What Moves Sovereign Credit Risk? The Role of Information

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Abstract

This paper develops a return variance decomposition model to examine how sovereign credit risks respond to different sources of information and noise. Using data on sovereign credit default swaps (CDS), we decompose sovereign CDS spreads into four components: noise, global market information, country-specific private information revealed through trading, and country-specific information disclosed through public announcements. The findings indicate that 23% of the variance in spreads is attributable to noise, 36% to global market information, 22% to country-specific private information, and 19% to country-specific public information. We use the model to evaluate the market efficiency in pricing sovereign credit risks and examine how these information components respond to changes in global and domestic macroeconomic factors.

Keywords: Credit default swaps, Default risk, Sovereign debt, International financial markets

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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 for grasping the role of international financial markets and identifying the factors that influence borrowing costs and capital flows across 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. On the other hand, 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 new framework for analyzing sovereign credit risks by identifying the sources of information embedded in sovereign spreads and examining how global and domestic factors contribute to cross-country variations in these information sources. Sovereign credit risks are measured 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, thereby 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 effect of global and domestic factors on each source of information across countries. The global factors considered include indicators of U.S. monetary policy, financial market conditions, and global uncertainty. The domestic factors relate to country-specific economic fundamentals, such as growth rates and debt-to-output ratios.

The decomposition of sovereign CDS spread variations results in four components: noise, global market 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 market information component captures the response of spreads to global market 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 market 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 market returns captures the global market 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 quarterly changes in sovereign CDS spreads for 51 countries from 2014 to 2023. The results indicate that the global market information component accounts for 36% of the variance in quarterly spread changes, while noise contributes approximately 23%. The combined country-specific information (both public and private) comprises the majority of the variance, at 41%. Within this, the country-specific public and private information components contribute roughly equal shares, at 22% and 19%, respectively. For developed countries, country-specific information represents a larger portion of the variance compared to global market information (50% versus 34%), with a higher proportion of country-specific private information relative to public information (30% versus 20%). In contrast, in emerging market economies, global market information dominates country-specific information (38% versus 32%), and within the country-specific category, the public component exceeds the private component (19% versus 13%). These findings suggest that sovereign credit risks in emerging market economies are more driven by global financial market conditions and information disclosed through public announcements of the country's economic conditions.

We proceed by examining the influence of global and domestic factors on the variations in the information components across countries. To capture global economic conditions, we include variables such as changes in the five-year constant maturity Treasury (CMT) yield, the S&P 500 index, and financial risk uncertainty, as measured by the VIX index. For domestic economic conditions, we incorporate the real GDP growth rate and the ratios of domestic and international debt to GDP. Our findings reveal that global factors contribute to an increase in the global market information component while reducing the noise component. Additionally, favorable domestic conditions, such as rising growth rates or declining debt ratios, are associated with a decreased role of country-specific public information and an increased role of country-specific private 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 return decomposition literature.

The literature on sovereign credit risks, beginning with Longstaff et al. (2011), primarily attributes these risks to global factors. Augustin and Tédongap (2016) reinforce this view by emphasizing the role of global macroeconomic factors in explaining variations in sovereign CDS spreads. Chernov and Schneider (2020) provide a model showing that U.S. CDS premiums reflect risk-adjusted probabilities of fiscal default, while Augustin et al. (2022b) emphasize a country's fiscal capacity in linking economic growth shocks to sovereign default risk. Additionally, studies like Pan and Singleton (2008) and Augustin (2018) examine the term structure of sovereign spreads, with findings suggesting that both global factors and country-specific heterogeneity play significant roles. We contribute to this literature by examining sovereign credit risks from the perspective of information sources. Our analysis incorporates the role of noise and enables the separate measurement of public and private country-specific information.

We further contribute to the literature using CDS trading data to investigate how trading volumes influence the pricing of CDS contracts. Oehmke and Zawadowski (2016) demonstrate that CDS markets act as alternative trading venues for hedging and speculation purposes. Shachar (2012) examine CDS trading volumes to explore the role of dealer liquidity provision and counterparty risk, while Du et al. (2023) analyze transaction-level data from 2010 to 2013 to assess the impact of counterparty risk on CDS pricing, finding minimal effects. Augustin et al. (2022a) study the determinants of positions in sovereign CDS contracts, emphasizing the significance of country-specific characteristics. Our analysis shows that by analyzing the responses of CDS spreads to shocks in CDS trading, one can identify country-specific private information from public information.

