ is slightly stronger ($r = 0.1683$). Although both correlations are relatively low, the pattern suggests that long-run uncertainty may have a more pronounced influence on market volatility as captured by the Dollar Index.

Overall, these results indicate that the short-run component of sovereign risk uncertainty does not significantly affect the Dollar Index, whereas persistent long-run uncertainty exerts a modest positive effect. This may reflect a market phenomenon where long-term uncertainty, perhaps linked to sustained geopolitical or fiscal challenges, leads to an increase in the Dollar Index, possibly due to flight-to-quality dynamics or risk premium adjustments in the currency markets.

B.10 Regression Analysis: Conclusions

Our empirical analysis decomposes sovereign risk uncertainty into short-run and long-run components and investigates their effects on several macroeconomic indicators. The regression results provide clear evidence that these two dimensions of uncertainty impact the economy in distinctly different ways.

The analysis of personal consumption reveals that transient (short-run) uncertainty has a modest or mixed impact on consumption, whereas persistent (long-run) uncertainty exerts a pronounced adverse effect. This finding is consistent with our theoretical framework: prolonged uncertainty stemming from sustained geopolitical tensions or debt crises can significantly depress consumption,

Table 24: Correlation between LongRunIndex and $\log(\text{DollarIdx})$

Variable	Correlation
ISRU	1.0000
$\log(\text{DollarIdx})$	0.1683

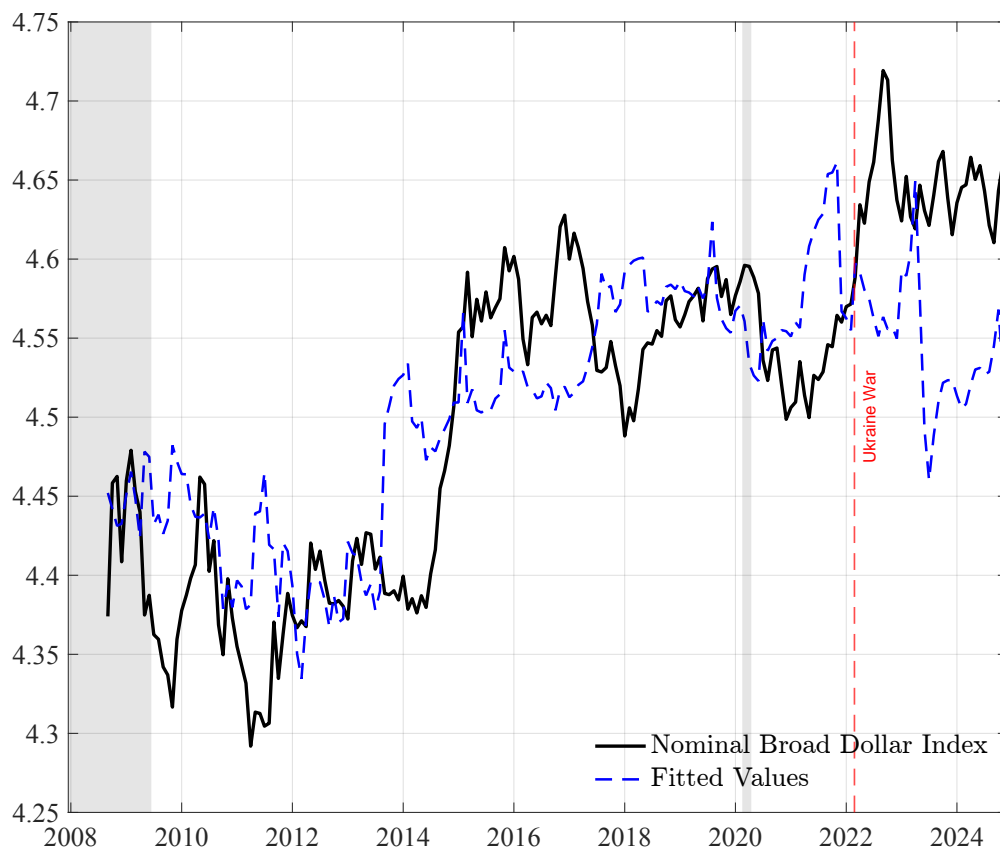


Figure 16: Dollar Index fitted values

likely by undermining long-term economic confidence and reducing investment.

Similarly, in our examination of industrial production, the evidence suggests that while short-run uncertainty may even have a slight stimulative or neutral effect on output, persistent uncertainty is significantly detrimental to industrial performance. These differences highlight the importance of differentiating between temporary shocks and enduring structural risks.

Our regression analysis on treasury debt indicates that transient uncertainty is moderately negatively correlated with the logarithm of treasury debt ($r = -0.3442$), whereas the long-run component exhibits a much stronger negative correlation ($r = -0.6464$). This suggests that persistent uncertainty, by increasing risk premiums or dampening market confidence, has a more pronounced impact on lowering the market value of debt.

In the case of personal saving rates, we find that transient uncertainty appears to reduce saving – possibly as households respond to immediate shocks by increasing consumption – while persistent uncertainty shows a marginal positive effect. Although the evidence for the long-run effect on saving is less robust, these contrasting impacts underscore that households respond differently to short-term versus sustained uncertainty.

Furthermore, our analysis of policy uncertainty (measured by the EPU index) indicates that while short-run fluctuations have little influence, persistent uncertainty is associated with a discernible negative impact. This may be interpreted as structural uncertainty altering policymaking dynamics, leading to a perception of lower policy uncertainty despite underlying sovereign risk.

Additional regressions show that the VIX, a proxy for market volatility, appears to be influenced only weakly by our uncertainty measures, suggesting that factors other than sovereign risk uncertainty are the primary drivers of market volatility. Persistent uncertainty is significantly associated with higher oil prices, implying that sustained risk may result in elevated risk premiums in energy markets. For housing prices, transient uncertainty is associated with higher prices, potentially reflecting short-term speculative adjustments. In contrast, persistent uncertainty is linked to lower housing prices, indicating that long-term uncertainty may undermine market confidence and investment in housing. Lastly, our analysis of the Dollar Index indicates that while short-run uncertainty does not significantly affect the index, persistent uncertainty exerts a modest positive influence. This may reflect a flight-to-quality phenomenon in which long-term geopolitical or fiscal risks drive investors towards the U.S. dollar.

Overall, the findings strongly support our theoretical framework by demonstrating that the short-run and long-run components of sovereign risk uncertainty have markedly different economic implications. Transient uncertainty seems to induce immediate, though mixed, responses in consumption, asset prices, and savings. In contrast, persistent uncertainty has more pronounced and lasting effects, significantly depressing consumption and output, lowering the market value of debt, and influencing broader macroeconomic variables such as oil prices, housing markets, and exchange rates.

