What Moves Sovereign Credit Risk? The Role of Information

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Abstract

This paper examines the role of information in sovereign spread movements. Using sovereign credit default swap spreads and trading data, we decompose spread movements into global-market information, country-specific trading and nontrading information, and noise. Country-specific information accounts for a larger share of spread variation than global-market information, while noise is sizable. We then develop a sovereign default model with global risk and a secondary trading market in which participants receive public and private news about next year's fundamentals. As default approaches, learning from public news and order flow widens the gap between trading and fundamental spreads.

Keywords Credit default swaps, Default risk, Sovereign debt, International financial markets
JEL G12, G15, F34

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1 Introduction

Rising debt levels and recurrent debt crises following the 2008 global financial crisis and the 2020 pandemic have raised concerns regarding sovereign credit risks. Understanding the determinants of sovereign credit risks is crucial to grasp the role of international financial markets and identify the factors that influence borrowing costs and capital flows between countries. The existing literature emphasizes the significant influence of global risk factors on fluctuations in sovereign credit risks (see Pan and Singleton (2008), Ang and Longstaff (2013), and Longstaff et al. (2011)). These findings suggest an important role for global financial intermediaries within sovereign debt markets. However, there is substantial evidence indicating that domestic financial conditions also play a critical role in shaping sovereign credit risks, with studies such as Acharya et al. (2014) and Bocola (2016) highlighting the interaction between domestic bank risks and sovereign defaults.

This paper presents a framework for analyzing sovereign credit risks by identifying the sources of information embedded in sovereign CDS spreads. We measure sovereign credit risks using sovereign credit default swap (CDS) spreads, following the approach of Longstaff et al. (2011). Our methodology utilizes the return variance decomposition model developed by Brogaard et al. (2022), which uses variations in trading data and explicitly accounts for the impact of noise on spread movements. Through this model, we decompose changes in sovereign CDS spreads into noise and information components. We then develop a sovereign default model to examine how information about future fundamentals is incorporated into secondary-market prices.

The decomposition of sovereign CDS spread variations results in four components consisting of noise, global-market information, country-specific nontrading information, and country-specific trading information. The noise component reflects transitory fluctuations in spreads, which may arise from liquidity needs, market sentiment, or market frictions. The global information component captures the persistent response of spreads to global shocks. The country-specific nontrading component represents information that affects a country's sovereign risk and is incorporated into spreads without being revealed through trading. In contrast, the country-specific trading component consists of information that is revealed through trading activities. These are empirical classifications of information in spread movements.

To achieve this decomposition, we analyze the responses of sovereign CDS spreads to three types of shocks, namely global spread changes, country-specific trading flows, and other country-specific shocks, as indicated by the spread residual. We use vector autoregression (VAR) impulse response functions to estimate the persistent components of spread changes

in response to these shocks. For example, a sudden surge in demand for sovereign CDS contracts might temporarily increase contract prices, which would subsequently adjust to a new equilibrium over time. By estimating the cumulative response to each shock, we distinguish persistent changes in spreads from transitory fluctuations. The transitory part is identified as the noise component. The persistent response of spreads to global spread changes captures global-market information. The persistent impact of a shock to country-specific trading flows on spreads is interpreted as country-specific trading information. Similarly, country-specific nontrading information is estimated as the persistent effect of a shock to the country-specific spread residual that is uncorrelated with contemporaneous global and trading shocks.

We estimate the VAR model using weekly changes in sovereign CDS spreads from 2012 to 2024. The estimation sample contains 527 country-year observations across 57 countries. We find that country-specific information accounts for a larger share than global-market information, while noise is sizable. The mean estimated shares are 41% for country-specific information, 20% for global-market information, and 39% for noise. Within country-specific information, the nontrading and trading components contribute 25% and 16%, respectively. Spreads in emerging market and developing economies have higher shares of global information than spreads in advanced economies. These findings suggest that global financial market conditions play a relatively larger role in sovereign credit risks in emerging market and developing economies.

Our findings complement the evidence that global factors are important for the comovement of sovereign spreads (Longstaff et al. (2011) and Gilchrist et al. (2022)). Our method uses the persistent responses of spreads to innovations in the global market spread, trading flows, and country spreads to distinguish information from transitory noise. This allows us to assess the information underlying individual countries' spread changes and how it is incorporated into prices. The distinction between cross-country comovement and within-country variation is important. Global shocks can generate common movements across countries even when country-specific information and noise account for a larger share of variation within each country.

We proceed by developing a sovereign default model with a secondary trading market. The government observes current output, fiscal expenditure, and global risk before making annual borrowing and default decisions. During the year, market participants receive public and private news about next year's output and fiscal expenditure. Informed traders act on private news, while competitive dealers learn from public news and order flow. Liquidity trading prevents dealers from perfectly inferring the informed traders' information. The model distinguishes the annual fundamental spread, determined by the sovereign's repayment

prospects and lenders' pricing of risk, from the trading spread that incorporates information arriving after the annual decision.

We calibrate the model to debt and fundamental-spread moments as well as the empirical variance shares. The model reproduces the relative importance of global-market information, country-specific information, and noise. We then compare the baseline economy with alternative models without public news, private news, or global risk. Removing public news reduces the nontrading information share and increases the relative importance of trading information. Removing private news substantially reduces the trading information share. The empirical trading and nontrading components do not correspond exactly to private and public news, since dealers also learn from order flow and past information. Removing global risk and re-solving the sovereign economy increases the relative contribution of country-specific information. The alternative models illustrate the different roles of news reaching the secondary market and global risk affecting sovereign borrowing and default.

The distinction between fundamental and trading spreads is particularly important as default approaches. In the simulated economy, the trading spread rises more sharply than the annual fundamental spread before default. Most of the widening gap is due to public news and learning from private news and order flow, with an additional contribution from lenders' risk repricing. News about next year's output and fiscal expenditure can have large effects on repayment prospects near the default boundary. Moreover, at lower bond prices, the same price decline produces a larger increase in the spread. These mechanisms amplify the response of trading spreads to adverse information in the periods leading up to default.

Related literature The paper is closely related to the empirical literature that studies the determinants of sovereign credit risks, informational role of trading positions and volumes in CDS markets, and asset return decomposition.

We contribute to the sovereign risk literature by complementing the analysis of cross-country comovements with an analysis of the information sources underlying individual spread movements. We decompose sovereign credit spread movements into global-market information, country-specific trading and nontrading information, and noise, allowing us to quantify the informational content of spreads while accounting for temporary movements.

Existing work emphasizes the importance of global factors for sovereign credit spreads and their comovement (Longstaff et al., 2011; Augustin and Tédongap, 2016). Structural and term-structure models further show how global shocks interact with country-specific fundamentals, such as fiscal capacity and growth dynamics, to generate sovereign default risk and spread variation (Pan and Singleton, 2008; Chernov and Schneider, 2020; Augustin, 2018; Augustin et al., 2022b). Gilchrist et al. (2022) document substantial comovement in

sovereign spreads and persistent responses to global financial risk, particularly changes in the risk-bearing capacity of U.S. intermediaries. Our analysis complements their findings by distinguishing global-market information, country-specific information revealed through trading or incorporated without trading, and noise. Changes in risk compensation can contribute to the persistent information components. Our noise component is therefore distinct from risk premia in general.

We further contribute to the literature by using CDS trading data to examine how trading activity shapes the pricing of sovereign CDS contracts. Existing studies show that CDS markets serve as alternative venues for hedging and speculation (Oehmke and Zawadowski, 2016), and that trading volumes reflect dealer liquidity provision and counterparty risk (Shachar, 2012). Using transaction-level data, Du et al. (2023) find limited effects of counterparty risk on CDS pricing, while Augustin et al. (2022a) document that sovereign CDS positions are largely driven by country-specific characteristics. Building on this work, we show that the responses of CDS spreads to shocks in CDS trading activity can be used to disentangle country-specific trading information from nontrading information embedded in sovereign spreads.

Our analysis also relates to the return decomposition literature. Seminal work by Campbell and Shiller (1988a,b) decomposes asset price fluctuations into cash-flow news and discount-rate news, with the latter reflecting revisions to expected returns. Chen et al. (2013) extends this framework by incorporating market forecasts of future cash flows, and Brogaard et al. (2022) further isolate informational and noise components using the Beveridge–Nelson decomposition (Beveridge and Nelson, 1981). Applying a related decomposition approach, Nozawa (2017) shows that expected returns and expected credit losses contribute comparably to the cross-sectional variance of corporate bond spreads. We adapt the framework of Brogaard et al. (2022) to sovereign CDS markets to quantify the roles of global and country-specific information in sovereign credit risk.

The quantitative analysis builds on the sovereign default literature. The government issues long-duration debt and chooses whether to repay, following Hatchondo and Martinez (2009) and Chatterjee and Eyigungor (2012). Our treatment of global risk in lenders' pricing is related to Bianchi et al. (2018). The information structure connects to Durdu et al. (2013), who study sovereign default with news about future income, and Fourakis (2019), who studies how imperfect information about persistent income components shapes borrowing and sovereign spreads. In our model, public and private news about next year's fundamentals arrives after the government's annual choices and affects secondary-market prices through learning.

