What Moves Sovereign Credit Risk? The Role of Information

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Abstract

This paper develops a variance decomposition framework to study how sovereign credit risk responds to different sources of information and noise. Using dealer's data from sovereign credit default swap (CDS) markets, we decompose sovereign CDS spread movements into four components: global-market information, country-specific public information, country-specific private information revealed through trading, and noise. We find that variation in sovereign CDS spreads is driven primarily by country-specific information, although noise remains a quantitatively important component. We further examine how country's macroeconomic fundamentals shape the relative importance of these informational and noise components and how information driven volatility is priced in sovereign credit markets.

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 the 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, studies such as Acharya et al. (2014) and Bocola (2016) highlighting the interaction between domestic bank risks and sovereign defaults.

This paper presents a new framework for analyzing sovereign credit risks by identifying the sources of information embedded in sovereign CDS spreads and examining how global and domestic factors contribute to variations in these information sources. We measure sovereign credit risks using sovereign credit default swap (CDS) spreads, following the approach of Longstaff et al. (2011). Compared to the sovereign bond market, the sovereign CDS market is more liquid and responsive to economic shocks, offering more accurate measures of credit spreads. 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 investigate the effects and drivers of information-driven volatility in CDS spreads.

The decomposition of sovereign CDS spread variations results in four components: noise, global information, country-specific public information, and country-specific private information. The noise component reflects fluctuations in spreads driven by liquidity needs, market sentiment, or market frictions. The global information component captures the response of spreads to global shocks. The public country-specific component represents information that affects a country's sovereign risk and is available to all market participants. In contrast, the private country-specific component consists of information that influences a country's credit risks but is only available to a subset of market participants, and this information is revealed through trading activities.

To achieve this decomposition, we analyze the responses of sovereign CDS spreads to three types of shocks: global returns, country-specific trading (order) flows, and other country-specific shocks, as indicated by the spread residual. We use vector autoregression (VAR) impulse response functions to estimate the permanent 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 long-run equilibrium response to each shock, we can distinguish between permanent and transitory changes in spreads. The transitory part of spreads is identified as the noise component. The long-run response of spreads to global returns captures the global information. The long-run impact of a shock to country-specific trading flow on spreads is interpreted as private country-specific information. Similarly, the country-specific public information is estimated as the long-run effect of a shock to the country-specific spread residual that is uncorrelated to trading flows.

We estimate the model using weekly changes in sovereign CDS spreads for 51 countries from 2012 to 2024. We find that sovereign credit spreads are mostly driven by country-specific information instead of global-market information, in contrast to the existing literature that emphasizes on the global factor as a main driver of spreads across countries. In particular, country-specific information component accounts for 47% of the variance in weekly spread changes, while global-market information contributes approximately 21%, and noise of 32%. Within the country-specific information, the country-specific public and private information components contribute at 37% and 10%, respectively. Spreads in emerging market economies have higher shares in global information than spreads of developed economies. These findings suggest that sovereign credit risks in emerging market economies are more driven by global financial market conditions.

We proceed by examining whether macroeconomic fundamentals explain the amount of information driven volatility in sovereign credit spreads and assessing how information and noise are priced into sovereign credit risk. In particular, we study the effect of macroeconomic fundamentals on variance shares and the responses of sovereign CDS spreads to information and components. Our results indicate that the sovereign credit spread dynamics are increasingly dominated by noise when macroeconomic fundamentals are strong, whereas weaker fundamentals amplify the role of informational components in driving spread movements. We also find that sovereign credit spreads respond strongly to noise and to country-specific information more than global-market information.

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

We contribute to the sovereign risk literature by shifting the focus from cross-country comovements in sovereign credit spreads to the information sources underlying their dynamics. We decompose sovereign credit spread movements into global-market information, country-specific public and private information, and noise, allowing us to quantify the informational content of spreads and assess how macroeconomic fundamentals shape their underlying drivers.

Existing work largely emphasizes the dominant role of global factors in sovereign risk premia, beginning with Longstaff et al. (2011) and reinforced by evidence linking sovereign CDS spreads to global macroeconomic conditions (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). Our framework complements this literature by distinguishing different informational and noise components of sovereign spread dynamics.

We further contribute to the literature by using CDS transaction 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 private information from public 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 capturing variations in risk premia and investor sentiment.[1] 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 similar variance decomposition approach, Nozawa (2017) show that expected returns and expected credit losses contribute comparably to movements in 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.

[1] Discount-rate news reflects changes in expected returns, while cash-flow news captures revisions to fundamentals; see Chen et al. (2023) for a recent discussion.

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 shows the effects of global and domestic factors on information components. Section 6 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. This approach also enables an analysis of how these components relate to country-specific characteristics.

We estimate the response of sovereign credit risk to three types of shocks: (i) innovations in the global market spread, (ii) country-specific trading flows, and (iii) residual country-specific shocks, as captured by the spread residual. 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 treated as a proxy for country-specific private information. Our interpretations can be rationalized from a simple theoretical model shown in Appendix A.