These results suggest that policy interventions and risk management strategies should be tailored to address not only the immediate shocks but also the persistent, structural uncertainties that can have far-reaching consequences for economic stability.

B.11 Rolling Granger Causality Analysis

To analyze the time-varying relationship between sovereign risk uncertainty and macro-financial variables, we employ a rolling-window Granger causality test. This approach allows us to identify periods where the causal influence of short-run and long-run uncertainty strengthens, weakens, or disappears, reflecting shifts in market dynamics due to major economic or geopolitical events.

C Kalman Filter Estimation Methodology

In this paper, we model the (log) CDS spreads for different maturities using a state-space framework. The observation (measurement) equation is given by

$$y_t = \beta N_t + \Gamma x_t + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0, R), \quad (\text{C.1})$$

where:

- $y_t \in \mathbb{R}^n$ is the vector of observed (log) CDS spreads at time t for n different maturities;
- N_t is the scalar latent state (the latent component of CDS spreads), which – through the loading vector $\beta \in \mathbb{R}^n$ – affects the CDS spreads differently across maturities (e.g., short vs. long maturities);
- $x_t \in \mathbb{R}^k$ is a vector of exogenous variables (with k elements);

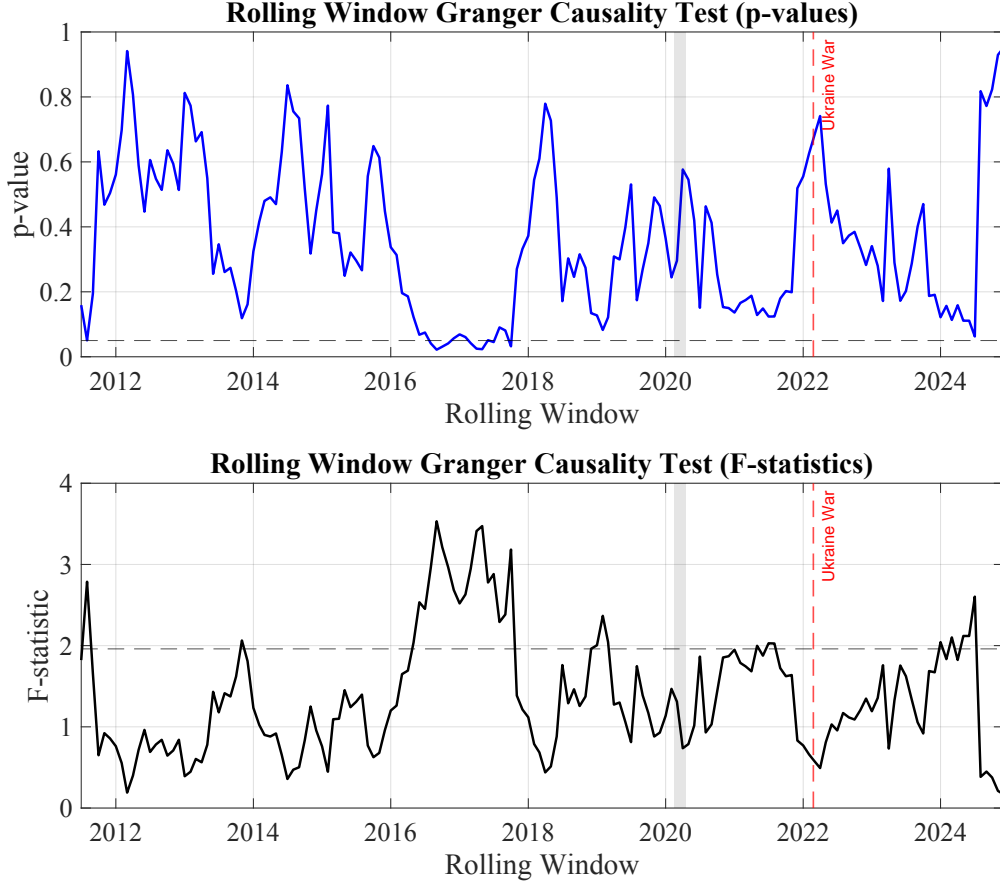


Figure 17: Short-run Rolling Window Granger Industrial Production Index

- $\Gamma \in \mathbb{R}^{n \times k}$ is the matrix capturing the sensitivity of the CDS spreads to the exogenous variables;
- ε_t is the measurement noise, assumed to be multivariate normal with covariance matrix $R \in \mathbb{R}^{n \times n}$.

The state (transition) equation for the latent variable is specified as

$$N_t = \alpha N_{t-1} + \eta_t, \quad \eta_t \sim \mathcal{N}(0, Q), \quad (\text{C.2})$$

where α is the persistence parameter and Q is the process noise variance. In our implementation, we ensure $Q > 0$ by reparameterizing it as

$$q = \log(Q) \quad \implies \quad Q = \exp(q).$$

C.1 Kalman Filtering and Smoothing

Given the model in Equations Eq. (C.1) and Eq. (C.2), the Kalman filter is used to compute filtered estimates of the latent state. At each time t , the following steps are performed:

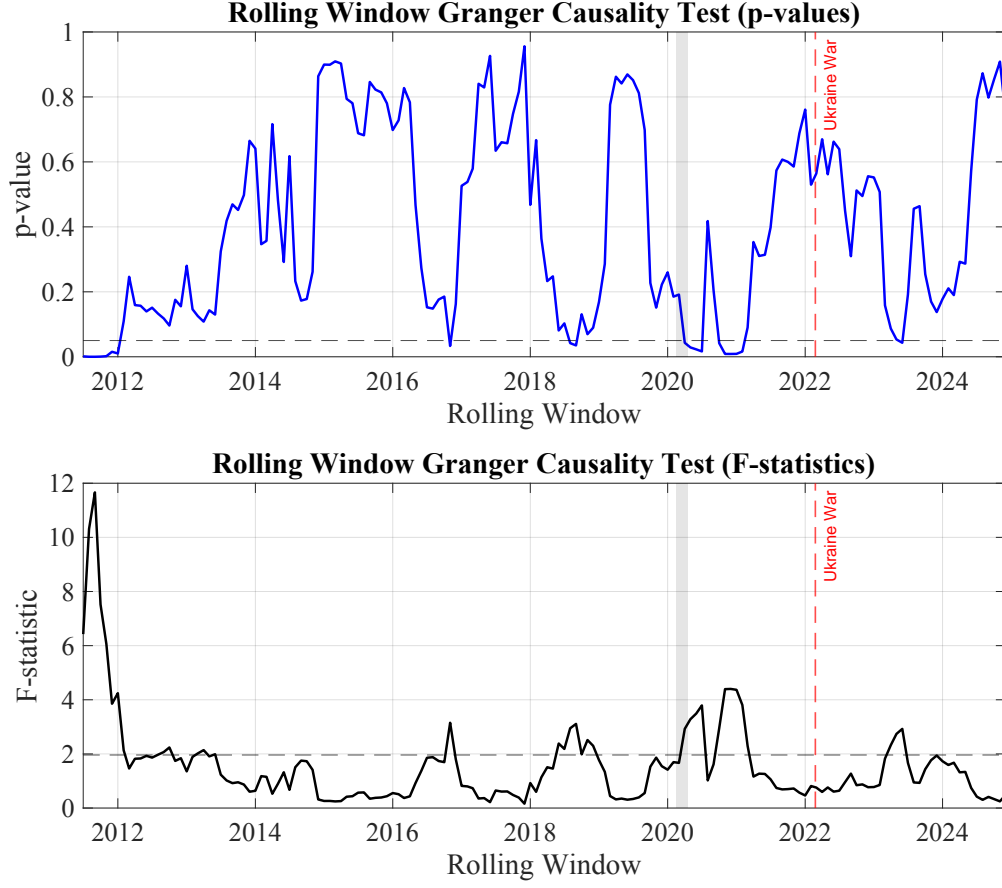


Figure 18: Long-run Rolling Window Granger Industrial Production Index

Prediction:

$$N_{t|t-1} = \alpha N_{t-1|t-1}, \quad (\text{C.3})$$

$$P_{t|t-1} = \alpha^2 P_{t-1|t-1} + Q. \quad (\text{C.4})$$

Measurement Update: The predicted measurement is

$$\hat{y}_t = \beta N_{t|t-1} + \Gamma x_t, \quad (\text{C.5})$$

with innovation (or residual)

$$\varepsilon_t = y_t - \hat{y}_t. \quad (\text{C.6})$$

The innovation covariance is computed as

$$S_t = \beta P_{t|t-1} \beta' + R. \quad (\text{C.7})$$

The Kalman gain is then given by

$$K_t = P_{t|t-1} \beta' S_t^{-1}. \quad (\text{C.8})$$

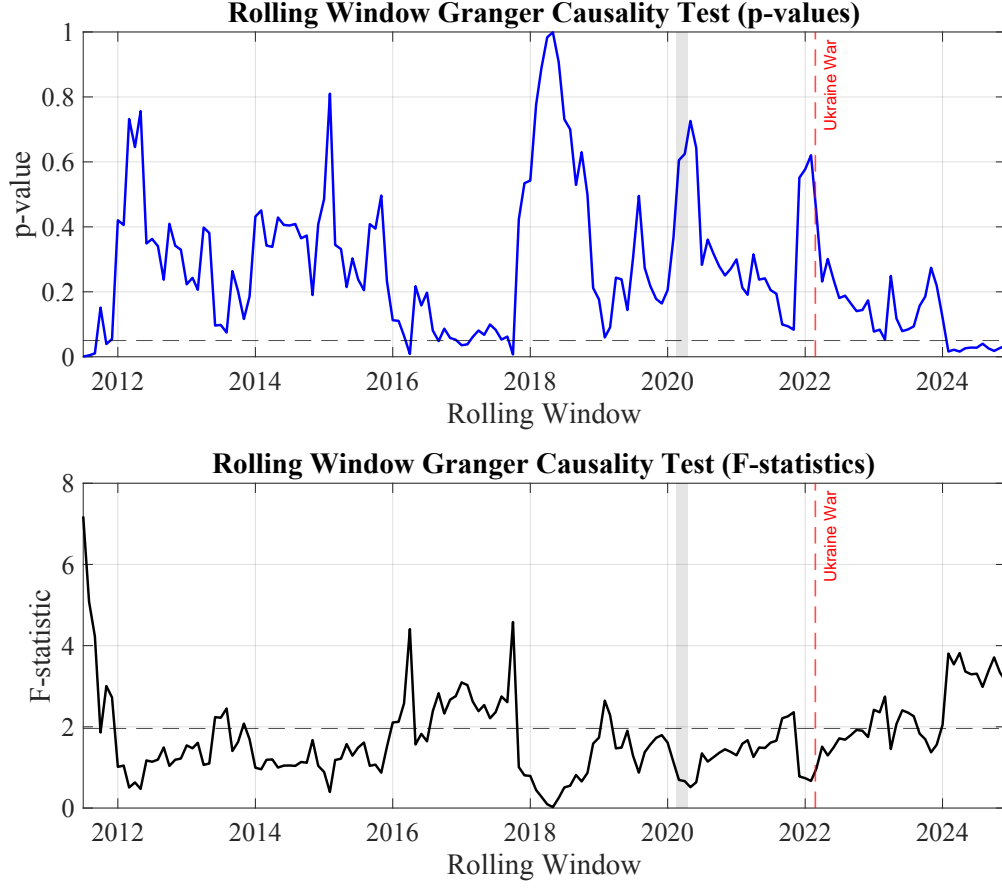


Figure 19: Short-run Rolling Window Granger Personal Consumption Expenditure

The filtered state and its variance are updated as

$$N_{t|t} = N_{t|t-1} + K_t \varepsilon_t, \quad (\text{C.9})$$

$$P_{t|t} = (1 - K_t \beta) P_{t|t-1}. \quad (\text{C.10})$$

The log-likelihood contribution at each time step is

$$\ell_t = -\frac{1}{2} \log \det(2\pi S_t) - \frac{1}{2} \varepsilon_t' S_t^{-1} \varepsilon_t, \quad (\text{C.11})$$

and the total log-likelihood is

$$\ell = \sum_{t=1}^T \ell_t. \quad (\text{C.12})$$

After filtering, we apply the Rauch-Tung-Striebel (RTS) smoother to obtain smoothed estimates of the latent state that incorporate information from the entire sample (RAUCH et al., 1965). The