The literature on return decomposition includes seminal works such as Campbell and Shiller (1988a,b) which distinguish stock price variations into cash flow news and discount rate news.[1] Chen et al. (2013) introduces a method for decomposing stock returns using market forecasts of future cash flows. Brogaard et al. (2022) build on this by isolating information from noise using Beveridge and Nelson (1981)'s methodology. Nozawa (2017) applies this variance decomposition to corporate bond spreads, finding that expected returns and expected credit losses contribute similarly to the variation in credit spreads. We apply Brogaard et al. (2022)'s framework to sovereign CDS spreads to understand the role of global market and country-specific information in sovereign credit risks.

[1]Discount rates new contains more firm's fundamental news, and discounted rate news is more related to the variations in risk aversion or investor sentiments. See Chen et al. (2023).

Outline The rest of the paper is organized as follows. Section 2 provides the sources and descriptions of the data. Section 3 presents the variance decomposition model and explains the identification strategy. 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 Data Sources and Descriptive Statistics

2.1 Data

Sovereign CDS Trading Data We collect sovereign CDS trading data from the Depository Trust and Clearing Corporation (DTCC).[2] 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 top 1000 single names by reference entity from the DTCC's OTC repository data.[3] We scrape the DTCC quarterly transactions data from 2012/03/20 to 2022/12/20 (44 quarters), which contains 45,772 transaction records. To extract the country-specific information from the transaction data, we focus on a subsample of 2212 transaction records made by the Sovereign reference entity.[4] In the sample, the average daily notional is 91.84 million dollars.

Sovereign Spread Data Utilizing CDS spread data offers several advantages (Longstaff et al. (2011), Bai and Wei (2017)). First, the sovereign CDS spread serves as a direct proxy for sovereign credit risk. Compared to sovereign bond pricing, which is influenced by changes in interest rates and exchange rates, sovereign CDS spreads provide a more straightforward measure. 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 contributing to sovereign credit risk. Additionally, the sovereign CDS market often exhibits higher liquidity than the corresponding sovereign bond market, increasing the accuracy of credit spread estimates.

We acquire the daily sovereign CDS spread data with a five-year maturity from Bloomberg. We aggregate the daily data into quarterly averages. Subsequently, we integrate the CDS spread data with the DTCC transactions data, eliminating any missing observations and trading quarters less than 20 quarters. The final sample comprises 1,350 observations.

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

Global Index We construct a measure for the global index by taking the real GDP-weighted average of the daily spreads.

Macroeconomics Variables In Session 5, we characterize the extent to which time series differences in the different information components are driven by country-specific fundamentals, global financial risk, uncertainty factors, or other common drivers. We obtain the quarterly real GDP data from the World Bank's World Development Indicators database.[5] We retrieve the central government debt-to-GDP ratio data from the Quarterly Public Sector Debt Statistics (QPSD) database, jointly developed by the World Bank and the International Monetary Fund.[6] Also, we collected the constructed quarterly debt data reported by the Bank for International Settlements (BIS). The BIS reports the quarterly total debt securities, domestic debt securities, international debt securities, and BIS International debt securities for each country. The CBOE VIX index is a standard measure of global financial risk and uncertainty, and we obtain the VIX index data from the CBOE website.[7] The S&P 500, is a stock market index that aggregates the stock performance of 500 of the largest companies listed on stock exchanges in the United States. It is used by investors as a benchmark to track the overall performance of the stock market. It is obtained from Federal Reserve Economic Data.[8] We also obtain the five-year constant maturity Treasury (CMT) yield reported by the Federal Reserve.[9]

2.2 Variables Construction

We remove the country samples with fewer than 20 valid observations to ensure the variance decomposition model, estimated separately for each country, has sufficient observations.

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

2.3 Summary Statistics

Table 1 summarizes the spread, trading volumes, and macroeconomic fundamentals used in the later analysis. The mean sovereign CDS spread is 196 in the sample period from 2014/04/01 to 2023/01/01. The average of signed dollar volumes is -1218.79 million dollars. The average of the global index is about 88.90. The average change in 5-year constant maturity treasury yield is 0.05. The average real GDP growth rate is 0.52.

[5]See https://databank.worldbank.org/source/world-development-indicators for the details.
[6]See https://www.worldbank.org/en/programs/debt-statistics/qpsd/cross-country-tables for the details.
[7]See https://www.cboe.com/tradable_products/vix/vix_historical_data/ for the details.
[8]See https://fred.stlouisfed.org/series/SP500 for the details.
[9]See https://fred.stlouisfed.org/series/DGS5 for the details.