Our analysis also connects to work on how market structure shapes sovereign debt prices. Alves Monteiro and Fourakis (2025) study how primary-market auction protocols affect government borrowing incentives and sovereign spreads. In secondary markets, Passadore and Xu (2022) show that search frictions generate liquidity premia that account for a substantial share of sovereign spreads, while Chaumont (2026) and Chaumont et al. (2024) examine the interaction between trading frictions and sovereign default. Particularly close to our information mechanism, Fourakis (2026) studies how costly acquisition of private information about future growth generates adverse selection and affects sovereign bond liquidity and trading volumes. We emphasize how public news and information revealed by trading shape the difference between fundamental and trading spreads.

Outline The rest of the paper is organized as follows. Section 2 presents the variance decomposition model and explains the identification strategy. Section 3 provides the sources and descriptions of the data. Section 4 provides the variance decomposition results. Section 5 presents the sovereign default model and its equilibrium. Section 6 reports the calibration, comparison of alternative models, and spread dynamics before default. Section 7 then concludes.

2 Variance Decomposition Model

We adopt the methodology developed by Brogaard et al. (2022), which employs a general variance decomposition framework to separate variation into distinct information and noise components. We estimate the response of sovereign credit risk to innovations in the global market spread, country-specific trading flows, and the country's own spread. We interpret the global market spread as a common factor proxying for global CDS market conditions, with its fluctuations reflecting changes in global market expectations. Dollar trading volumes in the sovereign credit market are used to identify country-specific trading information.

Consider the spread of a sovereign CDS contract at time t, r_t, as the sum of two components

$$r_t = m_t + s_t, \tag{1}$$

where m_t is the efficient spread and s_t is the pricing error. We assume that the efficient spread follows a random walk, $m_t = m_{t-1} + \mu + w_t$, with drift μ and innovations w_t. The change in spread then follows

$$\Delta r_t = \mu + w_t + \Delta s_t.$$

The innovations in the efficient spread can be decomposed into three parts

$$w_t = \theta_{rm}\varepsilon_{rm,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t}.$$

Thus, the change in spread is a sum of the drift, global information, country-specific trading information, country-specific nontrading information, and noise

$$\begin{aligned}\Delta r_t = &\underbrace{\mu}_{\text{drift}} + \underbrace{\theta_{rm}\varepsilon_{rm,t}}_{\text{global-market info}} + \underbrace{\theta_x\varepsilon_{x,t}}_{\text{trading info}} \\ &+ \underbrace{\theta_r\varepsilon_{r,t}}_{\text{nontrading info}} + \underbrace{\Delta s_t}_{\text{noise}}.\end{aligned} \tag{2}$$

We estimate these components using a structural VAR with four lags to allow for monthly serial correlation and lagged effects

$$\begin{aligned}\Delta r_{m,t} &= a_0 + \sum_{l=1}^{4} a_{1,l}\Delta r_{m,t-l} + \sum_{l=1}^{4} a_{2,l}x_{t-l} + \sum_{l=1}^{4} a_{3,l}\Delta r_{t-l} + \varepsilon_{rm,t}, \\ x_t &= b_0 + \sum_{l=0}^{4} b_{1,l}\Delta r_{m,t-l} + \sum_{l=1}^{4} b_{2,l}x_{t-l} + \sum_{l=1}^{4} b_{3,l}\Delta r_{t-l} + \varepsilon_{x,t}, \\ \Delta r_t &= c_0 + \sum_{l=0}^{4} c_{1,l}\Delta r_{m,t-l} + \sum_{l=0}^{4} c_{2,l}x_{t-l} + \sum_{l=1}^{4} c_{3,l}\Delta r_{t-l} + \varepsilon_{r,t}.\end{aligned} \tag{3}$$

Here $r_{m,t}$ is the global market spread, x_t is signed dollar trading volume in the country's CDS market, and r_t is the country's spread. Both spread variables enter in weekly changes, while trading volume enters in levels. The VAR includes an intercept in each equation and is estimated separately for each country-year pair.

The structural VAR incorporates contemporaneous relationships among the variables. First, global market information can be immediately reflected in spreads. However, given that each sovereign CDS constitutes a small portion of the global market spread, we assume that individual countries' spreads and trades do not affect the overall global market spread within the same week. Trading activity in a sovereign CDS may respond contemporaneously to the global spread and, in turn, influence the domestic spread, though not vice versa. This ordering assigns the persistent effect of trading innovations to trading information. Nontrading information captures the persistent effect of the remaining country-specific spread innovations after accounting for global-market movements and trading. These empirical components differ from the public and private news introduced in the sovereign default model.

Public news can also affect trading, so the two classifications need not coincide. Appendix B provides details on the estimation.

We use the cumulative spread responses through horizon 12 to estimate the coefficients θ_{rm}, θ_x, and θ_r. These responses measure the persistent effect of each innovation on the spread. The global-market innovation captures information common to sovereign CDS markets. The trading innovation captures country-specific trading information, while the remaining spread innovation captures country-specific nontrading information. The estimated noise component is the change in spread remaining after removing the spread-equation intercept and these information components

$$n_t = \Delta r_t - c_r - \theta_{rm}\varepsilon_{rm,t} - \theta_x\varepsilon_{x,t} - \theta_r\varepsilon_{r,t}, \tag{4}$$

where c_r is the intercept in the reduced-form spread equation.

The innovations in the structural model are contemporaneously uncorrelated by construction. Taking the variance of the estimated innovations in the efficient spread therefore gives

$$\sigma_w^2 = \theta_{rm}^2\sigma_{\varepsilon_{rm}}^2 + \theta_x^2\sigma_{\varepsilon_x}^2 + \theta_r^2\sigma_{\varepsilon_r}^2.$$

Writing the variance of the estimated noise component as σ_n^2, the estimated components of variance are expressed as shares of their sum

$$\begin{aligned}
\text{Global-market information share} &= \frac{\theta_{rm}^2\sigma_{\varepsilon_{rm}}^2}{\sigma_w^2 + \sigma_n^2},\\
\text{Trading information share} &= \frac{\theta_x^2\sigma_{\varepsilon_x}^2}{\sigma_w^2 + \sigma_n^2},\\
\text{Nontrading information share} &= \frac{\theta_r^2\sigma_{\varepsilon_r}^2}{\sigma_w^2 + \sigma_n^2},\\
\text{Noise share} &= \frac{\sigma_n^2}{\sigma_w^2 + \sigma_n^2}.
\end{aligned}$$

This normalization allows us to compare the relative importance of the information and noise components across countries and over time. The distinction between global-market and country-specific information is conditional on the global market measure and the identifying assumptions of the VAR.

3 Data

Sovereign spread We acquire daily sovereign CDS spread data with a five-year maturity, denominated in U.S. dollars, from Bloomberg. Using CDS spread data offers several advantages, as argued by Longstaff et al. (2011) and Bai and Wei (2017). First, the sovereign CDS spread serves as a direct proxy for sovereign credit risk. Second, while government bonds are often denominated in local currency, the CDS contracts in our sample are denominated in U.S. dollars. This choice provides a common measure of sovereign credit risk across countries. We take the last available spread in each week and use weekly spread changes in the variance decomposition.

Sovereign CDS trading We collect sovereign CDS trading data from the Depository Trust and Clearing Corporation (DTCC). The DTCC's OTC repository provides aggregated transaction data by reference entity. To extract country-specific information from the transaction data, we focus on records for sovereign reference entities.[1]

Following Pástor and Stambaugh (2003) and Brogaard et al. (2022), we use the product of total weekly gross notional and the sign of the weekly sovereign CDS spread change as a proxy for signed dollar volume, x_t. The DTCC notional is already expressed in dollars. We therefore use the current week's notional, rather than its change or its product with the spread, and express volume in millions of dollars. A positive value corresponds to an increase in the spread, and a negative value to a decrease. This measure provides a proxy for trading direction when signed transactions are not observed.

Global market spread We construct a measure of the global market spread by taking the net-notional-outstanding-weighted average of sovereign CDS spreads in each week. Figure 1 shows the global market spread from 2012 to 2024. The index exhibits sharp spikes in early 2012 and 2020, reflecting periods of financial stress. It also varies substantially during 2022 and 2023. These movements capture changes in credit market conditions shared across countries. In Appendix C, we consider the first principal component of standardized spread changes and the VIX as alternative measures of global market conditions.

Sample selection To ensure sufficient observations for the variance decomposition estimated at the country-year level, we exclude country-year pairs with fewer than 20 valid weekly observations. The sample covers January 2012 to October 2024. After the estimation checks described in Appendix B, the final sample contains 527 country-year estimates across

[1]Public transaction data are available from DTCC's OTC repository. Appendix A.1 provides further details on the data.