Consider the spread of 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 m_t follows a random walk $m_t = m_{t-1} + \mu + w_t$ with drift μ and innovations w_t. Therefore, the change in spread follows

$$\Delta r_t = \mu + w_t + \Delta u_t$$

The random-walk innovations, w_t , can then 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 private information, country-specific public information, and noise.

$$\Delta r_t = \underbrace{\mu}_{\text{drift}} + \underbrace{\theta_{rm}\varepsilon_{rm,t}}_{\text{global market info}} + \underbrace{\theta_x \varepsilon_{x,t}}_{\text{private info}} + \underbrace{\theta_r \varepsilon_{r,t}}_{\text{public info}} + \underbrace{\Delta u_t}_{\text{noise}} \tag{2}$$

We then estimate the components of equation (2) using a structural VAR with four lags to allow monthly serial correlation and lagged effects:

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

where $r_{m,t}$ is the global market spread, x_t is the signed dollar volume of trading in the given country credit spread (positive values for net buying and negative values for net selling), and r_t is the spread.

The structural VAR in equation 3 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, individual countries' spreads and trades have a marginal contemporaneous impact on the overall global market spread. Trading activity in a sovereign CDS may respond contemporaneously to the global spread and, in turn, influence the domestic spread, though not vice versa. In segregating country-specific information into public and private components, our structural assumptions tend to estimate the upper limit on private information and the lower limit on public information. Appendix C provides detailed information on how we estimate this structural VAR.

Taking the variance of the innovations in the efficient spread we get $\sigma_w^2 = \theta_{rm}^2 \sigma_{\varepsilon_{rm}}^2 + \theta_x^2 \sigma_{\varepsilon_x}^2 + \theta_r^2 \sigma_{\varepsilon_r}^2$. The error terms in the structural model are contemporaneously uncorrelated by construction and, therefore, the covariance terms are all zero. The estimated components of variance, normalized by total variance, are then

$$\begin{aligned} \text{Global market information share} &= \theta_{rm}^2 \sigma_{\varepsilon_{rm}}^2 / (\sigma_w^2 + \sigma_s^2) \\ \text{Private information share} &= \theta_x^2 \sigma_{\varepsilon_x}^2 / (\sigma_w^2 + \sigma_s^2) \\ \text{Public information share} &= \theta_r^2 \sigma_{\varepsilon_r}^2 / (\sigma_w^2 + \sigma_s^2) \\ \text{Noise share} &= \sigma_s^2 / (\sigma_w^2 + \sigma_s^2) \end{aligned} \tag{4}$$

3 Data

Sovereign spread We acquire the daily sovereign CDS spread data with a five-year maturity USD denominated 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, government bonds are typically denominated in local currency, but sovereign CDS is commonly traded in a foreign currency, mitigating both inflation risk and foreign exchange risk for purchasers. This choice allows for a more precise identification of the components that contribute to the risk of sovereign credit. Furthermore, the sovereign CDS market often exhibits higher liquidity than the corresponding sovereign bond market, increasing the precision of credit spread estimates.

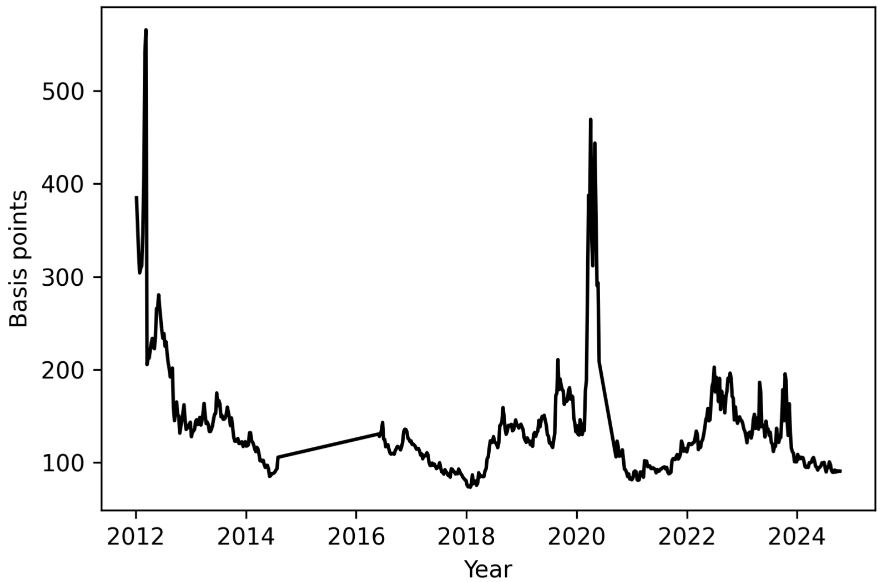
Sovereign CDS trading We collect sovereign CDS trading data from the Depository Trust and Clearing Corporation (DTCC). As part of its commitment to improving the Over-the-Counter (OTC) derivatives market infrastructure, the DTCC has been publishing market analyses quarterly since 2010. We acquire aggregated transaction data for the reference entity from the DTCC's OTC repository data. To extract the country-specific information from the transaction data, we focus on transaction records made by the Sovereign reference entity.[2]

Following Pástor and Stambaugh (2003) and Brogaard et al. (2022), we use the product of total weekly notional and the sign of the sovereign CDS's return as a proxy for the signed dollar volume, x_t.