And the average change of the VIX index is 0.15. The average ratio of central government debt to GDP is about 79.19 %. The average BIS international debt to GDP ratio is 22.43%.

Table 1: Summary Statistics

	N	mean	std	min	25%	50%	75%	max
Spread	1485.00	196.00	758.60	7.76	37.00	79.55	160.20	13165.85
Global Index	1485.00	88.90	31.21	48.00	66.43	84.52	99.18	181.44
Dollar Volume	1485.00	-1218.79	16070.87	-138775.00	-4500.00	-230.00	900.00	105800.00
Treasury Yield Difference	1182.00	0.05	0.39	-0.79	-0.14	-0.02	0.25	1.12
VIX Difference	1182.00	0.15	4.73	-8.85	-2.47	-0.21	1.86	17.02
S&P 500 Difference	1182.00	60.13	160.36	-358.19	-74.63	72.04	148.09	388.15
Real GDP growth	458.00	0.52	3.65	-28.19	0.07	0.65	1.28	23.88
Domestic Debt/GDP	458.00	79.19	51.99	13.81	36.89	70.45	107.47	239.43
BIS International Debt/GDP	458.00	22.43	19.48	2.45	8.65	16.22	31.67	124.18

Note: Table 1 reports summary statistics on the main variables used in our analysis. We report the mean, standard deviation, minimum, maximum, 25th, 50th, and 75th percentile values. Spread is the CDS Price of 5 Years maturity in USD for all countries outside of the US. The global index is the real GDP-weighted average of spreads. Dollar Volume is the signed dollar volume and is measured in USD billions. The real GDP growth rate is calculated by the real gross domestic product(GDP) reported by the World Bank. The debt variables refer to the domestic and international debt outstanding. The sample period extends from 2014/04/01 to 2023/01/01. The column titled "N" refers to the number of observations. CDS trading data are obtained from DTCC, and GDP and debt data are obtained from the World Bank and Bank for International Settlements, respectively.

3 Model

It is vital to accurately capture the types and amounts of different sources of information embedded in the sovereign credit spread, which helps us to understand the nature and dynamics of credit spread pricing from an informational perspective. This paper applies the methodology developed by Brogaard et al. (2022) and investigates the decomposition of different sources of information components in the sovereign credit risk market. Essentially, the general variance decomposition allows the separation of variance into multiple information and noise components. Moreover, we can establish correlations between the dynamics of information and noise components and the specific characteristics of each country.

The key assumptions in our sovereign credit risk decomposition model are that global index returns capture global market information and that the permanent effect of trading in the sovereign CDS captures private information. We treat the global index returns as a global factor indicating of the state of the global economy. Economies across the globe are tightly connected through the trades on consumption goods, investment portfolios, etc. For example, the COVID-19 pandemic has had a global impact on economies across countries. Consequently, we anticipate that shifts in the global index reflect expectations regarding the state of the global economy.

The country-specific trading volume information captures the information belonging to a specific country.

Although each country releases public reports of its GDP growth, debt, trades, fiscal policy, monetary policy, etc, the information related to the states of fundamentals cannot be observed by all market participants only through those public reports. Traders have a greater incentive to actively seek and integrate any valuable information of sovereign credit risks into the spreads through speculative trading. A key assumption here is that the trading dollar volumes in the sovereign credit market reflect country-specific private information. We are interested in separating the public country-specific information from the private country-specific information.

This section provides a detailed description of the return variance decomposition used by Brogaard et al. (2022). The empirical strategy is to use a vector autoregression (VAR) to measure how a sovereign credit risk responds to three shocks: (i) global returns, (ii) country-specific trading flows, and (iii) other country-specific shocks captured in the spread residual.

The empirical model is based on the permanent-transitory decomposition of Beveridge and Nelson (1981) to separate information and noise.

Consider the price of sovereign CDS contract at time t, p_t, as the sum of two components:

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

where m_t is the efficient price and s_t is the pricing error.

m_t follows a random walk with drift μ and innovations w_t :

$$m_t = m_{t-1} + \mu + w_t \tag{2}$$

The spread is the log difference of prices:

$$r_t = p_t - p_{t-1} = \mu + w_t + \Delta_{s_t} \tag{3}$$

The random-walk innovations, w_t , can then be decomposed into three parts:

$$w_t = \theta_{rm}\varepsilon_{rm,t} + \theta_x\varepsilon_{x,t} + \theta_r\varepsilon_{r,t} \tag{4}$$

Thus, the spread is a sum of the discounted rate, global market information, country-specific private information, country-specific public information, and noise.