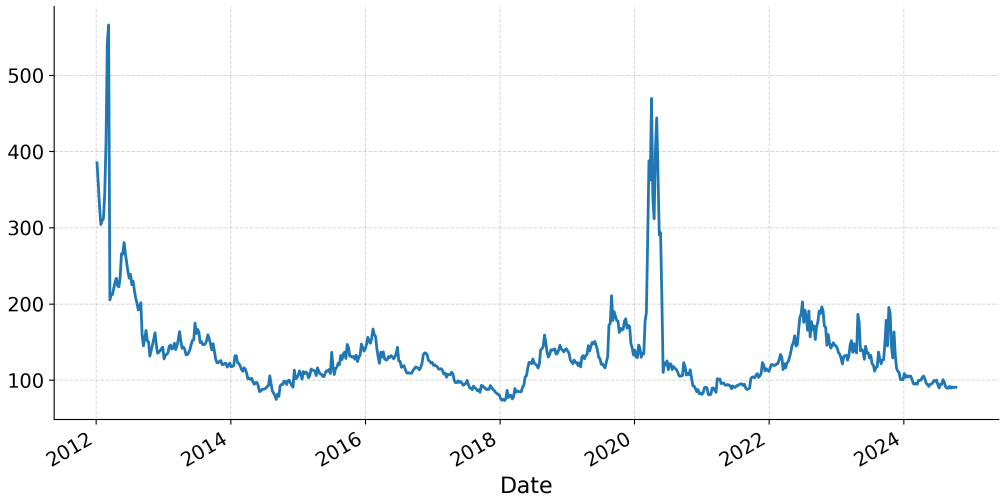


Figure 1. Global market spread

Note. This figure plots the weekly global market spread from 2012 to 2024. The spread is the net-notional-outstanding-weighted average of sovereign CDS spreads.

57 countries.[2] We classify countries as advanced or emerging and developing economies using the IMF's October 2024 classification. The sample includes 218 country-year estimates for advanced economies and 309 for emerging and developing economies.

4 Decomposition of Sovereign Credit Risk

We conduct the variance decomposition for every country-year pair. The model allows the relationship between spreads, trading, and the global market spread to differ across countries and years. We use impulse response analysis to distinguish persistent innovations in spreads from temporary movements. Appendix B provides further details on the estimation.

4.1 Share of Information and Noise Components

Table 1 presents the estimated variance shares from the baseline model for the main sample covering January 2012 to October 2024. As shown in the first column, country-specific information, comprising both trading and nontrading components, has a mean share of 41%, compared with 20% for global-market information. Within the country-specific component, nontrading information accounts for 25% and trading information for 16%. Noise has a sizable share of 39%.

[2]Abu Dhabi and Dubai enter as separate CDS series. Both follow the United Arab Emirates' economy classification.

Table 1. Estimated Shares of Information and Noise Components

	All	Advanced	Emerging	U.S. equity
Global-market info	20	18	21	8
Country-specific info	41	45	39	61
Trading	16	17	15	24
Nontrading	25	28	24	37
Noise	39	37	40	31
Country-year estimates	527	218	309	—

Note. This table reports mean estimated information and noise shares for January 2012 to October 2024. Shares are calculated for each country-year pair and expressed as percentages. U.S. equity estimates are from Brogaard et al. (2022). Shares are rounded to whole percentages and sum to 100.

These results differ from those reported for U.S. equity markets in Brogaard et al. (2022), shown in the final column of Table 1. Relative to U.S. equities, sovereign CDS markets exhibit a larger share of global-market information and a smaller share of country-specific information, primarily due to a lower contribution from trading information. Trading information accounts for 16% of sovereign CDS spread variation, compared with 24% for U.S. equities. Nontrading information is also less important in sovereign CDS markets, while the noise share is larger.

We compare the shares of information and noise components between advanced and emerging economies, as reported in the second and third columns of Table 1. Emerging economies exhibit a higher share of global-market information, whereas advanced economies display greater shares of country-specific information, both trading and nontrading. Noise accounts for a larger share in emerging economies. These differences indicate that sovereign credit risk in emerging markets is more closely associated with common market conditions, while country-specific information plays a larger role in advanced economies.

These findings indicate that country-specific information accounts for a larger share than global-market information, while noise remains sizable. They complement the evidence that global factors are important for the comovement of sovereign spreads (Longstaff et al., 2011; Gilchrist et al., 2022). We measure the contributions of information and noise to changes in individual countries' spreads, rather than the share of movements common across countries. A global factor can generate strong comovement without accounting for most of each country's spread variation. Moreover, the global-market share is greater than in U.S. equity markets and more pronounced in emerging economies. The qualitative importance of country-specific information and noise is also present when we use a principal-component-based global factor or the VIX, as reported in Appendix C.

4.2 Time series of information and noise shares

Figure 2 presents the variance decomposition of spreads over time from 2012 to 2024. Country-specific nontrading information generally contributes more than trading information, although the relative importance of both components varies over time. The global-market information share is particularly high in 2020 and again in 2022 and 2023. These increases coincide with periods of heightened global uncertainty. By contrast, its contribution is smaller in 2012 and 2019. Noise remains an important component throughout the sample.

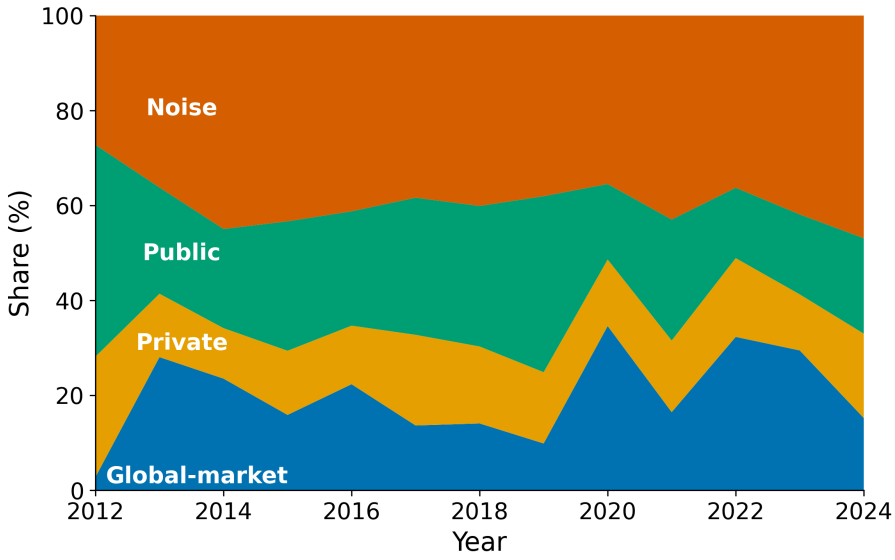
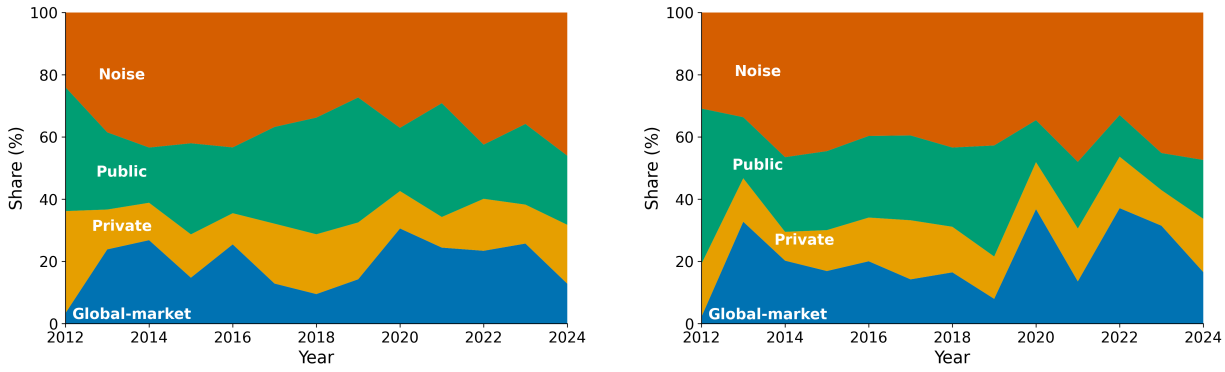


Figure 2. Information and noise shares over time for all countries

Note. This figure plots mean information and noise shares for all countries from 2012 to 2024. Each year gives equal weight to the available country-year estimates.

We compare the decomposition of spreads for advanced and emerging markets in Figure 3. In both groups, the global-market component rises in 2020. Emerging markets also exhibit a larger global share in 2022 and 2023. The nontrading information component fluctuates substantially across years and is particularly large in 2012 and 2019. Trading information remains an important component in both groups, but its share also varies over time. The noise share is generally larger in emerging markets over the full sample, although this difference is not present in every year.

The figures report averages across the country-year estimates available in each year. The number and composition of countries can therefore change over time. The time-series patterns describe how the information composition of the sample evolves, while the comparison between advanced and emerging economies highlights differences in the importance of global and country-specific information.



(a) Advanced economies

(b) Emerging economies

Figure 3. Time series comparisons of information and noise shares

Note. This figure plots mean information and noise shares from 2012 to 2024 for advanced economies in the left panel and emerging economies in the right panel. Each year gives equal weight to the available country-year estimates within each group.

5 A Sovereign Default Model with Information

We develop a sovereign default model in which information about future repayment capacity reaches financial markets between the government's borrowing decisions. The annual economy determines debt, default, and the fundamental value of government obligations. A weekly secondary market determines transaction prices as dealers learn from public news and informed trading. This distinction allows market spreads to respond to news before the underlying annual fundamentals change.

The sovereign block follows the sovereign default literature with long-term debt (Hatchondo and Martinez, 2009; Chatterjee and Eyigungor, 2012) and global lender risk pricing as in Bianchi et al. (2018). We introduce public and private news about next year's fundamentals, related to Durdu et al. (2013), and learning through secondary trading. News arrives after annual government choices.