Global market spread We construct a measure for the global market spread by taking the net notional outstanding amount-weighted average of the daily spreads. Figure 1 shows the daily global market spread from 2012 to 2024. The global market spread exhibits high

[2] The DTCC estimates that its service covers approximately 98% of all standard credit derivatives contracts. See https://www.dtcc.com/repository-otc-data#Top1000 for public transaction data. If the reference entity is a sovereign or government, it is identified as a "sovereign." Appendix B.1 provides more details on the DTCC data.

volatility, with sharp spikes in early 2012 and 2020, reflecting periods of financial stress. Additional fluctuations appear in late 2015 and mid-2021, though of lesser magnitude.



Note: Figure 1 plots the daily the global market spread constructed as the net notional outstanding amount-weighted average of the daily sovereign CDS spreads.

Figure 1: Global market spread

Macroeconomics variables In Section 5, we examine the extent to which the information components are driven by country-specific fundamentals and global factors. As measures of global financial conditions, we include the CBOE VIX index (sourced from the CBOE) and the S&P 500 index from the Federal Reserve Economic Data, and the five-year constant maturity Treasury (CMT) yield published by the Federal Reserve. Real GDP data is obtained from the World Bank's World Development Indicators, and government debt-to-GDP ratios from the International Monetary Fund. We also use debt data from the Bank for International Settlements (BIS), including BIS international debt securities by country.

Sample selection To ensure sufficient observations for the variance decomposition model estimated at the country-year level, we exclude country-year pairs with fewer than 20 valid weekly observations.

4 Decomposition of Sovereign Credit Risk

We conduct the variance decomposition for every country-year pair. The model assumes that each country exhibits a steady state over each year. We estimate this steady state using impulse response analysis, which allows us to distinguish permanent innovations in spreads from temporary ones. Appendix C shows results on the reduced-form 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 public and private components) is the largest contributor, accounting for approximately 47% of spread variance. Global market information accounts for 21%. Within the country-specific component, public information explains 37% of the variance, while private information accounts for the remaining 10%. Noise contributes a substantial 32% to overall spread variance.

Table 1: Estimated Shares of Information and Noise Components

	All	Developed	Emerging	U.S. Equity (Brogaard et al. (2022))
Global-market info	21	16	24	8
Country-specific info	47	49	46	61
Private	10	10	9	24
Public	37	39	37	37
Noise	32	35	30	31

Note: Table 1 shows the average variance shares (expressed as percentages of total variance) for the period from January 2012 to October 2024. Spread variance is decomposed into global market information, public country-specific information, private country-specific information, and noise. The variance-component shares are calculated separately for each country over each year. Results from Brogaard et al. (2022) is reported in the final column for comparison.

These results differ significantly 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 (21% vs. 8%) and a smaller share of country-specific information (47% vs. 61%), primarily due to a lower contribution from private country-specific information (10% vs. 24%).

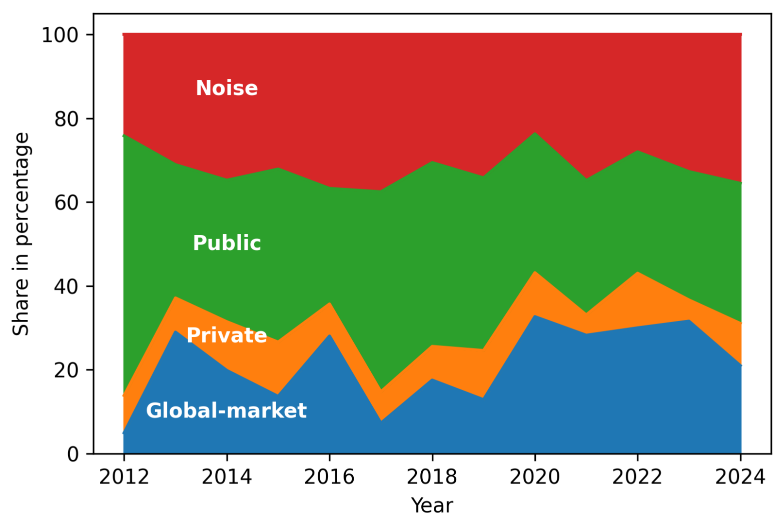
We compare the shares of information and noise components between developed and emerging economies, as reported in the second and third columns of Table 1. Emerging economies exhibit a higher share of global market information, whereas developed economies display greater shares of country-specific information (both public and private) and noise.