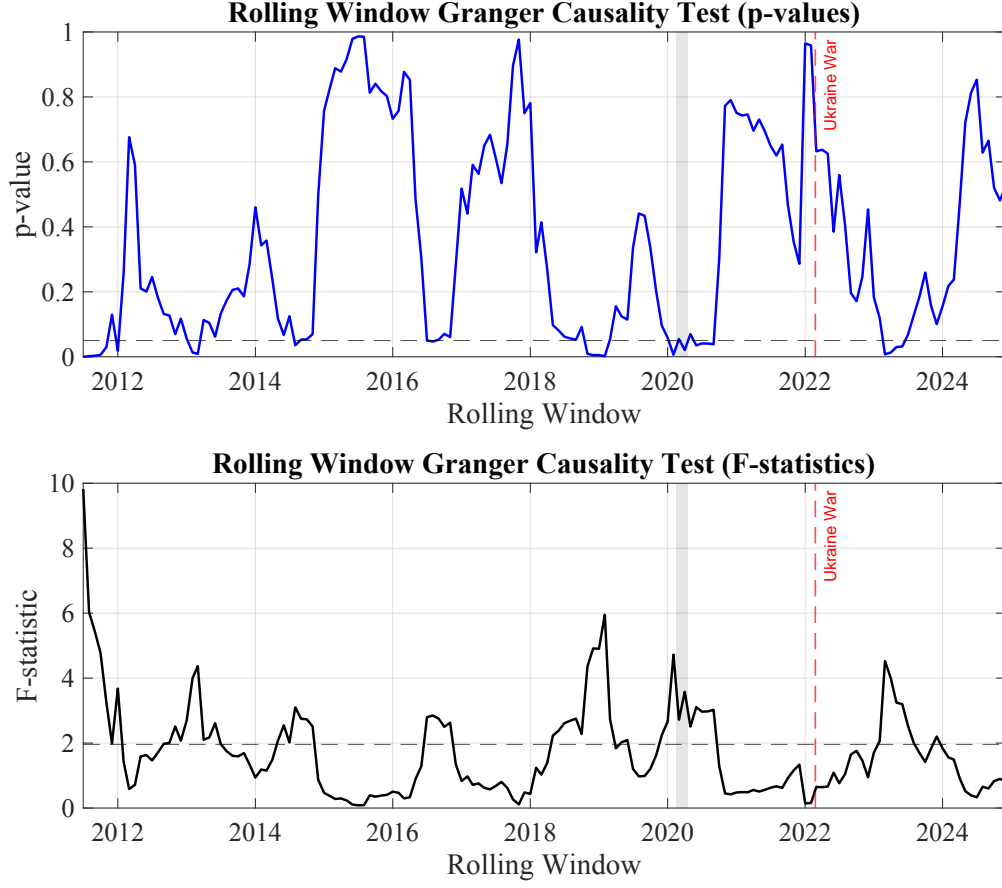


Figure 20: Long-run Rolling Window Granger Personal Consumption Expenditure

backward recursion is given by

$$A_t = \frac{P_{t|t} \alpha}{P_{t+1|t}}, \quad t = T - 1, \dots, 1, \quad (\text{C.13})$$

$$N_t^s = N_{t|t} + A_t (N_{t+1}^s - N_{t+1|t}), \quad (\text{C.14})$$

$$P_t^s = P_{t|t} + A_t^2 (P_{t+1}^s - P_{t+1|t}), \quad (\text{C.15})$$

with $N_T^s = N_{T|T}$ and $P_T^s = P_{T|T}$.

D Robustness check

As a robustness check, we re-estimate the model with an alternative grouping of CDS maturities: the short-run group includes 6-month, 1-year, and 2-year maturities, while the long-run group consists of 7-year, 10-year, and 30-year maturities. Additionally, we replace the macroeconomic variables with the VIX, EPU, oil prices, and the Dollar Index as exogenous regressors. The results remain qualitatively similar and are detailed in Appendix D.

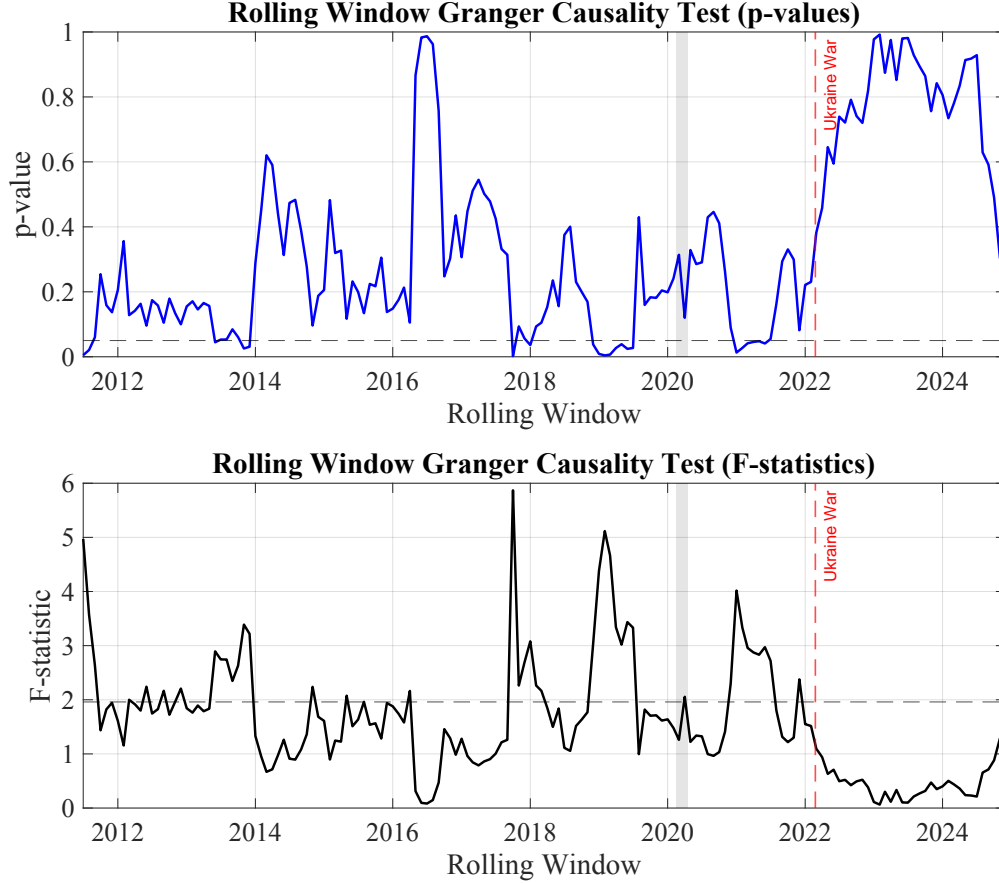


Figure 21: Short-run Rolling Window Granger Treasury Debt

D.1 Bayesian Estimation via MCMC

The complete parameter vector is given by

$$\theta = \begin{bmatrix} \theta_\alpha \\ \beta \\ \text{vec}(\Gamma) \\ q \\ \text{vech}(R) \end{bmatrix},$$

with $q = \log(Q)$ ensuring that $Q = \exp(q) > 0$ and $\text{vech}(R)$ denoting the vectorization of the lower-triangular part of R . For the long-run group, the covariance matrix R is further reparameterized via its Cholesky factor to guarantee positive-definiteness.

D.1.1 Short-Run Estimation

Parameters for the short-run maturities are estimated using a block-update random-walk Metropolis-Hastings algorithm. The update is performed in two blocks: Block 1, comprising $\{\theta_\alpha, \beta, \text{vec}(\Gamma)\}$, uses slice sampling for θ_α ; Block 2, comprising $\{q, \text{vech}(R)\}$, is updated with a standard random-walk proposal.