5.1 Environment and timing

Time is annual in the sovereign economy. A small open economy receives stochastic output y and faces exogenous fiscal expenditure g. The government values household consumption according to $u(c) = c^{1-\gamma}/(1-\gamma)$ and discounts future utility by β. The government cannot commit to repay its obligations and chooses whether to default after observing the current state. It borrows from competitive international lenders through long-term bonds. The risk-free rate is r. Output and fiscal expenditure follow independent Markov processes, whose

continuous counterparts are

$$\log y' = \rho_y \log y + \varepsilon'_y, \qquad \log(1+g') = \rho_g \log(1+g) + \varepsilon'_g, \tag{5}$$

with independent, mean-zero Gaussian innovations of variances σ_y^2 and σ_g^2. Fiscal expenditures are expressed in normalized units, as described in Appendix D.

International lenders price output risk using a public global state M. Denote $X = (y, g, M)$ for the current aggregate state and B for outstanding government debt. The global state follows a finite Markov chain at weekly frequency. Its annual transition matrix is the fifty-second power of the weekly matrix, so the sovereign and trading blocks use a common global-risk process.

At the beginning of each year, the government observes X and chooses repayment or default. Conditional on repayment, it selects next-period debt B'. Primary issuance takes place at the fundamental price $q(B', X)$. Current output, fiscal fundamentals, the global state, and the debt choice are public. During the following 52 weeks, public and private news provide information about next year's output and fiscal fundamentals. Dealers observe public news and aggregate order flow, while informed traders additionally receive private news. Current country fundamentals remain fixed within the year, and the public global state can change weekly. The next annual fundamentals are then realized and the government makes its next decision. Secondary prices do not determine issuance proceeds or enter the sovereign policy functions. Thus the government and financial markets observe the same current country fundamentals when debt is issued. The information advantage of informed traders concerns future output and fiscal expenditures.

Figure 4 summarizes the timing of the model. The government's annual default and borrowing decisions precede the weekly secondary-market trading phase. During each trading round, news arrives, investors submit orders, and the dealer updates beliefs and quotes a trading price after observing order flow.

5.2 The government's problem

Debt has geometric duration. A fraction δ matures each year, and each surviving unit pays coupon z. The repayment budget constraint is

$$c + [\delta + (1-\delta)z]\, B = y - g + q(B', X)\,[B' - (1-\delta)B]\,. \tag{6}$$

The government uses output and issuance proceeds $B' - (1-\delta)B$ to finance consumption, fiscal expenditure, and payments on outstanding debt. Since part of the bond remains

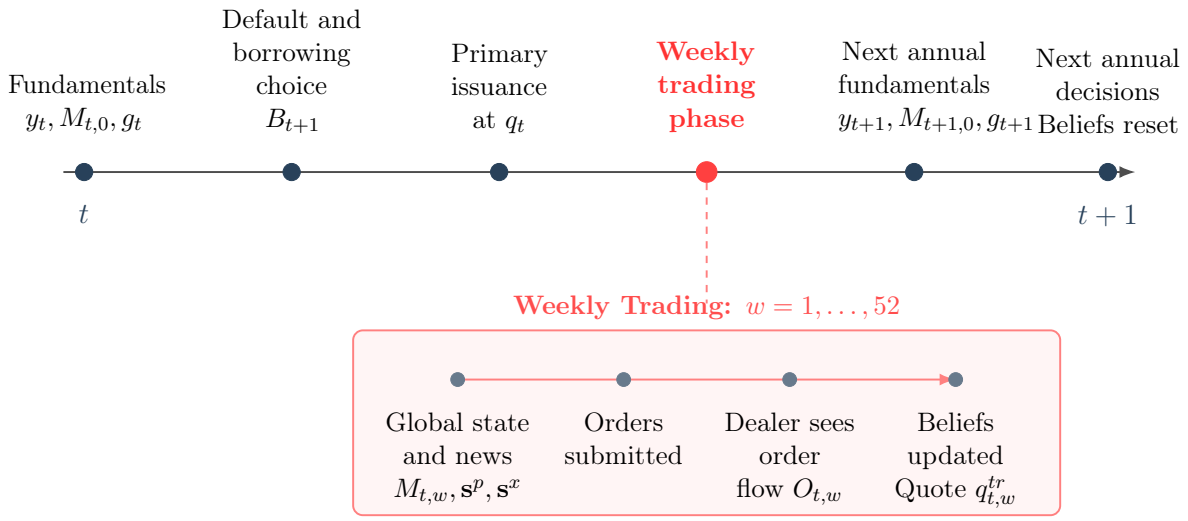


Figure 4. Model timeline

Note: This figure plots the timing of the model. The upper timeline shows the annual sequence of government decisions and market activity. The lower timeline details each weekly round of trading.

outstanding after the current payment, its value also depends on future borrowing and default decisions.

Let V^R and V^D denote the values of repayment and exclusion. The value of repayment is

$$V^R(B, X) = \max_{B'} \{u(c) + \beta \mathbb{E}[V(B', X') \mid X]\}. \tag{7}$$

Default eliminates outstanding debt and prevents borrowing. Output losses are $\phi(y) = \max\{0, d_0 y + d_1 y^2\}$. Following an excluded year, the government regains market access with probability ψ and zero debt. The default value satisfies

$$V^D(X) = u(y - g - \phi(y)) + \beta \mathbb{E}\left[\psi V(0, X') + (1 - \psi) V^D(X') \mid X\right]. \tag{8}$$

The government's value function is

$$V(B, X) = \max\left\{V^R(B, X), V^D(X)\right\} \tag{9}$$

The government repays when the value of continued access to borrowing exceeds the value of default. Repayment capacity and willingness to repay jointly determine the price schedule faced at issuance.

5.3 Fundamental bond prices

Lenders use the following stochastic discount factor

$$m(y, y', M) = \exp\left\{-r - \kappa_M M \varepsilon'_y - \tfrac{1}{2}(\kappa_M M)^2 \sigma_y^2\right\}. \tag{10}$$

The global state governs the price lenders place on output risk. A higher value of M increases the relative valuation weight on low-output outcomes. Consequently, changes in the price of risk can move bond prices even when current country fundamentals and debt are unchanged.

Let $d(B', X')$ be next year's default probability and let $\bar{q}(B', X')$ be the expected price of the surviving claim after the government's next debt choice, conditional on repayment. Competitive primary-market pricing requires

$$q(B', X) = \mathbb{E}\left[m(y, y', M)\big(1 - d(B', X')\big)\left\{\delta + (1-\delta)\left[z + \bar{q}(B', X')\right]\right\} \mid X\right]. \tag{11}$$

The continuation price averages over the government's borrowing policy.

We refer to the spread implied by this price at the beginning of the year as the *annual fundamental spread*. It incorporates current fundamentals, future default risk, and lenders' risk compensation. It integrates over next year's uncertain outcomes rather than conditioning on their eventual realizations. Revaluing the same country state and debt at the current weekly global state gives the *weekly fundamental spread*. This second benchmark changes within the year as global risk is repriced, even before additional country-specific information is revealed through public news or trading.

For a bond price q, the model's annualized spread measure is

$$s(q) = \frac{\delta + (1-\delta)z}{q} - \delta - r. \tag{12}$$

We apply the same transformation to fundamental and trading prices. The empirical CDS decomposition provides credit-risk moments for the model; a separate protection contract is not priced.

5.4 Information and weekly trading

News concerns the next annual output innovation and the next fiscal state, $\log(1 + g')$. Each news item equals its respective future fundamental plus independent Gaussian noise and is either public or private. News does not reveal the future state directly. Their distributions and the transition laws are common knowledge. Both types of news arrive every week in the baseline.

Dealers start each year with the transition probabilities implied by observed current output and fiscal conditions. They update their beliefs using public news and the information conveyed by aggregate order flow. The baseline retains all available history since that year's issuance. History resets when the next annual fundamentals are realized. Issuance does not provide additional information about future innovations once current fundamentals are observed.

Information can therefore affect secondary prices without a contemporaneous change in output, fiscal expenditure, or government borrowing. News about next year's fundamentals changes the probabilities assigned to future repayment and continuation values. These revisions are incorporated into the dealer's quote as news arrives and trading reveals private information. They do not constitute an additional shock to current resources or alter the government's decision within the year.

Write v for the value of the bond conditional on next year's output and fiscal state, with future global risk and continuation policies integrated out. At issuance, before news and order-flow learning, its prior risk-adjusted expectation recovers the fundamental price. Both informed traders and dealers use the same risk-adjusted valuation measure, denoted Q. News changes their probabilities over future fundamentals. Appendix D defines the valuation normalization and its connection to the annual pricing equation.

Let $\mathcal{F}^x$ collect public information and the informed trader's private news. At an interior position, price-taking mean–variance demand satisfies

$$\chi = \frac{\mathbb{E}^Q[v \mid \mathcal{F}^x] - \mathbb{E}_U[p(\chi + U)]}{\rho^\chi \operatorname{Var}^Q(v \mid \mathcal{F}^x) + \kappa}, \qquad U \sim \mathcal{N}(0, \sigma_U^2), \tag{13}$$

subject to a position bound specified in the appendix. Here ρ^χ governs exposure to uncertain bond value, κ is a quadratic trading cost, and the expected execution quote averages over the current liquidity order U. The trader takes the expected execution quote as given, and consistency with the dealer's rule is imposed in equilibrium.