$$r_t = \underbrace{\mu}_{\text{discount rate}} + \underbrace{\theta_{rm}\varepsilon_{rm,t}}_{\text{global market info}} + \underbrace{\theta_x\varepsilon_{x,t}}_{\text{private info}} + \underbrace{\theta_r\varepsilon_{r,t}}_{\text{public info}} + \underbrace{\Delta_{s_t}}_{\text{noise}} \tag{5}$$

We calculate the noise and information components, which take out the discounted rate and the variations of spread:

$$\begin{aligned} MktComp &= \frac{\theta_{rm}\varepsilon_{rm,t}}{r_t - \mu} \\ PrivateComp &= \frac{\theta_x\varepsilon_{x,t}}{r_t - \mu} \\ PublicComp &= \frac{\theta_r\varepsilon_{r,t}}{r_t - \mu} \\ NoiseComp &= \frac{\Delta_{s_t}}{r_t - \mu} \end{aligned} \tag{6}$$

We then estimate the components of equation 5 using a structural VAR with four lags to allow quarters serial correlation and lagged effects:

$$\begin{aligned} r_{m,t} &= \sum_{l=1}^{4} a_{1,l} r_{m,t-l} + \sum_{l=1}^{4} a_{2,l} x_{t-l} + \sum_{l=1}^{4} a_{3,l} r_{t-l} + \varepsilon_{rm,t} \\ x_t &= \sum_{l=0}^{4} b_{1,l} r_{m,t-l} + \sum_{l=1}^{4} b_{2,l} x_{t-l} + \sum_{l=1}^{4} b_{3,l} r_{t-l} + \varepsilon_{x,t} \\ r_t &= \sum_{l=0}^{4} c_{1,l} r_{m,t-l} + \sum_{l=1}^{4} c_{2,l} x_{t-l} + \sum_{l=1}^{4} c_{3,l} r_{t-l} + \varepsilon_{r,t} \end{aligned} \tag{7}$$

where $r_{m,t}$ is the global return, 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 data is obtained from Bloomberg and DTCC.

The structural VAR in equation 7 incorporates contemporaneous relationships among the variables. Firstly, global market information can be immediately reflected in spreads. However, given that each sovereign CDS constitutes a small portion of the global index, individual countries' spreads and trades have a marginal contemporaneous impact on the overall global return. Secondly, trading activity in a sovereign CDS can be influenced contemporaneously by global market returns and, in turn, cause changes in the spread price, though not the other way around. Consequently, 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. By explicitly modeling the contemporaneous relations between variables, the structural VAR innovations ($\varepsilon_{rm,t}$, $\varepsilon_{x,t}$,$\varepsilon_{r,t}$) are contemporaneously uncorrelated. Refer to A.2

for detailed information on how we estimate this structural VAR.

Taking the variance of the innovations in the efficient price we get $\sigma_w^2 = \theta_{rm}^2 \sigma_{\varepsilon_{rm}}^2 + \theta_x^2 \sigma_{\varepsilon_x}^2 + \theta_r^2 \sigma_{\varepsilon_r}^2$. Recall, the errors 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 therefore

$$\begin{aligned} MktInfoShare &= \theta_{rm}^2 \sigma_{\varepsilon_{rm}}^2 / (\sigma_w^2 + \sigma_s^2) \\ PrivateInfoShare &= \theta_x^2 \sigma_{\varepsilon_x}^2 / (\sigma_w^2 + \sigma_s^2) \\ PublicInfoShare &= \theta_r^2 \sigma_{\varepsilon_r}^2 / (\sigma_w^2 + \sigma_s^2) \\ NoiseShare &= \sigma_s^2 / (\sigma_w^2 + \sigma_s^2) \end{aligned} \tag{8}$$

4 The Decomposition of Sovereign Credit Risk

We perform the variance decomposition on each sovereign across years separately. In our model, we assume that each country has a steady state across the sample periods. We perform the impulse response analysis to estimate the steady state for each country through the sample periods. This allows us to separate the permanent innovations from the temporary innovations in the spreads.

Table 2 reports the mean coefficients for the reduced-form VAR model used to perform the variance decomposition. The coefficients in the global market-return equation (panel A) show that there is a positive first-order serial correlation in global market 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 market 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.

4.1 Share of Information Components

Table 3 shows the estimated variance shares from the baseline model above for the main sample (from 2014/04/01 to 2023/01/01). The results show that using equal-weighted averages, global market information is the largest component, accounting for around 35.95% of spread variance, while country-specific information accounts for 41% (includes both the country-specific public and private information). Just over half of the

Table 2: VAR coefficient estimates

Dependent Variable	Independent Variable	$l = 1$	$l = 2$	$l = 3$	$l = 4$
A. Global market-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 2 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).

country-specific information is impounded in prices through private information (21.51% of variance), and the remaining country-specific public information accounts for 19.48%. Finally, noise accounts for a small portion of 23.06% of the overall variance in spreads.