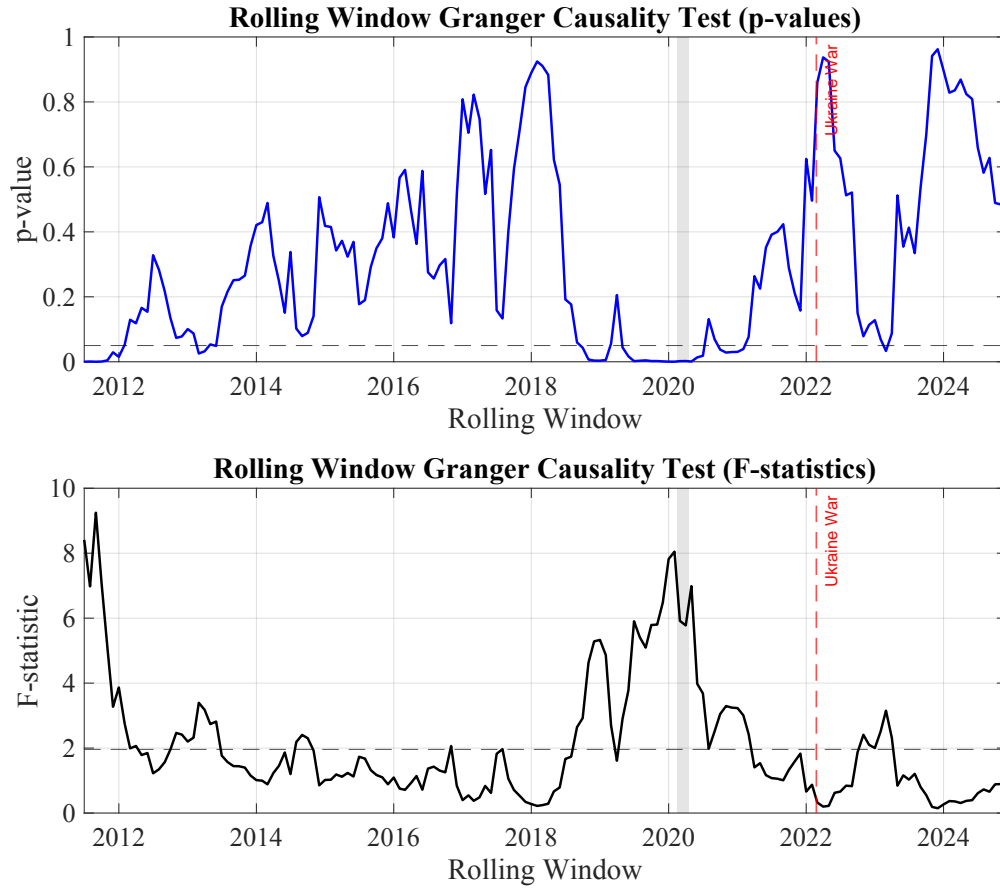


Figure 22: Long-run Rolling Window Granger Treasury Debt

D.1.2 Long-Run Estimation

For the long-run maturities, the parameters are estimated using a random-walk Metropolis-Hastings algorithm similar to the short-run procedure. The target value of α (i.e. $\alpha \approx 0.895$) is used to initialize the long-run sampler, ensuring that the high persistence of long-run uncertainty is captured. In our implementation, we adopt a block-update strategy analogous to that used for the short-run group. The differences in the posterior distributions of the short-run and long-run groups reflect the distinct dynamics in the term structure of CDS spreads.

D.2 Posterior Inference and Model Fit

After running multiple MCMC chains for both groups, convergence diagnostics were computed. For the short-run group, the acceptance ratio was 0.2215 with an effective sample size (ESS) of 55.29 and $\hat{R} = 1.00$. For the long-run group, the acceptance ratio was 0.1700, ESS was 44.48, and $\hat{R} = 1.01$. The posterior mean estimates are summarized as follows:

Short-Run Group:

$$\alpha = 0.41$$

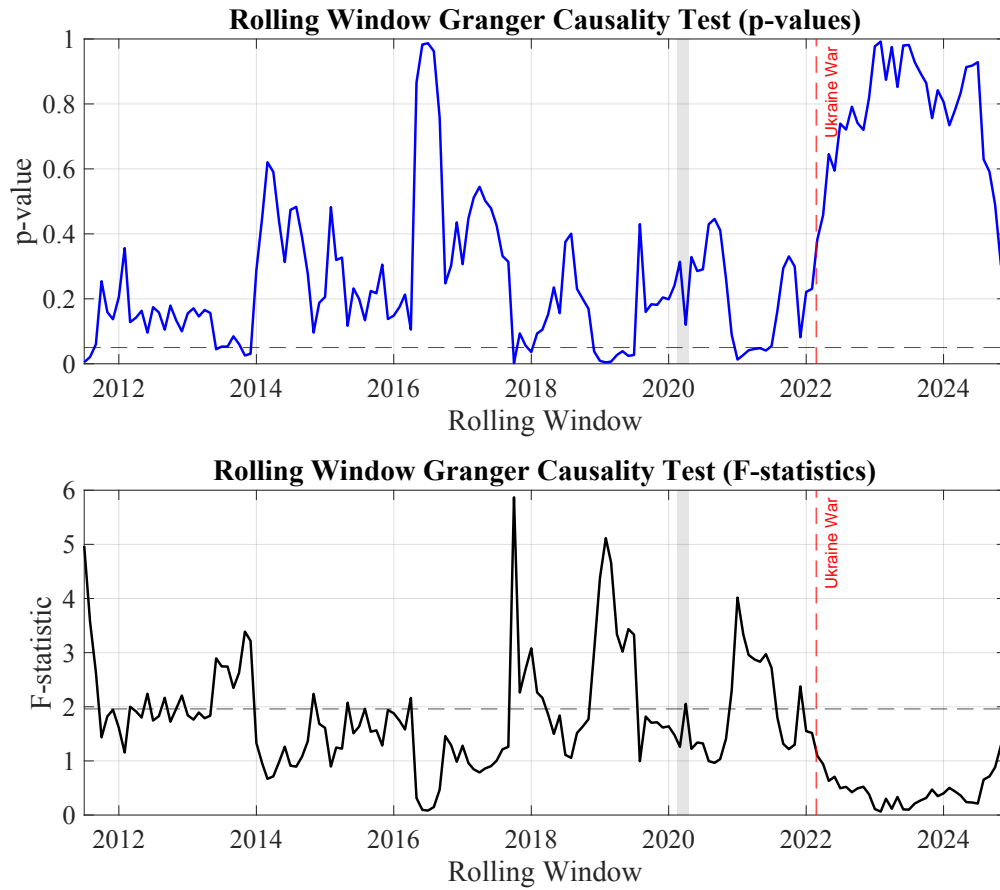


Figure 23: Short-run Rolling Window Granger Treasury Debt

$$\beta = \begin{bmatrix} 1.18 \\ 0.93 \\ 1.27 \end{bmatrix}$$

$$\Gamma = \begin{pmatrix} 0.20 & 0.15 & 0.13 & 0.05 \\ 0.06 & 0.10 & 0.52 & -0.08 \\ 0.26 & 0.15 & 0.11 & 0.15 \end{pmatrix}$$

$$Q = 0.17$$

$$R = \begin{pmatrix} 0.45 & 0.08 & 0.06 \\ 0.08 & 0.16 & 0.02 \\ 0.06 & 0.02 & 0.06 \end{pmatrix}$$