These findings indicate that country-specific information is the main driver of sovereign CDS spread variation, while global market information plays a comparatively smaller but still significant role. In particular, its influence is greater than in US equity markets and more pronounced in emerging economies.

In addition, the results are robust to alternative measures of global market conditions, including a principal-component-based global factor and the VIX, as reported in Appendix D.

4.2 Time series of information and noise shares

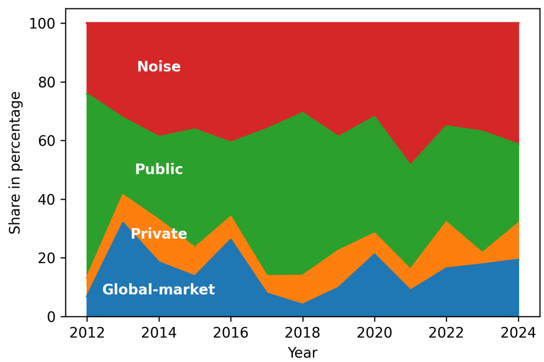
Figure 2 presents the variance decomposition of spreads over time from 2012 to 2024. Public country-specific information accounts for most of the variation, while global market information remains modest and more volatile. The global market information share increases during periods of financial stress, particularly between 2012–2016 and 2020–2024.



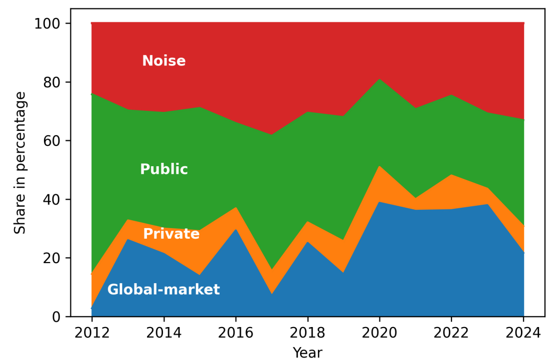
Note: Figure 2 plots the information and noise shares over time for all countries in the sample.

Figure 2: Information and noise shares over time: All countries

We compare the decomposition of spreads for developed and emerging markets in Figure 3. In developed markets, the global market component remains modest and relatively flat. In contrast, emerging markets show a rising global market share, particularly after 2020. The noise component is more prominent in developed economies and consistently accounts for a larger share than in emerging markets. Country-specific public information varies across groups, with emerging markets having a higher share in 2012–2016, while developed markets dominate in 2020–2024. The private component remains stable across groups. These patterns suggest that global market information plays a more important role in emerging markets, while private information is a consistent driver in both groups.



(a) Developed Markets



(b) Emerging Markets

Note: Figure 3 plots the information and noise shares over time for developed and emerging markets.

Figure 3: Time series comparisons of information and noise shares

5 Information Driven Volatility in Sovereign Credit Risk

In this section, we examine whether macroeconomic fundamentals explain the amount of information driven volatility and assess how information-driven volatility in CDS spreads is priced into sovereign credit risk and To do so, we analyze the effect of macroeconomic fundamentals on information and noise variance components and measure the response of sovereign CDS spreads to these components.

5.1 Macroeconomic determinants of information driven volatility

First, we study whether macroeconomic fundamentals explain the amount of information-driven volatility in sovereign CDS spreads. We specify the following panel regression

$$\text{Variance Share}_{it} = \alpha_i + \beta X_{it} + \gamma Y_t + \epsilon_{it}, \tag{5}$$

where Variance Share_{it} represent the information and noise variance shares in the sovereign CDS spreads and X_{it} is a vector of the macroeconomic fundamentals of the country, including real GDP growth, total public debt, external debt share, reserves, primary balance, current account, and exchange rate volatility. Public debt, reserves, primary balance, and current account are measured as percentage of GDP. External debt share is calculated as the percentage of international debt held by the government to total public debt. FX volatility is the variance of weekly changes in nominal exchange rates. We control for global financial conditions in Y_t which includes the VIX, S&P 500, and Treasury yield. Following the sovereign spreads literature, we treat stock variables such as debt, reserves, and debt composition as predetermined and include them lagged, while macroeconomic flow variables and global financial conditions enter contemporaneously.