Table 3: Estimated Shares of Information Components

	count	mean	std	min	25%	50%	75%	max
MktShare	1485.00	35.95	18.84	1.24	18.95	38.36	50.07	75.35
PrivateShare	1485.00	21.51	19.31	0.02	6.78	16.48	33.74	76.70
PublicShare	1485.00	19.48	22.83	0.02	1.86	9.36	27.97	90.17
NoiseShare	1485.00	23.06	16.67	0.00	9.91	18.39	33.46	69.39

Note: Table 3 shows the mean and variance shares (expressed as percentages of variance) for the period from 2014/04/01 to 2023/01/01. Spread variance is decomposed into global market information (MktShare), public country-specific information (PublicShare), private country-specific information (PrivateShare), and noise (NoiseShare). The variance-component shares are calculated separately for each country.

4.2 Comparison

We next study the differences in the variance shares of information components in different groups of countries. We first compare our decomposition results for developed and emerging market economies and then by quartiles of real GDP.

Table 4 shows the estimated variance shares for developed countries. The results show that using equal-weighted averages, global market information is the largest component, accounting for around 34.12% of spread variance, while country-specific information accounts for 49% (includes both the country-specific public and private information). The country-specific information impounded in prices through private information is higher compared to the whole sample dataset (29.62% of variance), and the remaining country-specific public information accounts for 19.82%. Finally, noise accounts for a small portion of 16.44% of the overall variance in spreads, which is smaller compared to our baseline results.

Table 4: Estimated Shares of Information Components for developed economies

	count	mean	std	min	25%	50%	75%	max
MktShare	756.00	34.12	18.84	4.96	18.43	30.58	47.38	75.35
PrivateShare	756.00	29.62	21.30	0.28	13.90	20.02	52.31	76.70
PublicShare	756.00	19.82	19.61	0.25	4.46	15.02	30.42	68.44
NoiseShare	756.00	16.44	10.05	1.91	9.04	13.33	23.81	46.07

Note: This table shows the mean and variance shares (expressed as percentages of variance) for the period from 2014/04/01 to 2023/01/01. Spread variance is decomposed into market-wide information (MktShare), public country-specific information (PublicShare), private country-specific information (PrivateShare),and noise (NoiseShare). The variance-component shares are calculated separately for each country.

Table 5 shows the estimated variance shares for emerging countries. The results show that using equal-weighted averages, global market information is the largest component, accounting for around 37.85% of spread variance, while country-specific information only accounts for 29% (country-specific information accounts for 40% and 49% in the whole sample and developed countries sample, respectively). Especially, the country-specific information impounded in prices through private information decreases a lot compared to the developing countries dataset (13.10% of variance). The remaining country-specific public information accounts for 19.13%, which is similar to that of the whole sample and developed countries sample. Finally, noise accounts for a small portion of 29.92% of the overall variance in spreads, which is higher compared to our baseline results and the developed countries sample.

Table 5: Estimated Shares of Information Components for emerging economies

	count	mean	std	min	25%	50%	75%	max
MktShare	729.00	37.85	18.67	1.24	23.71	43.18	50.14	69.25
PrivateShare	729.00	13.10	12.26	0.02	2.17	7.71	23.20	38.29
PublicShare	729.00	19.13	25.76	0.02	1.86	6.15	22.10	90.17
NoiseShare	729.00	29.92	19.20	0.00	15.37	27.39	44.04	69.39

Note: This table shows the mean and variance shares (expressed as percentages of variance) for the period from 2014/04/01 to 2023/01/01. Spread variance is decomposed into market-wide information (MktShare), public country-specific information (PublicShare), private country-specific information (PrivateShare),and noise (NoiseShare). The variance-component shares are calculated separately for each country.

Table 6 groups the observations into quartiles by country size (real GDP), and demonstrates the mean-variance shares (expressed as percentages of variance) for each quantile. There are no clear patterns for global market information share and private country-specific information share. The public information share is decreasing with the size of the country. We will explore the time series variations in information components in the next section.