Long-Run Group:

$$\alpha = 0.89$$

$$\beta = \begin{bmatrix} 0.38 \\ 0.35 \\ 0.33 \end{bmatrix}$$

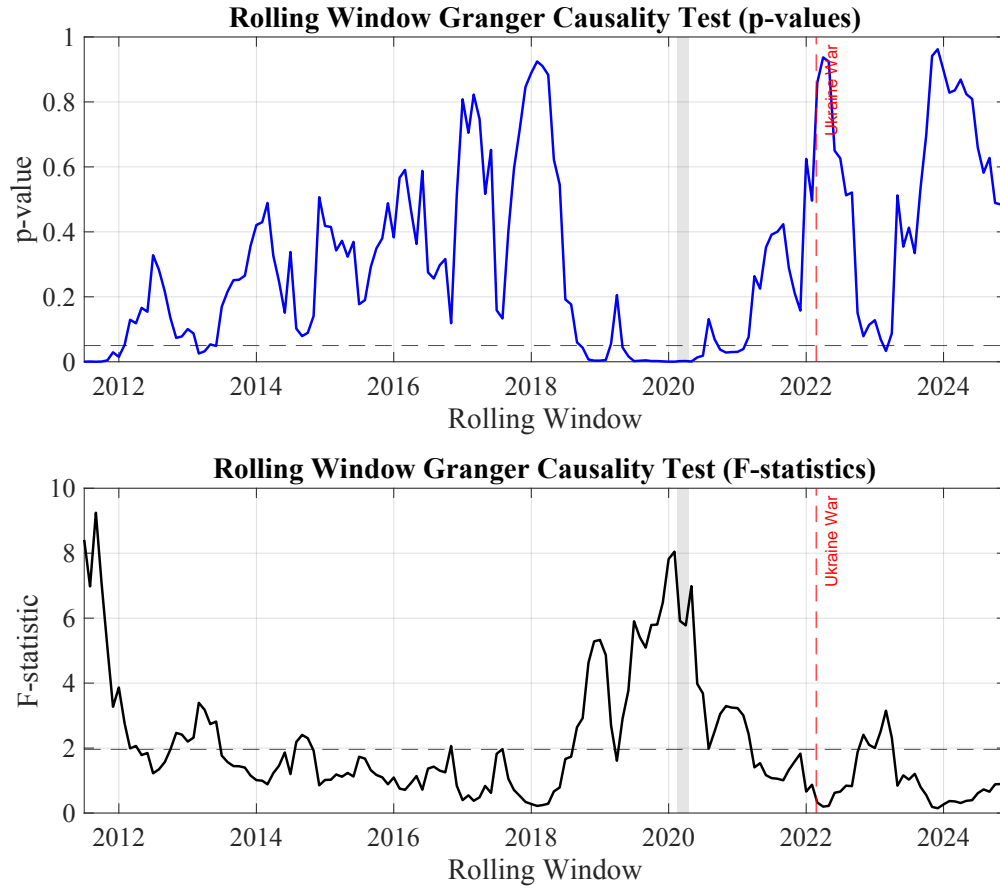


Figure 24: Long-run Rolling Window Granger Treasury Debt

$$\Gamma = \begin{pmatrix} 0.2221 & 0.2547 & 0.22 & 0.15 \\ 0.18 & 0.16 & 0.24 & 0.23 \\ 0.20 & 0.24 & 0.26 & 0.16 \end{pmatrix}$$

$$Q = 0.05$$

$$R = \begin{pmatrix} 0.0121 & -0.0014 & 0.0069 \\ -0.0014 & 0.0305 & -0.0019 \\ 0.0069 & -0.0019 & 0.0215 \end{pmatrix}$$

Model fit was assessed by comparing the observed and fitted CDS spreads. For the short-run maturities, the RMSEs (Root Mean Square Error) were 0.51, 0.35, and 0.14, with correlations of 0.77, 0.85, and 0.96. In contrast, the long-run maturities exhibited lower RMSEs of 0.08, 0.16, and 0.11, and higher correlations of 0.98, 0.90, and 0.94. These differences reflect the higher persistence and smoother dynamics in the long-run component, as predicted by the theoretical model.

D.3 Summary Statistics of CDS Spreads

Table 26 presents the summary statistics for the short-run CDS spreads and the statistics of the alternative model estimations. For each maturity, the table reports the observed mean, fitted mean