Table 2: Macroeconomic determinants of variance components

	(1) Global-Market Info	(2) Public Info	(3) Private Info	(4) Noise
Real GDP growth	-30.8	3.03	-4.05	31.8***
	(45.7)	(49.3)	(26.2)	(11.6)
Public debt	0.088	-0.19**	-0.049	0.15
	(0.11)	(0.077)	(0.22)	(0.14)
External debt share	0.96*	-0.66	-0.10	-0.19
	(0.53)	(0.62)	(0.30)	(22.8)
Reserves	-0.16	0.55	-0.20	-0.19
	(0.24)	(0.53)	(0.45)	(0.24)
Primary balance	0.36	-0.59	-0.10	0.33
	(0.45)	(0.41)	(0.37)	(0.24)
Current account	-0.03	-0.05	0.28	-0.20
	(0.30)	(0.37)	(0.30)	(0.27)
FX volatility	3.38*	-2.13	0.32	-1.56**
	(1.91)	(1.67)	(1.05)	(0.76)
R-squared (within)	0.12	0.053	0.014	0.15
No. obs	279	279	279	279
Global controls	Y	Y	Y	Y
Country FE	Y	Y	Y	Y

Note: Table 2 shows the results of regressing information and noise shares on country's macroeconomic fundamentals, controlling for global financial conditions. Public debt, reserves, primary balance, and current account are measured as percentage of GDP. External debt share is calculated as the percentage of international debt held by the government to total public debt. FX volatility is the variance of weekly changes in nominal exchange rates. Global controls are VIX, S&P 500, and Treasury yield. Standard errors are clustered at the country level. */**/*** denotes significance at the 10/5/1 percent levels.

Table 2 reports the results for equation (5). We find that countries experiencing stronger economic growth exhibit sovereign credit spreads whose fluctuations are driven more significantly by noise and less significantly by both global-market and country-specific information. Higher levels of public debt are associated with a larger role for country-specific public information in explaining spread variability, while a higher share of external debt increases the contribution of global-market information. Volatility of exchange rates significantly increases the share of global-market information and reduces the contribution of noise to sovereign spread movements. In contrast, reserves, the primary balance, and the current account balance do not have statistically significant effects on the variance components. Overall, the results indicate that when macroeconomic fundamentals are strong, sovereign spread movements tend to be more dominated by noise, whereas weaker fundamentals increase the importance of informational components in driving spread dynamics.

5.2 Pricing of sovereign credit risk

We next assess whether the pricing of sovereign credit risk takes into account information driven volatility in CDS spreads. We specify a panel regression of sovereign CDS spreads on information and noise components as follows

$$\log(r_{it}) = \alpha_i + \beta' \log(\text{Variance Component}_{it}) + \gamma' X_{it} + \lambda' Y_t + \epsilon_{it}, \tag{6}$$

where r_{it} is the sovereign CDS spread and Variance Component$_{it}$ is the information or noise component. Our control variables are the vector of lagged spreads and country's macroeconomic fundamentals X and the vector of global financial conditions Y.[3] We apply a logarithmic transformation to improve the distributional properties of the data and to allow the regression coefficients to be interpreted as elasticities of sovereign CDS spreads with respect to their information and noise components.

As Table 3 shown, we find positive and statistically significant elasticities of sovereign CDS spreads with respect to all information and noise components, with the largest elasticity associated with noise and the smallest with country-specific private information. Moreover, sovereign credit spreads are more sensitive to changes in country-specific public information than to changes in global-market information.

[3]The macroeconomic fundamentals are defined before as real GDP growth, total public debt, external debt share, reserves, primary balance, current account, and exchange rate volatility. Global financial conditions are captured by VIX, S&P 500, and Treasury yield.

Table 3: Analysis of spreads on variance components

	(1)	(2)	(3)	(4)
Global-Market Info	0.047***			
	(0.0117)			
Public Info		0.063***		
		(0.022)		
Private Info			0.038***	
			(0.0097)	
Noise				0.1147***
				(0.021)
R-squared (within)	0.48	0.47	0.46	0.49
No. obs	279	279	279	279
Controls	Y	Y	Y	Y
Country FE	Y	Y	Y	Y

Note: Table 3 reports analysis of the information and noise components on sovereign CDS spreads. Controls are real GDP growth, total public debt, external debt share, reserves, primary balance, current account, and exchange rate volatility, VIX, S&P 500, and Treasury yield. Standard errors are clustered at the country level. */**/*** denotes significance at the 10/5/1 percent levels.

6 Conclusion

This paper revisits the long-standing debate on whether sovereign CDS spreads are primarily driven by global or country-specific forces by examining 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 public and private information, and noise. We find that the largest share of the variation in sovereign spread is attributable to country-specific information, although noise remains a quantitatively important component. Within country-specific information, public information plays a substantially larger role than private information.

We further examine how macroeconomic fundamentals help explain cross-country variation in these informational components and how information driven volatility in sovereign CDS spreads is priced. Our results show that weaker fundamentals amplify the role of informational components in driving spread dynamics, and sovereign CDS spreads are more sensitive to noise and public information.

The importance of global information is particularly pronounced in emerging market economies, where sovereign CDS spreads are more sensitive to global-market information than to country-specific factors. However, even in these economies, public country-specific information dominates private information in explaining spread fluctuations.