Total order flow is $O = \chi + U$. The competitive dealer observes O, but cannot distinguish the informed and liquidity orders. If $\mathcal{F}^D$ collects public information, including the current order flow, the quote is

$$q^{tr} = p(O) = \mathbb{E}^Q[v \mid \mathcal{F}^D]. \tag{14}$$

The dealer has no inventory cost. Liquidity orders affect quotes because they alter the inference drawn from observed trading, while trader risk aversion and trading costs affect how much private information is revealed through orders. Public news affects both the trader's valuation and the dealer's beliefs directly. Private news affects the dealer's valuation through

the orders submitted by informed traders. Since liquidity orders are also present, the dealer cannot infer private news perfectly from a single observation of order flow.

Equilibrium. A recursive equilibrium consists of government value and policy functions, a fundamental price schedule, and weekly trading strategies, pricing rules, and beliefs such that

- Government policies solve the annual repayment, borrowing, and default problems[3]
- In weekly market, informed demand and the dealer's quote jointly satisfy equations (13) and (14), and beliefs obey Bayes' rule under the news and order-flow distributions generated by those strategies. Aggregate orders are absorbed by
- Annual resource constraint (6) is satisfied
- Fundamental prices satisfy equation (11)

We compute the annual equilibrium first and then solve the weekly trading equilibria along its simulated states, preserving this timing and information structure.

6 Quantitative Analysis

We calibrate the model to match the debt and spread moments and the empirical information shares. We use the resulting economy to study the roles of global risk and news and the behavior of spreads before default.

6.1 Calibration

Table 2 reports the parameterization. We first calibrate externally risk aversion, debt structure, and the processes for output, fiscal expenditure, and global risk. The five-state weekly global process implies the annual transition matrix used in the sovereign problem. The risk-price loading remains fixed at one. We then calibrate β, d_0, d_1 internally to match debt and fundamental-spread moments, and choose four standard deviations of the noise in public and private news and liquidity-order volatility to match the empirical VAR shares. Market participants receive news about next year's fundamentals weekly, and beliefs retain the full history since annual issuance.

Following Chatterjee and Eyigungor (2012), we calibrate the sovereign block parameters using Argentine debt and spread moments. We target a debt-to-output ratio of 20 percent, an average spread of 8.15 percent, and spread volatility of 4.43 percentage points. Table 3

[3]Appendix D provides details for the choice-shock specification.

Table 2. Model parameters

Parameter	Value	Interpretation
Fixed annual processes, preferences, and debt structure		
(ρ_y, σ_y)	$(0.8094, 0.05)$	Log-output persistence and innovation SD
(ρ_g, σ_g)	$(0.70, 0.029)$	Log fiscal-expenditure persistence and innovation SD
$\mathcal{M}$	$\{0, 4.41, 7.43, 12.78, 22\}$	Weekly global-risk states
κ_M	1.00	Lender risk-price loading
(γ, r)	$(2.00, 0.04)$	Government risk aversion and risk-free rate
(z, δ)	$(0.12551, 0.20)$	Coupon and bond decay rate
ψ	0.1453	Annual re-entry probability
(ρ^χ, κ)	$(2.00, 2.00)$	Trader risk aversion and quadratic trading cost
Parameters chosen against annual moments		
β	0.78387	Government discount factor
d_0	-0.31325	Linear coefficient of default output cost
d_1	0.40049	Quadratic coefficient of default output cost
Parameters chosen against information shares		
$(\sigma_{p,g}, \sigma_{x,g})$	$(0.07792, 0.15047)$	Noise SDs in public/private news for next year's $\log(1+g')$
$(\sigma_{p,y}, \sigma_{x,y})$	$(0.75162, 0.59368)$	Noise SDs in public/private news for next year's log-output innovation
σ_U	4.5829×10^{-4}	Liquidity-order SD

Note. This table presents the baseline model parameters. SD denotes standard deviation. Public and private news arrives weekly, and beliefs retain the history since annual issuance. Parameter values are rounded.

reports the targeted moments and their model counterparts. The model closely matches the debt and fundamental-spread targets. We also choose the news precisions and liquidity-order volatility to match the empirical information shares.

The model uses the empirical VAR specification and component formulas. Its global input is the change in the public risk state, and its trading input is actual order flow. The empirical counterparts are global CDS spread changes and signed gross notional. The model closely matches the nontrading-information share but generates somewhat larger global-market and trading-information shares and less noise. Weekly learning affects secondary valuations after government choices, without feeding back into that year's issuance or default decision.

6.2 The roles of global risk and news

The baseline model combines global risk with public and private news about next year's fundamentals. To understand how these features contribute to the information shares, we compare it with three alternative models, each removing one of these sources of risk or

Table 3. Calibration targets and model outcomes

Moment	Target	Model
Panel A. Sovereign calibration		
Mean debt/output (%)	20.00	19.42
Mean spread (%)	8.15	8.25
SD of spread (pp)	4.43	4.52
Panel B. Weekly trading-spread outcomes		
Mean trading spread (%)	—	8.63
SD of weekly trading-spread levels (pp)	—	7.98
Panel C. VAR component shares (%)		
Global-market information	20	22
Trading information	16	18
Nontrading information	25	25
Noise	39	35

Note. This table presents the calibration targets and model outcomes. The debt target is rounded, and spread targets follow Chatterjee and Eyigungor (2012). Model results use 3,000 simulated years after a 500-year burn-in, with two weekly information histories. Spreads are annualized. SD and pp denote standard deviation and percentage points. VAR shares are rounded to sum to 100.

information. Table 4 reports the resulting VAR decompositions. These comparisons help explain why information is incorporated into spreads through trading or without trading, and how global risk affects the relative importance of country-specific information.

Global risk changes lenders' valuation of sovereign payoffs and the government's borrowing and default incentives. In the model without global risk, we solve the sovereign economy again, allowing debt and default decisions to adjust. This alternative model therefore captures changes in both the annual sovereign economy and secondary-market valuations.

The other two alternative models examine how dealers learn about future repayment prospects. The model without public news considers how information reaches prices when dealers learn about next year's fundamentals through orders rather than direct public news. The model without private news assesses the role of informed traders in revealing these fundamentals. Since weekly news arrives after the government's annual choices, both models retain the baseline sovereign policies and macroeconomic path. Their comparison with the baseline connects the availability of news to the trading and nontrading information measured by the VAR.

In the model without global risk, country-specific information accounts for 74 percent, compared with 43 percent in the baseline. Noise accounts for the remaining 26 percent, compared with 35 percent in the baseline. These shares describe the composition of spread

Table 4. Global risk, news, and the VAR decomposition

Component (%)	Data	Baseline	No global risk	No public news	No private news
Global-market information	20	22	0	30	31
Country-specific information	41	43	74	35	34
Trading	16	18	31	28	5
Nontrading	25	25	43	7	29
Noise	39	35	26	35	35

Note. This table reports mean information and noise shares for the data, baseline model, and alternative models. Shares are expressed as percentages and rounded to sum to 100. Country-specific information is the sum of trading and nontrading information.

variation after allowing sovereign policies and secondary valuations to adjust to the absence of global risk.

Without public news, the nontrading-information share falls from 25 to 7 percent, while the trading-information share rises from 18 to 28 percent. Public news provides information that dealers can incorporate directly into quotes. When public news is absent, order flow remains a source of dealer learning, and the VAR assigns a larger relative share to trading information.

Without private news, the trading-information share falls from 18 to 5 percent, while the nontrading-information share rises from 25 to 29 percent. Private news gives informed traders information about next year's repayment prospects that dealers learn through orders. Removing private news limits the information that informed orders can reveal. The estimated shares shift away from trading information and toward information incorporated without trading.

The two alternative models without news connect public and private news in the model to the channels measured by the VAR. Public news is particularly important for nontrading information, while private news is particularly important for trading information. The mapping need not be one-to-one, since public news can also affect informed orders and the VAR classifies information by its relation to trading. Removing either type of news increases the relative global share despite an unchanged global process. These shares describe the relative importance of the components. A positive estimated trading-information share can remain in finite samples without private news.

6.3 Spread dynamics before default

Figure 5 compares annual fundamental and trading spreads around 103 default entries. At the final predefault quote, they average 14.08 and 27.36 percent, respectively. The trading–

annual-fundamental gap increases from 0.65 percentage points 52 weeks earlier to 13.28. Adverse news and informed orders reveal deteriorating future repayment prospects before output and fiscal expenditure enter the next annual state. This anticipatory channel is related to Durdu et al. (2013), although our government does not revise its annual choices after weekly news arrives. The fundamental benchmark integrates over future states, and it does not observe the realized future shocks.