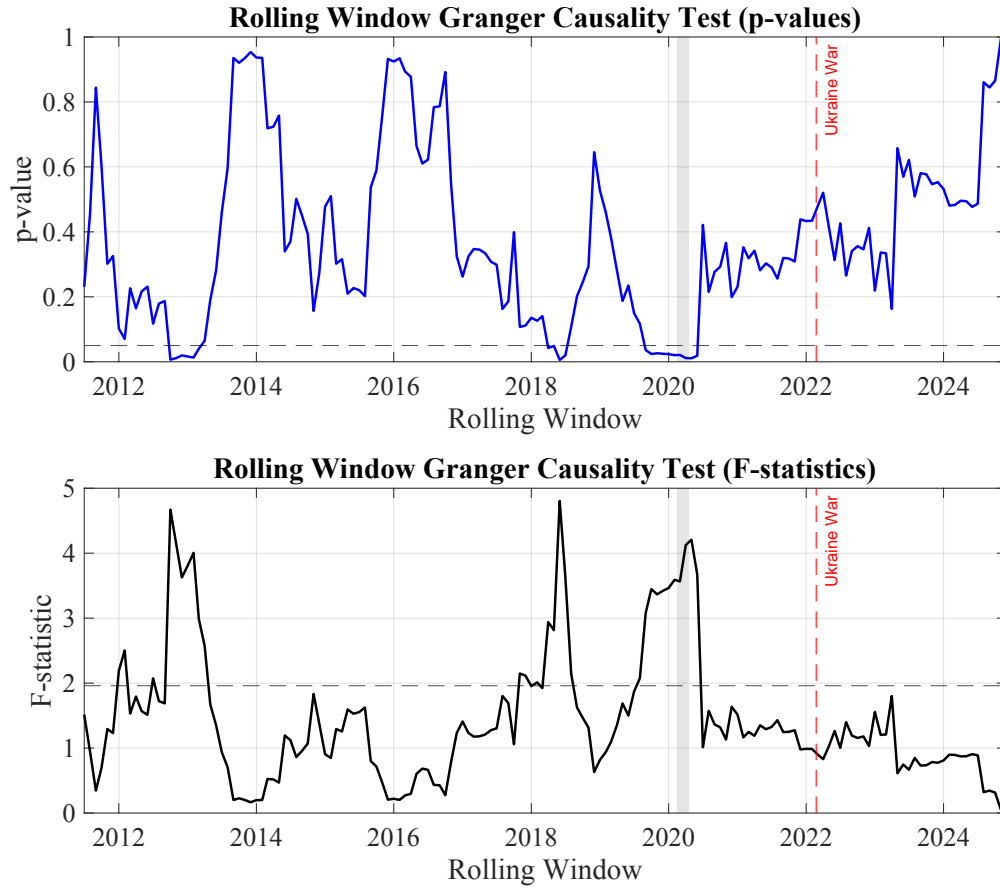


Figure 25: Short-run Rolling Window Granger VIX

(as obtained from the Kalman filter estimation), the root mean square error (RMSE), and the correlation between the observed and fitted spreads.

Table 27 shows the summary statistics for the long-run CDS spreads.

D.4 Posterior Estimates for the Persistence Parameter α

The posterior distribution of the persistence parameter α was estimated separately for the short-run and long-run components. For the short-run component, the posterior summary statistics for θ_α (the unconstrained parameter) are:

$$\text{mean} = -0.8472, \quad \text{median} = -0.8472, \quad \text{std} = 0.0033, \quad \text{min} = -0.8598, \quad \text{max} = -0.8351.$$

For the long-run component, the corresponding summary statistics for θ_α are:

$$\text{mean} = 4.9777, \quad \text{median} = 4.7626, \quad \text{std} = 0.5293, \quad \text{min} = 4.3055, \quad \text{max} = 5.8776.$$

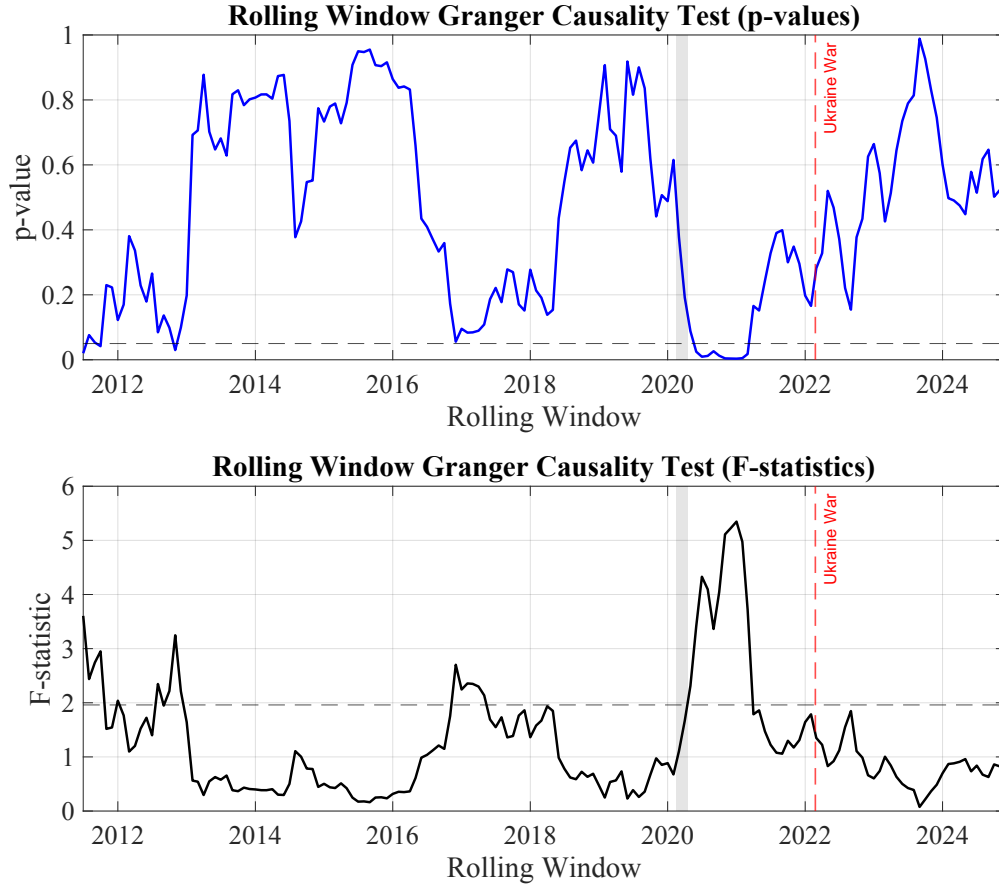


Figure 26: Long-run Rolling Window Granger VIX

Recall that α is obtained via the transformation

$$\alpha = 0.2 + (0.9 - 0.2) \sigma(\theta_\alpha), \quad \text{with} \quad \sigma(x) = \frac{1}{1 + \exp(-x)},$$

which ensures that α lies in $[0.2, 0.9]$. Thus, a target value of $\theta_\alpha \approx -0.85$ corresponds to $\alpha \approx 0.41$ for the short-run component, while $\theta_\alpha \approx 4.93$ implies $\alpha \approx 0.895$ for the long-run component.

E The Variance Inflation Factor (VIF)

Interpretation: The Variance Inflation Factor (VIF) measures how much the variance of an estimated regression coefficient increases due to multicollinearity among the predictors. Generally, a VIF below 5 (or in some cases 10) suggests that multicollinearity is not a serious concern. In Table 28, the VIF values range from 1.44 to 3.67, indicating moderate correlations among the predictors but nothing at a level that would lead to severe inflation of the coefficient variances. Therefore, the exogenous variables used in our model appear to be adequately independent for reliable inference.