Table 6: Estimated Shares of Information Components (Quantile)

	MktInfo Share(%)	PublicInfo Share(%)	PrivateInfo Share(%)	Noise Share(%)
Q1 (Low)	31.31	28.02	19.40	21.26
Q2	37.37	22.17	21.39	19.07
Q3	36.59	20.67	19.14	23.61
Q4 (High)	36.76	5.56	32.91	24.77

Note: Table 6 groups the observations into quartiles by country size (real GDP), and reports the mean variance shares (expressed as percentages of variance) for the period from 2014/04/01 to 2023/01/01. Spread variance is decomposed into global market information (MktInfoShare), public country-specific information (PublicInfoShare), private country-specific information (PrivateInfoShare),and noise (NoiseShare). The variance-component shares are calculated separately for each country.

5 Effects on Information Components

In this session, we examine the factors that potentially influence the information components. We estimate the effect of the change in five-year constant maturity treasury (CMT) yield, the change in CBOE VIX, the change in S&P 500 index, real GDP growth rate, and debt variables on different information component shares in the sovereign CDS spreads. For the debt variables, we explore the domestic debt/GDP ratio and BIS international debt to GDP ratio. We specify the following baseline panel regression:

$$\begin{aligned} InformationComponentShare_{i,t} =& \alpha + \beta_1 treasury + \beta_2 \Delta VIX + \beta_3 \Delta S\&P500 \\ & + \beta_4 \Delta RGDPgrowth + \beta_3 DebtVariables + \kappa_i + \varepsilon_{i,t}, \end{aligned} \tag{9}$$

where $InformationComponentShare_{i,t}$ is the information component share for each country and each quarter. They are information components scaled by the spread deducted from the discount rate. $teasury$ is the five-year constant maturity Treasury (CMT) yield, VIX is the CBOE VIX index, a standard measure of foreign financial-market uncertainty,$S\&P500$ is the S&P 500 index, a proxy for U.S. stock market performance, $RGDPgrowth$ is the real GDP growth rate, $DomesticDebt$ is the percentage of domestic debt in the total GDP, $InternationalDebt$ is the percentage of the BIS international debt in the GDP.

5.1 Determinants of Global Market Information Component

We apply equation 9 in the regression, and Table 7 demonstrates the relationship between the variations in the market information component share and the macroeconomic variables. Column 1 explores the relationship between the global market information component and the global economic conditions. Column 2 demonstrates the effect of country-specific economic variables on the global market information component. Column 3 includes both the general economic conditions and country-specific economic variables. In Column 1, we find a positive effect of the change in the VIX on the market information component share. In Column 2, we do not find a significant effect of country-specific economic variables on market information share. In Column 3, we include both the general and country-specific economic conditions; there is a positive relationship between the change in treasury yield and the market information share. Also, the change in VIX is positively associated with the market information component share. The domestic debt-to-GDP ratio negatively affects the global market information component share.

Table 7: Time Series Analysis of Global Market Information Component

	Market Information Share		
$\Delta treasury$	138.10		458.03
	(91.224)		(378.44)
$\Delta SP500$	0.5665		2.1800
	(0.4901)		(1.8635)
ΔVIX	10.079		34.319
	(9.6226)		(32.208)
RGDP growth		19.418	-18.482
		(33.412)	(17.861)
Domestic Debt		-22.582	-29.839
		(18.449)	(25.966)
International Debt		3.7813	-8.5423
		(13.842)	(12.344)
N	1182	458	420
Country	51	29	27
Country Effects	Yes	Yes	Yes
R-squared	0.0014	0.0061	0.0109

Note: Table 7 reports the time-series analysis of the global market information component in quarterly changes of sovereign CDS spreads. We include the treasury yield, VIX, S&P 500 index, the real GDP growth rate, the domestic debt-to-GDP ratio, and the international debt-to-GDP ratio in our regression analysis. We also control the country's effects. Standard errors clustered at the country and quarter level. */**/*** denotes significance at the 10/5/1 percent levels.

Overall, we find that the global information component is positively related to the change in the global economic factors and negatively related to the domestic factors.

5.2 Determinants of Country-specific Public Information Component

Table 8 shows the time-series analysis of the country-specific public information component share. We are interested in what drives the variations in the country-specific public information component share. Column 1 explores the relationship between public information share and the general economic conditions. Column 2 demonstrates the effect of country-specific economic variables on public information share. Column 3 includes both the general economic conditions and country-specific economic variables. In Column 1, we find a significant positive effect of the change in treasury yield on the public component share. Column 2 shows that there is a negative relationship between the country-specific public information component share and the real GDP growth, which implies that, during periods of economic expansion, the sovereign CDS spread reflects an decreasing portion of country-specific public information. Column 2 demonstrates that there is a negative relationship between the international debt ratio and public information component share. In Column 3, we include both the general economic condition variables and country-specific economic variables; the sign of the real GDP growth coefficient still hold.