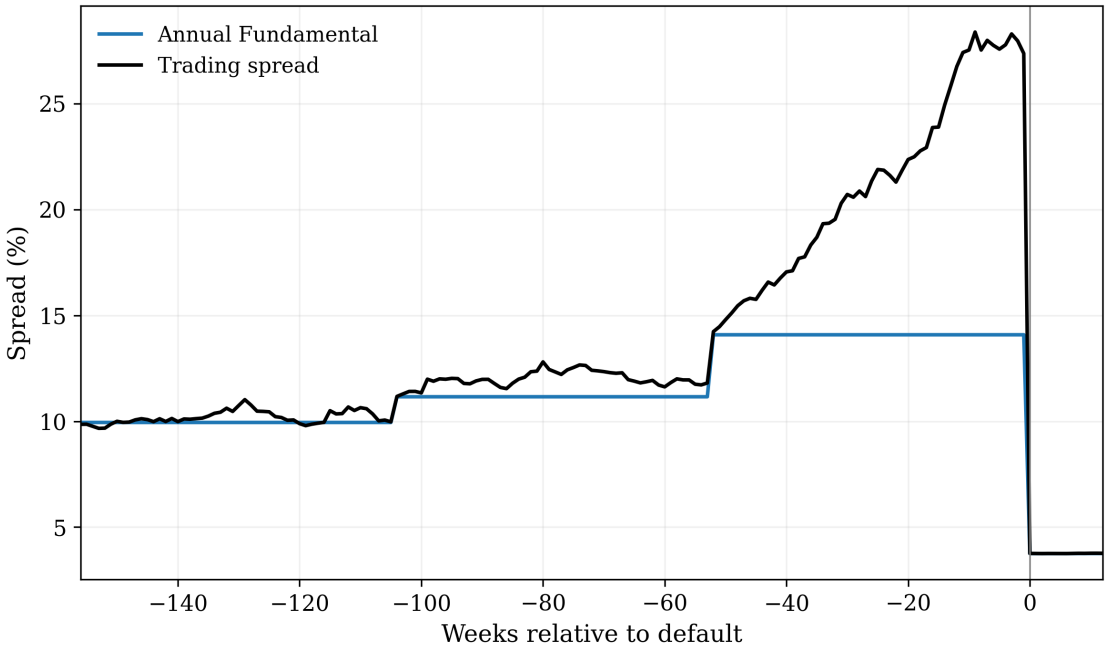


Figure 5. Trading and fundamental spreads around default

Note. This figure plots mean annual fundamental and trading spreads across 103 default episodes, in percent. Week 0 follows the debt reset. Postdefault quotes are hypothetical.

Two features can amplify the response to adverse news. First, near the repayment–default boundary, a small belief revision can shift probability toward states in which repayment is unlikely or continuation values are low. The same news item can therefore produce a larger valuation change when repayment is precarious. Second, the price-to-spread transformation in equation (12) is decreasing and convex. An additional price decline produces a larger spread increase when the price is already low. The event averages do not separately quantify these amplifiers. They condition on subsequent default, so adverse news need not imply an unconditional upward bias in trading spreads.

Figure 6 accounts for the 12.63 percentage-point widening of the gap. The lender-risk term updates the annual valuation to the weekly global state. The weekly fundamental spread reaches 16.26 percent at the final predefault quote. Public news and information revealed through orders further change the valuation, while liquidity captures the current

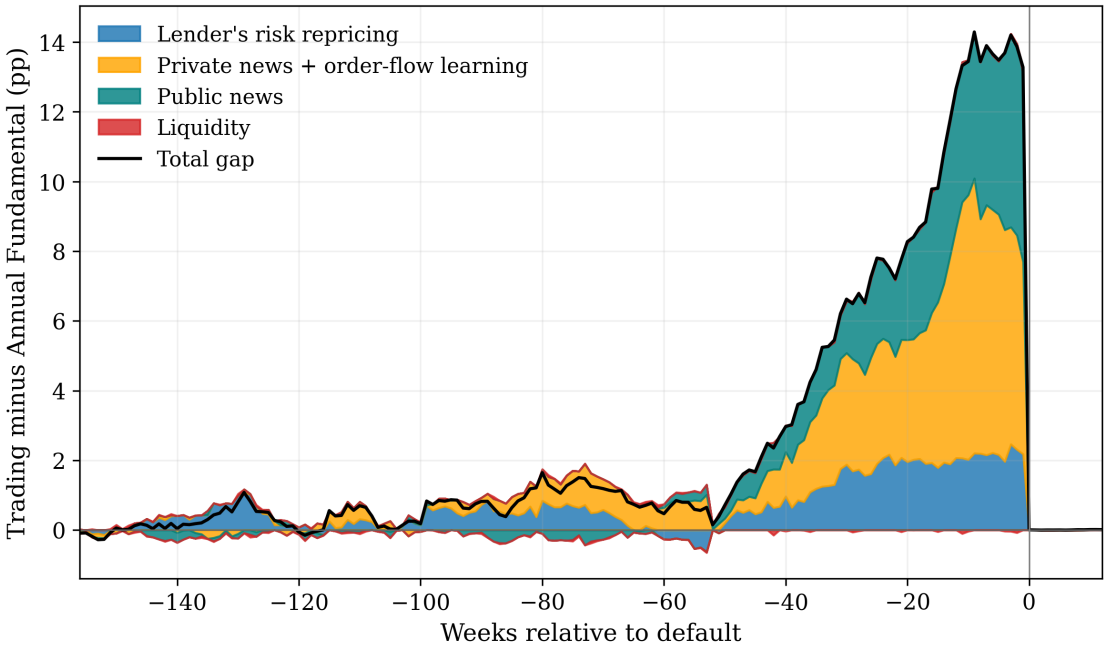


Figure 6. Trading–annual-fundamental spread gap around default

Note. This figure depicts the mean trading–annual-fundamental spread gap and its four valuation components across 103 default episodes, in percentage points. The components sum to the observed gap.

order realization. Public news contributes 5.11 percentage points to the widening, private news and order-flow learning 4.51, lender's risk repricing 2.80, and current liquidity 0.21. Country-specific learning therefore accounts for most of the widening. Annual fundamentals themselves rise 2.93 percentage points, bringing the trading-spread increase to 15.56. The allocation is sequential. Public news enters first, and the term for private news and order-flow learning retains past learning. Liquidity here differs from a search premium such as in Chaumont (2026). Appendix D gives the construction. The exercise measures advance information along default paths rather than a unique causal or variance decomposition.

7 Conclusion

This paper examines sovereign CDS spreads from the perspective of information sources. Using the variance decomposition framework of Brogaard et al. (2022), we decompose sovereign credit risk into global-market information, country-specific trading and nontrading information, and noise. Country-specific information accounts for a larger share than global-market information, while noise is sizable. Within country-specific information, nontrading information plays a larger role than trading information. These findings complement the evidence that global

financial conditions are important for sovereign spreads and their comovement. Global shocks can generate common movements across countries even when country-specific information and temporary movements explain a larger share of variation within each country.

The importance of global information is more pronounced in emerging market and developing economies than in advanced economies. However, even in these economies, country-specific nontrading information exceeds trading information in explaining spread fluctuations. These results highlight the importance of distinguishing global comovements from the information incorporated into individual countries' sovereign spreads.

We develop a sovereign default model to study how information is incorporated into sovereign debt prices between annual borrowing and default decisions. Market participants receive public and private news about next year's output and fiscal expenditure, while dealers learn from public news and order flow. The calibrated model produces information and noise shares close to their empirical counterparts. The comparison of alternative models connects the model's news to the empirical information components. In particular, removing public news reduces the nontrading information share and increases the relative importance of trading information, while removing private news substantially reduces the trading information share. Removing global risk increases the relative contribution of country-specific information.

The model also generates a widening gap between trading and annual fundamental spreads as default approaches. Public news and learning from private news and order flow account for most of this widening. Near the default boundary, revisions to expected fundamentals have large effects on repayment prospects, while the nonlinear conversion from prices to spreads amplifies the response of spreads. These results show how market information can raise trading spreads ahead of the annual fundamental benchmark.

This paper contributes to the literature on sovereign credit risk by complementing the analysis of comovement with an analysis of the information sources underlying individual spread movements. By decomposing country-specific information into trading and nontrading components using CDS trading data, we provide new insights into the informational structure of sovereign credit markets. The model complements this evidence by linking market learning to sovereign repayment prospects. Future research could allow governments to respond to information arriving within the year or examine how these information components vary along the term structure of sovereign debt.

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A Data definitions

A.1 DTCC data

We collect sovereign CDS trading data from the Depository Trust and Clearing Corporation (DTCC) Trade Information Warehouse. The publicly available data provide weekly trading activity and notional amounts outstanding for individual reference countries. Our analysis uses Weekly Activity Gross Notional to measure trading and Net Notional Outstanding to construct the global market spread.

Weekly gross notional reflects the dollar amount of trading across the entire maturity spectrum for each reference country. It does not depict the amount traded at each specific maturity or the amount traded at the five-year point. This distinction matters because trading activity can be distributed across many maturity dates, while our spread measure refers to a five-year CDS contract. The weekly activity measure is already expressed in U.S. dollars. We multiply it by the sign of the contemporaneous spread change and divide by one million to obtain signed dollar volume. We use its current weekly level in the VAR.

Net notional outstanding measures the outstanding amount used to weight each country's spread in the global index. It is distinct from gross weekly trading activity. For each week, the global market spread is the sum of country spreads multiplied by their net notional amounts, divided by the sum of those amounts.

A.2 Other data definitions and sources

We obtain five-year, U.S.-dollar sovereign CDS spreads from Bloomberg. We convert daily quotes to weekly observations by retaining the last available daily observation in each week ending Friday. Spread changes are calculated between consecutive observed calendar weeks.

We match these observations with the DTCC weekly data. Advanced and emerging and developing economies follow the IMF's October 2024 classification, which is held fixed throughout the sample.

We use two alternative measures of global market conditions. The first principal component is constructed from standardized weekly sovereign CDS spread changes. Each country's observed changes are standardized by their sample mean and standard deviation. Missing observations are completed using the fitted first component while keeping observed values unchanged. The resulting component enters the VAR directly. The second measure is the VIX from the CBOE's daily history. We retain the last available closing value in each week ending Friday and use its change between consecutive weeks. We do not fill changes across missing weeks.