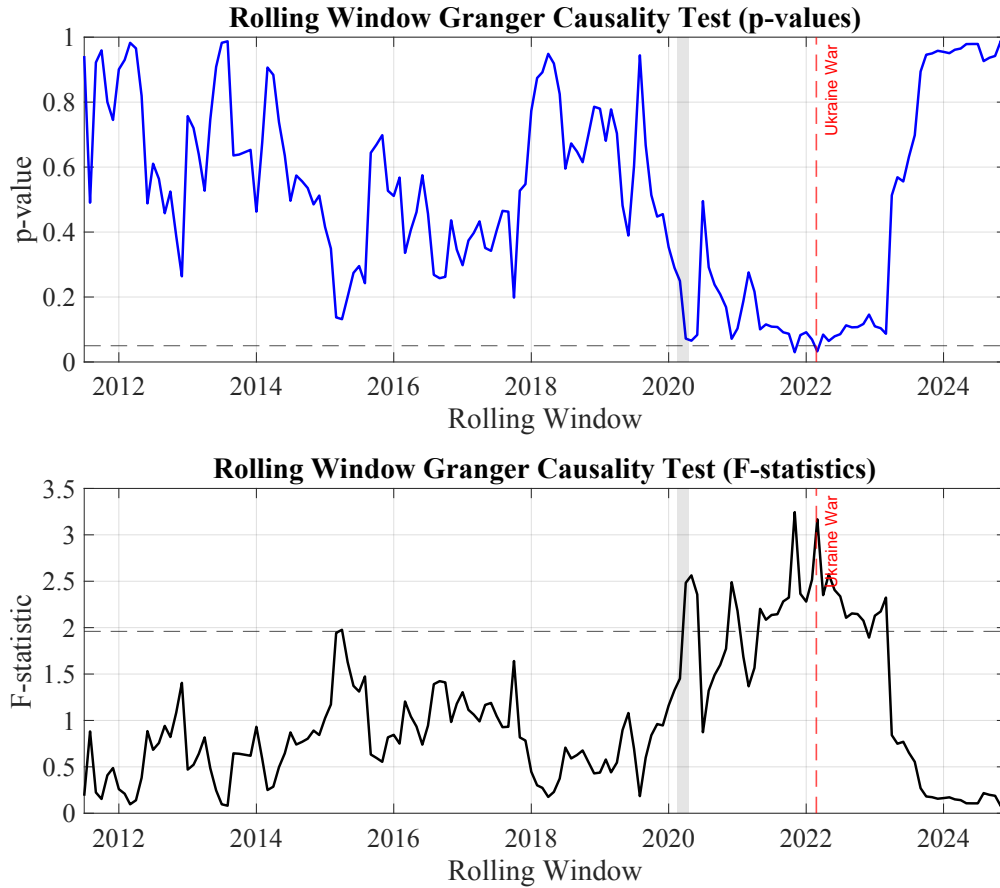


Figure 27: Short-run Rolling Window Granger EPU

Table 25: Benchmark Model vs. Alternative Specification

	Benchmark Model	Alternative Specification
Short-Run CDS Maturities	6M, 1Y, 2Y, 3Y	6M, 1Y, 2Y
Long-Run CDS Maturities	7Y, 10Y, 20Y, 30Y	7Y, 10Y, 30Y
Exogenous Variables	INDPRO, PCE, Debt, Savings	VIX, EPU, Oil Prices, Dollar Index
Estimation Method	Bayesian MCMC (Metropolis-Hastings)	Bayesian MCMC (Metropolis-Hastings)
Purpose	Main Estimation	Robustness Check

Notes: The benchmark model estimates sovereign risk uncertainty using macroeconomic fundamentals, while the alternative specification tests the robustness of results with financial uncertainty indicators.

Table 26: Short-run CDS Summary Statistics

Maturity	Observed Mean	Fitted Mean	RMSE	Correlation
6 Months	2.2879	2.2167	0.62825	0.63705
1 Year	2.6485	2.6064	0.48297	0.66465
2 Years	2.8260	2.8097	0.31753	0.82982

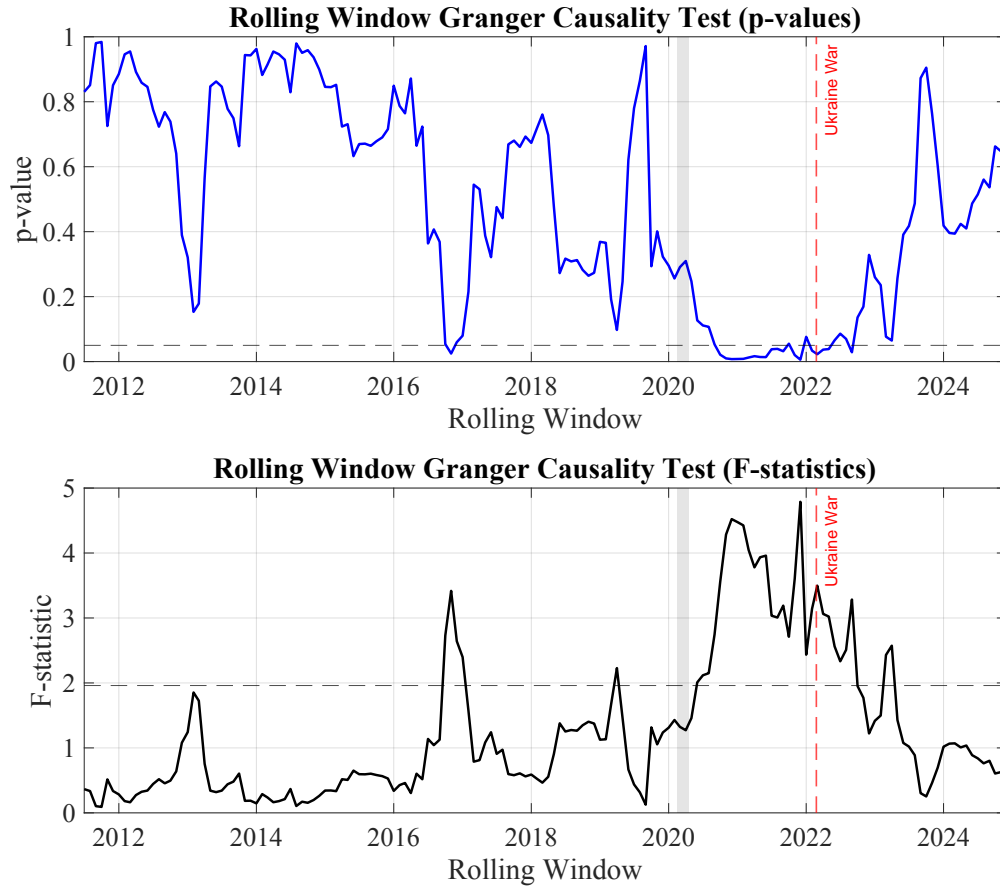


Figure 28: Long-run Rolling Window Granger EPU

Table 27: Long-run CDS Summary Statistics

Maturity	Observed Mean	Fitted Mean	RMSE	Correlation
7 Years	3.5667	3.5669	0.10252	0.96293
10 Years	3.4111	3.4244	0.20524	0.85176
20 Years	3.7188	3.7166	0.19086	0.81101

Table 28: Variance Inflation Factors (VIF) for the Predictors

Variable	VIF
s-Sovereign Risk Uncertainty Idx	2.84
l-Sovereign Risk Uncertainty Idx	3.67
log(PersonalConsumption)	1.44
log(INDPRO)	3.18
log(TreasuryDebt)	2.62
log(PersonalSavingRates)	1.81