Table 8: Time Series Analysis of Public Information Component

	Public Information Share		
$\Delta treasury$	-28.350		-12.511
	(59.082)		(283.73)
$\Delta SP500$	-0.3093		-1.0849
	(0.3623)		(1.1971)
ΔVIX	-7.0390		-23.480
	(8.1463)		(25.897)
RGDP growth		-10.267	-1.2136
		(14.215)	(15.678)
Domestic Debt		6.0168	8.7815
		(3.9707)	(7.1239)
International Debt		-9.2986*	-3.2348
		(5.6093)	(4.8133)
N	1182	458	420
Country	51	29	27
Country Effects	Yes	Yes	Yes
R-squared	0.0014	0.0024	0.0105

Note: Table 8 reports the time-series analysis of the country-specific public information component in the quarterly sovereign CDS spread. We include the treasury yield, VIX, S&P 500 index, the real GDP growth rate, the domestic debt-to-GDP ratio, and the international debt-to-GDP ratio in our regression analysis. We also control the country's effects. Standard errors clustered at the country and quarter level. */**/*** denotes significance at the 10/5/1 percent levels.

The results indicate that the country-specific public information component share is negatively related to the real GDP growth rate and international debt to GDP ratio. We also find that there is a negative effect of the change in financial market uncertainty or the change in the S&P 500 index on the country-specific public information component share.

5.3 Determinants of Country-specific Private Information Component

Table 9 investigates the time series relationship between the country-specific private information component share and macroeconomic variables. We are interested in what drives the variations in the country-specific private information component share. In Column 1, we find a negative effect of the change in treasury yield and the change in the S&P 500 index on the public component share. This implies that when the difference in treasury yield becomes larger, there will be a smaller component of private information in the spread. A larger change in the financial market will cause a smaller component of private information component share in the spread. Column 2 and 3 shows that there is a significant positive effect of international debt ratio on the private information component share.

Table 9: Time Series Analysis of Private Information Component Share

	Private Information Share		
$\Delta treasury$	-4.8644		-234.84
	(53.872)		(215.87)
$\Delta SP500$	-0.0038		-0.7025
			(0.6504)
ΔVIX	1.9942		-2.8310
RGDP growth		-14.212	4.4434
		(24.818)	(20.486)
Domestic Debt		15.941	18.760
		(14.595)	(18.769)
International Debt		15.001**	20.445**
		(7.5157)	(9.0938)
N	1182	458	420
Country	51	29	27
Country Effects	Yes	Yes	Yes
R-squared	4.151e-05	0.0063	0.0073

Note: Table 9 reports the time-series analysis of the country-specific private information component in the quarterly sovereign CDS spread. We include the change in treasury yield, VIX, S&P 500 index, the real GDP growth rate, the domestic debt-to-GDP ratio, and the international debt-to-GDP ratio in our regression analysis. We also control the country's effects. Standard errors clustered at the country and quarter level. */**/*** denotes significance at the 10/5/1 percent levels.

The findings are that the country-specific private information components are negatively related to the change in treasury yield and the financial market index. Also, the international debt ratio has a significant positive effect on the country-specific private information components.

5.4 Determinants of Noise Component

Table 10 investigates the cross-sectional relationship between the noise components and macroeconomic variables. As indicated by Column 2, the change in treasury yield and S&P 500 index has a positive significant effect on the noise component. The country-specific noise information components tend to increase with changes in global factors and decrease with domestic factors.

Table 10: Time Series Analysis of Noise Component

	Noise Share		
$\Delta treasury$	-2.9709		31.816**
	(13.471)		(15.858)
$\Delta SP500$	-0.0401*		0.0128
	(0.0237)		(0.0392)
ΔVIX	0.3857		2.3520
	(0.7313)		(1.5275)
RGDP growth		-35.579	-35.500
		(60.062)	(71.333)
Domestic Debt		-0.4962	-0.6383*
		(0.3117)	(0.3639)
International Debt		-1.2880	-0.6138
		(1.2049)	(0.8619)
N	894	410	340
Country	47	25	21
Country Effects	Yes	Yes	Yes
R-squared	0.0025	0.0097	0.0420

Note: Table 10 reports the time-series analysis of the noise component in the quarterly sovereign CDS spread. We include the change in the treasury yield, VIX, S&P 500 index, the real GDP growth rate, the domestic debt-to-GDP ratio, and the international debt-to-GDP ratio in our regression analysis. We also control the country's effects. Standard errors clustered at the country and quarter level. */**/*** denotes significance at the 10/5/1 percent levels.