This study contributes to the literature on sovereign credit risk by moving beyond comovement-based explanations to examine the information sources underlying sovereign CDS spread dynamics. By decomposing country-specific information into public and private components using CDS trading data, we provide new insights into the informational structure of sovereign credit markets. Our cross-country analysis highlights the state-dependent nature of information in sovereign risk pricing. Future research could explore how these information components vary along the term structure of sovereign debt and how exchange rate dynamics interact with sovereign credit risk.

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A Theoretical Framework

This section develops a simple theoretical framework that illustrates the role of information and noise in determining CDS prices. We incorporate global-market and public information into the one-shot trading model of Kyle (1985). We show that private information influences CDS prices via trading activity, whereas global market and public information affect prices directly but do not alter trade volumes. This distinction supports the empirical strategy of identifying private information embedded in sovereign credit spreads through variations in sovereign CDS trading volume.

Environment The economy consists of four types of agents: private traders, public traders, noise traders, and market makers. A single one-period CDS is traded, with a stochastic value affected by a global market index. Private traders receive a private signal about the CDS's ex-post value, while public traders observe only a public signal and the global market index. Noise traders submit random trades. Market makers are risk-neutral and set prices competitively based on the total order flow, the public signal, and the global market index.

The CDS value v follows

$$v = \mu + \beta M + \eta, \quad \eta \sim \mathcal{N}(0, \sigma_\eta^2),$$

where μ is baseline component of CDS value, potentially reflecting fixed fundamentals, and M is the global market index. β represents the sensitivity of the CDS value to global market index.

Information There are two signals over the CDS value. The public signal s^g is observed by all agents and defined as

$$s^g = \eta + \epsilon^g, \quad \epsilon^g \sim \mathcal{N}(0, \sigma_g^2),$$

and the private signal s^p is only observed by the private traders

$$s^p = \eta + \epsilon^p, \quad \epsilon^p \sim \mathcal{N}(0, \sigma_p^2)$$

Trading Trading occurs in two stages. In the first stage, traders submit market orders by selecting trade quantities. In the second stage, market makers set the price and execute trades to clear the market.

The public traders choose trade size z to maximize expected profit

$$\max_z \quad \mathbb{E}[(v-p)\cdot z \mid M, s^g]$$

The private traders choose trade size y to maximize expected profit

$$\max_x \quad \mathbb{E}[(v-p)\cdot x \mid M, s^g, s^p],$$

and the noise traders submit random trade $u \sim \mathcal{N}(0, \sigma_u^2)$. The total trade flow is $q = x+z+u$.

In the second stage, market makers observe the total trade flow q and determine the CDS price as

$$p = \quad \mathbb{E}[v \mid M, s^g, q]$$

Equilibrium price and trading strategies In equilibrium, the price reflects the information embedded in the global market index M, the public signal s^g, and the total trade q. There exist constants λ and γ such that

$$p = \mu + \beta M + \lambda q + \gamma s^g$$

We next show that the optimal trading choice of the public traders is zero. Because all information known to the public traders is already embedded in the price, there is no profits to trading. That is,

$$\mathbb{E}[v \mid M, s^g] = \mathbb{E}[p \mid M, s^g]$$

$$\mathbb{E}[(v-p)\cdot z \mid M, s^g] = 0$$

Any non-zero trade yields zero expected profit, and since trading incurs risk (due to noise trades u), the optimal choice is $z = 0$.

In contrast, private traders have additional information from the private signal beyond what is incorporated in the price and trade on this basis. The expected profit of the private traders is:

$$\mathbb{E}[(v-p)\cdot x \mid M, s^g, s^p] = \mathbb{E}[(\eta - \lambda(x+u) - \gamma s^g)\cdot x \mid s^p]$$

Taking expectations conditional on s^p gives $\max_x \mathbb{E}[\eta \mid s]x - \lambda x^2 - \gamma s^g x$. Therefore, the private trader's optimal strategy is

$$x = \alpha(s^p - \delta s^g),$$

where $\alpha = \frac{\sigma_\eta^2}{2(\sigma_\eta^2+\sigma_p^2)\lambda}$ and $\delta = \frac{\gamma(\sigma_\eta^2+\sigma_p^2)}{\sigma_\eta^2}$.

Private traders base their trades solely on the residual component of their private signal, net of the portion already reflected in the public signal. We define the residual private signal as private information, $s^x \equiv s^p - \delta s^g$.

In summary, the equilibrium price and trading flow follow

$$p = \mu + \beta M + \lambda \alpha s^x + \gamma s^g + \lambda u$$

$$q = \alpha s^x + u$$

The equations show that private information, s^x, influences prices indirectly through its effect on trading flow. In contrast, global market information, captured by M, and public information, represented by s^g, enter the price directly. In the following section, we outline the empirical strategy that leverages variation in trading volumes to identify the presence of private information.