B Estimation of the Structural VAR

We estimate the reduced-form counterpart of equation (3) separately for each country-year. Each equation includes an intercept and four lags of the global market spread change, signed dollar volume, and the country's spread change. It is possible to rewrite the reduced-form residuals as linear functions of the structural-model residuals

$$\begin{aligned} e_{rm,t} &= \varepsilon_{rm,t}, \\ e_{x,t} &= \varepsilon_{x,t} + b_{1,0}\varepsilon_{rm,t} = b_{1,0}e_{rm,t} + \varepsilon_{x,t}, \\ e_{r,t} &= \varepsilon_{r,t} + (c_{1,0} + c_{2,0}b_{1,0})\varepsilon_{rm,t} + c_{2,0}\varepsilon_{x,t} \\ &= c_{1,0}e_{rm,t} + c_{2,0}e_{x,t} + \varepsilon_{r,t}. \end{aligned} \tag{B.1}$$

The structural innovations are uncorrelated with one another. Specifically, we estimate $b_{1,0}$ by regressing $e_{x,t}$ on $e_{rm,t}$, and estimate $c_{1,0}$ and $c_{2,0}$ by regressing $e_{r,t}$ on $e_{rm,t}$ and $e_{x,t}$. These residual regressions do not include additional intercepts.

From the estimated parameters and the variances of the reduced-form residuals, we obtain the variances of the structural shocks by taking the variance of equation (B.1) and rearranging

$$\begin{aligned} \sigma^2_{\varepsilon_{rm}} &= \sigma^2_{e_{rm}}, \\ \sigma^2_{\varepsilon_x} &= \sigma^2_{e_x} - b^2_{1,0}\sigma^2_{e_{rm}}, \\ \sigma^2_{\varepsilon_r} &= \sigma^2_{e_r} - (c^2_{1,0} + 2c_{1,0}c_{2,0}b_{1,0})\sigma^2_{e_{rm}} - c^2_{2,0}\sigma^2_{e_x}. \end{aligned} \tag{B.2}$$

We estimate the cumulative spread responses of the structural model by computing the equivalent reduced-form shocks and feeding them through the reduced-form model. A unit

global-market shock, a unit trading shock, and a unit country-specific spread shock have the respective reduced-form equivalents

$$\begin{pmatrix} 1 \\ b_{1,0} \\ c_{1,0} + c_{2,0}b_{1,0} \end{pmatrix}, \qquad \begin{pmatrix} 0 \\ 1 \\ c_{2,0} \end{pmatrix}, \qquad \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix}. \tag{B.3}$$

For each shock, we sum the response of the country's spread change from impact through horizon 12, including both endpoints. Denote these cumulative responses by θ_{rm}, θ_x, and θ_r. Multiplying each response by its structural innovation gives the global-market, country-specific trading, and country-specific nontrading information contributions, respectively.

The estimation follows five steps

(i) Estimate the reduced-form counterpart of equation (3), saving the residuals and their variance–covariance matrix.

(ii) Estimate $b_{1,0}$, $c_{1,0}$, and $c_{2,0}$ from the residual regressions in equation (B.1).

(iii) Estimate the structural innovation variances using equation (B.2).

(iv) Estimate the cumulative spread responses to the unit shocks in equation (B.3) over horizons zero through 12.

(v) Combine the structural innovation variances with the cumulative responses to obtain the information variances. Calculate noise using equation (4) and express all four components as shares of their total variance.

For clarity, if T observations remain after including lags and K regressors enter each equation, the estimated information variance for shock j is

$$V_j = \theta_j^2 \frac{\sum_t \varepsilon_{j,t}^2}{T - K}, \qquad j \in \{rm, x, r\}. \tag{B.4}$$

With four lags and an intercept, $K = 13$. The noise variance is the sample variance of the remaining spread changes

$$V_n = \frac{\sum_t (n_t - \bar{n})^2}{T - 1}, \qquad \text{Share}_j = 100 \frac{V_j}{V_{rm} + V_x + V_r + V_n}, \tag{B.5}$$

where n_t is defined in equation (4), and the share formula also applies to noise. Information and noise need not have zero covariance. Consequently, the denominator is the sum of the

four estimated component variances and need not equal the sample variance of observed spread changes.

We retain country-year estimates with stable dynamics and a full-rank regression and give each retained estimate equal weight in the reported means. The baseline retains gaps between valid weekly observations, so its response horizon counts observed rows. A separate check restricts the sample to consecutive weeks. The simulated decomposition uses the same lag length, intercept, recursive ordering, and cumulative response horizon, with the global state and order flow replacing the empirical global index and signed-volume proxy. Complete simulated annual windows contain 52 spread changes. When the global state is constant, we estimate the remaining two-variable system and assign a zero global share.

Table B.1 reports the mean coefficient estimates for the baseline reduced-form VAR. Each coefficient is averaged across the selected country-year estimates.

Table B.1. VAR coefficient estimates

Dependent variable	Independent variable	$l = 1$	$l = 2$	$l = 3$	$l = 4$
A. Global-market spread equation					
$\Delta r_{m,t}$	$\Delta r_{m,t-l}$	-0.115	-0.122	-0.097	-0.088
	x_{t-l}	0.003	0.006	0.002	-0.001
	Δr_{t-l}	-0.118	0.267	-0.122	-0.113
B. Signed dollar volume equation					
x_t	$\Delta r_{m,t-l}$	-3.868	2.494	-4.909	-1.002
	x_{t-l}	-0.024	-0.057	-0.029	-0.059
	Δr_{t-l}	-0.485	-4.281	-4.947	-5.051
C. Country spread equation					
Δr_t	$\Delta r_{m,t-l}$	0.197	-0.115	0.101	-0.110
	x_{t-l}	-0.028	0.073	0.051	3.61×10^{-4}
	Δr_{t-l}	-0.082	-0.093	-0.045	-0.079

Note. This table reports mean VAR coefficients across the 527 country-year estimates. Spreads enter in weekly changes, and signed trading volume is measured in millions of U.S. dollars.

C Alternative measures of global market conditions

In this section, we assess the robustness of the variance decomposition by employing alternative measures to the global market spread. First, following Longstaff et al. (2011), we construct a global factor using principal component analysis applied to standardized weekly changes in sovereign CDS spreads and use the first principal component as an alternative global market index. Second, we use changes in the VIX as an alternative measure of global market

conditions. Table C.1 reports and compares the results from the baseline specification and these alternative approaches. To make the comparison on the same sample, we retain the 510 country-year estimates available under all three specifications.

Table C.1. Estimated Shares of Information and Noise Components

Component (%)	Baseline	Principal component	VIX
Global-market information	20	26	18
Country-specific information	42	35	45
Trading	16	13	18
Nontrading	26	22	27
Noise	38	39	37

Note. This table reports mean information and noise shares using alternative global measures. All specifications use a common sample of 510 country-years. Shares are expressed as percentages and rounded to sum to 100.

We find that the main decomposition results are robust across alternative specifications. Country-specific information consistently accounts for a larger share than global-market information, and noise remains quantitatively important. When the VIX is used as the measure for global market conditions, the decomposition attributes a larger share to country-specific nontrading information and a smaller share to global-market information relative to the other specifications.

D Model details

This appendix specifies the annual sovereign problem and the weekly trading equilibrium used in Section 5. The annual primary-market price is denoted by q and the secondary-market quote by q^{tr}.

D.1 Fundamental processes and the annual calendar

Write $h_t = \log(1 + g_t)$ for normalized fiscal expenditure. Values of g_t below zero represent expenditures below the normalization. The processes are

$$\log y_{t+1} = \rho_y \log y_t + \varepsilon^y_{t+1}, \qquad \varepsilon^y_{t+1} \sim \mathcal{N}(0, \sigma_y^2), \tag{D.1}$$

$$h_{t+1} = \rho_g h_t + \varepsilon^g_{t+1}, \qquad \varepsilon^g_{t+1} \sim \mathcal{N}(0, \sigma_g^2). \tag{D.2}$$

The innovations are independent of one another and of the global Markov process. The numerical model uses finite grids for output and the log fiscal state. Output transitions

are obtained by Tauchen discretization. Fiscal transitions integrate Gaussian quadrature innovations and interpolate the resulting next log fiscal state between adjacent grid points, with endpoint values assigned to the boundary nodes. Denote these transition matrices by Π_y and Π_g.

The global state takes five values in $\{0, 4.4050, 7.4257, 12.7757, 22\}$ and has weekly transition matrix Π_M^W. With $W = 52$ weeks per year, its annual transition is $\Pi_M^A = (\Pi_M^W)^W$. The annual sovereign problem uses Π_M^A. For simulation, annual endpoints are sampled first and weekly paths are drawn conditional on those endpoints. If the current global state is i, the next annual endpoint is j, and n transitions remain, the bridge transition to ℓ is

$$\Pr(M_{w+1} = \ell \mid M_w = i, M_{\text{end}} = j) = \frac{\Pi_M^W(i,\ell)(\Pi_M^W)^{n-1}(\ell,j)}{(\Pi_M^W)^n(i,j)}.$$

The annual endpoint is not observed by market participants. Integrating over endpoints recovers the weekly Markov law. Current output, fiscal conditions and debt remain fixed between annual decisions, while global risk and the information available to market participants change weekly.