6 Conclusion

Previous debates on sovereign CDS spreads have focused on whether global or country-specific factors primarily drive their variations. Utilizing the approach developed by Brogaard et al. (2022), we perform a variance decomposition of sovereign credit risk. Our findings indicate that 36% of the quarterly spread variance is attributed to global market information, while 41% is due to country-specific information. Within the country-specific information, public information and private information each account for a significant share, with 19% and 22% of the variance, respectively. The remaining 28% of the spread variance is attributed to noise.

Additionally, we investigate the determinants of cross-country variations in these information components.

Our results reveal that global market information components are positively correlated with changes in global factors. Favorable domestic economic conditions are associated with reduced country-specific public information and increased country-specific private information.

In emerging market economies, sovereign credit spreads are more influenced by global market information than by country-specific factors, with the public component of country-specific information being more dominant than the private component.

Our study contributes to the literature by analyzing information sources of sovereign credit risks and decomposing country-specific information into public and private components within sovereign CDS spreads, using trading data. The cross-sectional analysis provides deeper insights into the complex dynamics of the sovereign credit risk market. Further works include understanding how information components vary with the term structure of sovereign debt and the interaction of exchange rate dynamics and credit risks.

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A Appendix

A.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. [10]

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) (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.[11]

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

[10]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.

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

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.

A.2 Estimation of the Structural VAR

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

$$\begin{aligned} e_{rm,t} &= \varepsilon_{rm,t} \\ e_{x,t} &= \varepsilon_{x,t} + b_{1,0}\varepsilon_{rm,t} = b_{1,0}e_{rm,t} + \varepsilon_{x,t} \\ e_{r,t} &= \varepsilon_{r,t} + (c_{1,0} + c_{2,0}b_{1,0})\varepsilon_{rm,t} + c_{2,0}\varepsilon_{x,t} = c_{1,0}e_{rm,t} + c_{2,0}e_{x,t} + \varepsilon_{r,t} \end{aligned} \tag{A2}$$

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 [A2]), 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 [A2])

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:

$$\begin{aligned}
\sigma^2_{\varepsilon_{rm}} &= \sigma^2_{e_{rm}} \\
\sigma^2_{\varepsilon_x} &= \sigma^2_{e_x} - b^2_{1,0}\sigma^2_{e_{rm}} \\
\sigma^2_{\varepsilon_r} &= \sigma^2_{e_r} - (c^2_{1,0} + 2c_{1,0}c_{2,0}b_{1,0})\sigma^2_{e_{rm}} - c^2_{2,0}\sigma^2_{e_x}
\end{aligned} \tag{A3}$$

We estimate the long-run cumulative impulse response functions of the structural model by computing the equivalent reduced-form shocks (using Equation [A2]) 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 $[e_{rm,t}, e_{x,t}, e_{r,t}]' = [0, 0, 1]'$. (A4)

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 [A2]);

(iii) Estimate the variances of the structural innovations using equation(A3);

(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 equations (A4); 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.

A.3 Data Appendix

Table A1: Data description

Variables	Label	Source	Definition
Real GDP growth rate	RGDP growth	World Bank	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
Financial risk uncertainty	VIX	CBOE VIX website	VIX index is a good gauge of U.S. equity market volatility and a proxy for financial market uncertainty. We aggregate the daily data into quarterly data and calculate the average of the open and close values as the VIX index value.
Share of central government debt to GDP ratio	CentGovDebt	World Bank	The central government debt includes all maturities and all instruments issued by the central government measured in % of GDP
Total debt to GDP ratio	Total Debt	BIS, World Bank	We use the total debt divided by the total real GDP as the total debt-to-GDP ratio.
Domestic debt to GDP ratio	Domestic Debt	BIS, World Bank	Domestic debt comprises debt securities issued in the local market of the country where the borrower resides, regardless of the currency in which the security is denominated. We use the domestic debt divided by the total real GDP as the domestic debt-to-GDP ratio.
BIS international debt to GDP ratio	BIS International Debt	BIS	International debt comprises debt securities issued in a market other than the local market of the country where the borrower resides.We use the international debt divided by the real GDP as the BIS international debt-to-GDP ratio

Note: Table A1 report the definitions and data sources of the main variables used in the analysis. The sources are the Depository Trust and Clearing Corporation (DTCC), the Bank for International Settlements (BIS), CBOE, the World Bank, and Bloomberg.