B Data

B.1 DTCC Data

On March 1, 2010, various market participants, including dealers, buy-side institutions, and industry associations, jointly submitted a letter to a group of global supervisors outlining their commitments to enhancing the infrastructure of the Over-the-Counter (OTC) derivatives market. As part of this initiative, the signatories specifically requested the Depository Trust and Clearing Corporation (DTCC) to conduct an analysis of single-name credit default swaps (CDS) by April 15, 2010. The purpose was to aid in expanding the range of products eligible for clearing, utilizing data from the DTCC Trade Information Warehouse (TIW).

The DTCC had previously made versions of this data publicly accessible. In continuation of their commitment, the letter's signatories asked DTCC to perform such analyses on a quarterly basis going forward. Consequently, the results of the most recent analysis, including aggregated transaction data organized by reference entity, will be released on our public website, covering the period from June 20, 2018, to December 22, 2023. [4]

The primary objective of this analysis was to offer valuable insights to both market participants and regulators, specifically focusing on comprehending the market structure and traded volumes. To achieve this, a more detailed examination was carried out for the top 1,000 reference entities outstanding in the DTCC Trade Information Warehouse (TIW)

[4]Note: The authors scrape the public data from https://www.dtcc.com/repository-otc-data when the March 20, 2012 to March 24, 2023 repository is available.

(www.dtcc.com).

The analysis contains key attributes based on the provided definitions, including Region, Index Constituent, Total Number of Clearing Dealers, Average Monthly Clearing Dealers, Average Daily Notional, Average Number of Trades per Day, and Restructuring Percentage. The careful examination of these attributes aimed to provide a comprehensive understanding of market dynamics, with the resulting insights intended to inform decision-making regarding clearing activities.

Attribute Definitions

Here, we give a brief description of the attributes that are relevant to our analysis.[5]

Region

In the "Region" category, it specifies the region linked to the predominant trading style related to each reference entity name. This association is established based on the documentation type of the underlying trades. For instance, transactions conducted under the label "StandardNorthAmericanCorporate" would be affiliated with the Americas Region. The determination of regions is based on whether more than 25% of the transactions are associated with a particular region. Consequently, there are instances where this attribute may reflect two or more regions. The regions identified align with those recognized by the Determinations Committees within the International Swaps and Derivatives Association, Inc. (ISDA). If the reference entity is a sovereign or governmental entity, it is identified as a "sovereign", regardless of whether the entity is a country, state, or city.

Average Daily Notional (USD equivalent)

The "Average Daily Notional (USD equivalent)" column demonstrates the Average Daily Notional (USD equivalent) of transactions conducted on each reference entity name. This notional value reflects the average daily amount traded across the entire maturity spectrum for each reference entity. It's important to clarify that this average does not depict the amount traded at each specific maturity point or the amount traded at the five-year point.

For the most liquid reference entities, which may have 40 or more maturity dates with activity, each representing quarterly buckets for ten years, the trading volume at individual maturity points can be notably lower than the total. All trading values have been converted to their USD equivalent using FX rates from the end of June. To maintain consistency, the average daily notional amounts have been rounded up to the nearest 2.5MM for values less than 25MM and rounded up to the nearest 25MM for amounts exceeding 25MM.

[5]For more details, please refer to https://www.dtcc.com/-/media/Files/Downloads/Settlement-Asset-Services/DerivSERV/CDS_Snapshot_Analysis_Sep17-2010.pdf

B.2 Other Data Definitions and Sources

- Real GDP growth: Real GDP data are in constant 2010 prices, expressed in U.S. million dollars. We calculate the real GDP growth as the log difference between the current period and the previous period. Source: World Bank.

- Public debt: Public debt refers to the total amount of government debt. Source: WEO.

- International debt: International debt comprises debt securities issued in a market other than the local market of the country where the borrower resides. Source: BIS.

- VIX: We use VIX as a proxy for financial market uncertainty. We aggregate the daily data into year data and calculate the average of the open and close values as the VIX index value. Source: CBOE VIX website.

C Estimation of the Structural VAR

It is possible to rewrite the reduced-form residuals as linear functions of the structural-model residuals:

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

Specifically, we estimate $b_{1,0}$ by regressing the reduced-form innovation $e_{x,t}$ on $e_{rm,t}$ (as per the second equation in [B.1]), and we estimate $c_{1,0}$ and $c_{2,0}$ by regressing the reduced-form innovation $e_{r,t}$ on $e_{rm,t}$ and $e_{x,t}$ (as per the third equation in [B.1])

From the estimated parameters $b_{1,0}$,$c_{1,0}$,and $c_{2,0}$ and the estimated variances of the reduced-form residuals ($\sigma^2_{e_{rm}}$,$\sigma^2_{e_x}$, and $\sigma^2_{e_r}$), we obtain estimates of the variances of the structural model shocks by taking the variance of (A.2) 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 long-run cumulative impulse response functions of the structural model by computing the equivalent reduced-form shocks (using Equations [B.1]) and feeding them through the reduced-form model:

(i) A structural shock to market returns $[\varepsilon_{rm,t}, \varepsilon_{x,t}, \varepsilon_{r,t}]' = [1, 0, 0]'$ has a reduced-form equivalent $[e_{rm,t}, e_{x,t}, e_{r,t}]' = [1, b_{1,0}, (c_{1,0} + c_{2,0}b_{1,0})]'$.
(ii) A structural shock to trading $[\varepsilon_{rm,t}, \varepsilon_{x,t}, \varepsilon_{r,t}]' = [0, 1, 0]'$ reduced form equivalent $[e_{rm,t}, e_{x,t}, e_{r,t}]' = [0, 1, c_{2,0}]'$.
(iii) A structural shock to the stock returns $[\varepsilon_{rm,t}, \varepsilon_{x,t}, \varepsilon_{r,t}]' = [0, 0, 1]'$ has a reduced-form equivalent

$$[e_{rm,t}, e_{x,t}, e_{r,t}]' = [0, 0, 1]' \tag{B.3}$$

Summary of the five-step procedure:

(i) Estimate the reduced-form VAR in equation (A1), saving the residuals and variance/covariance matrix of residuals;

(ii) Estimate the parameters $b_{1,0}$, $c_{1,0}$, and $c_{2,0}$ from regressions of the reduced-form residuals (second and third equations in [B.1]);

(iii) Estimate the variances of the structural innovations using equations in [B.2];

(iv) Estimate the long-run (permanent) cumulative return responses to unit shocks of the structural-model innovations, θ_{rm}, θ_x, and θ_r, using reduced-form-model impulse response functions with the shocks given in equation B.3; and

(v) Combine the estimated variances of the structural innovations from step (iii) with the long-run return responses from step (iv) to get the variance components and variance shares following equations (9) and (10) in the paper.

Table B.1 reports the mean coefficients for the reduced-form VAR model used to perform the variance decomposition. The coefficients in the global-return equation (panel A) show that there is a positive first-order serial correlation in global returns, which is consistent with the effects of nonsynchronous trading (Scholes and Williams (1977)) and slow market reaction. However, lags of trading volumes and spreads have no explanatory power on the current global returns. The coefficients in the signed dollar volume equation (panel B) indicate a proclivity for sales to occur after positive market returns. Furthermore, these coefficients reveal a negative serial correlation in signed dollar volume, indicating the reversal of the order flow. The coefficients in the spread equation (panel C) show that the spread tends to be negatively related to the lagged market return. The lagged trading has a positive impact on the spread return, which indicates that the trading information takes time to be fully reflected in the price.

Table B.1: VAR coefficient estimates

Dependent Variable	Independent Variable	$l = 1$	$l = 2$	$l = 3$	$l = 4$
A. global-return equation					
$r_{m,t}$	$r_{m,t-l}$	-0.202	-0.196	-0.116	-0.181
	x_{t-l}	0.003	0.004	0.001	-0.001
	r_{t-l}	-0.521	-0.321	-0.334	-0.092
B. Signed dollar volume equation					
x_t	$r_{m,t-l}$	61.39	20.288	-5.268	8.094
	x_{t-l}	0.106	0.014	0.078	-0.17
	r_{t-l}	-77.113	-25.131	-8.453	21.695
C. Spread equation					
r_t	$r_{m,t}$	0.019	-0.779	-0.306	-0.846
	x_{t-l}	0.008	0.011	0.002	-0.005
	r_{t-l}	-0.349	-0.387	-0.166	-0.141

Note: Table B.1 reports the mean coefficient estimates for the baseline VAR model used to perform the variance decomposition. The VAR model is estimated separately for the country in the sample using quarterly observations. For the purpose of this table, each of the model coefficients is averaged across years and reported in the table. The variables used in the VAR are quarterly market returns ($r_{m,t}$), quarterly signed dollar volume in \$ million (x_t), and quarterly spreads (r_t). The columns $l = 1$ to $l = 4$ correspond to lags of the independent variables. The sample consists of sovereign CDS trading observations from 2012/09/20 to 2022/12/24 (a total of 596 observations).

D 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 the panel of sovereign CDS spreads and use the first principal component as an alternative global market index. Second, we use the VIX as a direct measure of the global market index. Table B.2 reports and compares the results from the baseline specification and these alternative approaches.

Table B.2: Estimated Shares of Information and Noise Components

	Baseline	Principle Component	VIX
Global-market info	21	29	12
Country-specific info	47	39	54
Private	10	9	10
Public	37	30	45
Noise	32	32	33

Note: Table B.2 shows the variance shares for the baseline analysis using global spread, analysis using the first principle component, and analysis using the VIX as the global index.

We find that the main decomposition results are robust across alternative specifications. Country-specific information consistently accounts for a larger share of sovereign CDS spread variance than global-market information. Across specifications, noise and country-specific private information contribute similar magnitudes to overall spread variability. When the VIX is used as the measure for global market conditions, the decomposition attributes a larger share of variance to country-specific public information and a correspondingly smaller share to global-market information relative to the other specifications.