D.2 Sovereign choices and numerical smoothing

Let $k = \delta + (1-\delta)z$ denote the annual payment on a unit of outstanding debt, and let $a(B, B') = \alpha_1[\exp(\alpha_2|B' - B|) - 1]$ be the issuance adjustment cost. Given $X = (y, g, M)$, repayment consumption associated with B' is

$$c(B, B', X) = y - g - kB + q(B', X)[B' - (1-\delta)B] - a(B, B').$$

Default entails an output loss $\phi(y) = \max\{0, d_0 y + d_1 y^2\}$ and consumption $c^D(X) = y - g - \phi(y)$. The implementation imposes a positive consumption floor in evaluating utility. Default eliminates outstanding debt, and market access is restored with probability ψ after each excluded period, including the initial default period.

The numerical solution introduces small nested-logit choice shocks. To state the exact equations, define deterministic repayment and default indices

$$J(B'; B, X) = u(c(B, B', X)) + \beta E^P[V(B', X') \mid X], \tag{D.3}$$

$$J_D(X) = u(c^D(X)) + \beta E^P[\psi V(0, X') + (1-\psi)V^D(X') \mid X]. \tag{D.4}$$

The repayment inclusive value, ex ante value, and excluded-state value satisfy

$$R_\sigma(B,X) = \eta\sigma \log \sum_{B' \in \mathcal{B}} \exp\{J(B';B,X)/(\eta\sigma)\}, \tag{D.5}$$

$$V(B,X) = \sigma \log\left[\exp\{J_D(X)/\sigma\} + \exp\{R_\sigma(B,X)/\sigma\}\right], \tag{D.6}$$

$$V^D(X) = J_D(X) + \mu, \qquad \mu = -\sigma\gamma_E, \tag{D.7}$$

where $\mathcal{B}$ is the debt grid and γ_E is Euler's constant. The default probability and borrowing distribution conditional on repayment are

$$d(B,X) = \frac{\exp\{J_D(X)/\sigma\}}{\exp\{J_D(X)/\sigma\} + \exp\{R_\sigma(B,X)/\sigma\}}, \tag{D.8}$$

$$G(B' \mid B,X) = \frac{\exp\{J(B';B,X)/(\eta\sigma)\}}{\sum_{\widetilde{B}\in\mathcal{B}} \exp\{J(\widetilde{B};B,X)/(\eta\sigma)\}}. \tag{D.9}$$

We set $\sigma = 0.001$ and $\eta = 0.25$. As smoothing vanishes, these equations approach the repayment, default and borrowing maxima in the main text. The small location adjustment μ is retained in the numerical excluded-state continuation value.

For subsequent pricing, define the expected payoff on debt B entering state X by

$$\mathcal{R}(B,X) = (1 - d(B,X)) \left[k + (1-\delta) \sum_{B'} G(B' \mid B,X) q(B',X)\right].$$

The annual price solves $q(B',X) = E^P[m(y,y',M)\mathcal{R}(B',X') \mid X]$, using $m(y,y',M) = \exp\{-r - \kappa_M M(\log y' - \rho_y \log y) - \frac{1}{2}(\kappa_M M)^2 \sigma_y^2\}$. Annual borrowing proceeds depend on this primary-market price. Secondary quotes and news arriving subsequently do not enter the government's within-year budget or revise its annual borrowing and default decisions.

D.3 Future news, physical learning and valuation beliefs

Both current y_t and current g_t are public. The unknown country state is $Z = (y_{t+1}, h_{t+1})$. At issuance its physical prior is $\pi_0^P(Z) = \Pi_y(y_t, y_{t+1})\Pi_g(h_t, h_{t+1})$. Once current fundamentals are observed, the issuance choice does not provide additional information about future innovations. Public and private news take the form

$$s^j_{y,w} = \varepsilon^y_{t+1} + e^j_{y,w}, \qquad s^j_{g,w} = h_{t+1} + e^j_{g,w}, \qquad j \in \{p,x\},$$

with independent Gaussian errors of the calibrated standard deviations. Fiscal news concerns the future log fiscal *level*, while output news concerns the future log-output *innovation*. Fresh

news arrives every week in the baseline. Numerically, news realizations are assigned to finite bins, and Bayesian updates use their Gaussian bin probabilities.

Let $L_p(s \mid Z)$ and $L_x(s \mid Z)$ denote these news likelihoods and $\mathcal{H}_{w-1}$ the retained public news and orders. Physical beliefs incorporate the historical likelihoods

$$\pi_w^P(Z) \;\propto\; \pi_0^P(Z) \prod_{\ell \in \mathcal{H}_{w-1}} \left[L_p(s_\ell^p \mid Z) \sum_{s^x} L_x(s^x \mid Z) \varphi_{\sigma_U}(O_\ell - \chi_\ell(s^x)) \right],$$

where the sum over private-news realizations is taken separately within each historical factor, and φ_{σ_U} is the Gaussian liquidity density. The strategy χ_ℓ is the strategy actually used at that historical public information set. History is reset at annual issuance. The memory setting of 52 retains all available within-year observations, at most 51 past weeks plus the current week. There is no additional within-year reset mixture.

Weekly valuation uses the annual payoff operator evaluated at current global risk. Define

$$C_w(Z) = \sum_{M'} \Pi_M^A(M_{t,w}, M') \mathcal{R}(B_{t+1}, (y', e^{h'} - 1, M')), \tag{D.10}$$

$$D_w = \sum_{y'} \Pi_y(y_t, y') m(y_t, y', M_{t,w}), \qquad v_w(Z) = D_w C_w(Z). \tag{D.11}$$

The operator uses Π_M^A at each week. It does not replace it with a remaining-weeks transition or shorten the valuation horizon within the year. Given the physical history posterior, the common valuation prior is

$$\pi_w^Q(Z) = \frac{m(y_t, y', M_{t,w}) \pi_w^P(Z)}{\sum_{\widetilde{Z}} m(y_t, \widetilde{y}', M_{t,w}) \pi_w^P(\widetilde{Z})}.$$

Current news and current order flow then update this prior through their likelihoods. Historical learning is performed under P. The current SDF tilt is applied once, rather than repeatedly to retained observations. The discount mass D_w is fixed at its no-news value conditional on public $(y_t, M_{t,w})$, including after news arrives. Thus the specified pricing rule is a conditional mean of v_w under normalized Q beliefs, and should not be replaced by an unnormalized conditional expectation $E^P[mC_w \mid \text{news}]$. Without news or order-flow information, $E^Q[v_w] = q(B_{t+1}, (y_t, g_t, M_{t,w}))$ exactly. This identity links secondary valuation to the sovereign pricing equation.

D.4 Competitive trading and quote consistency

Fix the current public history and public news. For private news s^x, write $\mu_x = E^Q[v_w \mid s^p, s^x, \mathcal{H}_{w-1}]$ and $\nu_x = \mathrm{Var}^Q(v_w \mid s^p, s^x, \mathcal{H}_{w-1})$. The competitive mean–variance demand at an expected execution quote $\bar{p}_x$ is $(\mu_x - \bar{p}_x)/(\rho^\chi \nu_x + \kappa)$, subject to an order bound. An equilibrium consists of an order schedule χ contingent on private news and a quote rule p satisfying

$$\chi(s^x) = \mathrm{clip}_{[-\bar{\chi},\bar{\chi}]} \frac{\mu_x - E_U[p(\chi(s^x) + U)]}{\rho^\chi \nu_x + \kappa}, \qquad \bar{\chi} = 5\sigma_U, \tag{D.12}$$

$$O = \chi(s^x) + U, \quad U \sim \mathcal{N}(0, \sigma_U^2), \qquad p(O) = E^Q[v_w \mid s^p, O, \mathcal{H}_{w-1}]. \tag{D.13}$$

The dealer's order likelihood is the private-type mixture appearing in the physical-history update above. Traders take expected execution quotes as given when forming competitive demands. The quote consistency is imposed jointly with the dealer's inference rule. Consequently, the demand equation contains no strategic price-impact derivative. Its risk penalty is the conditional variance of v_w, not the variance of the trading profit including the quote.

D.5 Valuation accounting around default

Let q_A and q_W be the annual and weekly fundamental prices. Let q_P use only the retained public news, excluding past and current orders, and let q_F average the quote over current liquidity orders at the actual private news and trading history. Applying the spread transformation to each conditional mean price gives

$$\begin{aligned} s(q^{tr}) - s(q_A) = {} & \underbrace{s(q_W) - s(q_A)}_{\text{lender's risk repricing}} + \underbrace{s(q_P) - s(q_W)}_{\text{Public news}} \\ & + \underbrace{s(q_F) - s(q_P)}_{\text{Private news and order-flow learning}} + \underbrace{s(q^{tr}) - s(q_F)}_{\text{liquidity}}. \end{aligned} \tag{D.14}$$

This identity holds observation by observation. The public-first ordering assigns interactions to the private-news and order-flow term, which also retains past liquidity effects on inference. The last term isolates current liquidity. The lender-risk contrast holds current country fundamentals and debt fixed. The annual benchmark already incorporates its annual global state. These are signed valuation contrasts, not structural VAR innovations or variance shares. Event averages use the same 103 baseline defaults and the first weekly information simulation. Week zero is the first quote after the default decision and debt reset, and the final predefault quote is week -1.