How Global is Latin American Sovereign Debt?

Evidence from Chinese Macroeconomic Influences

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Executive Summary

This study examines the influence of both global and local macroeconomic variables on sovereign CDS spreads across six Latin American countries over the period 2015 to 2024. Employing a comprehensive econometric framework—including multiple regressions, panel data models, and quantile regressions—it provides robust evidence that global financial conditions, particularly those linked to China and the United States, account for a substantial portion of the variation in CDS spreads. Local macroeconomic factors, by contrast, tend to exert significant influence primarily during periods of relative macroeconomic stability. A key finding of this thesis is that the Chinese Money Supply (M2) emerges as a dominant driver of CDS spread fluctuations in Latin American countries. Interestingly, the regression results reveal a positive coefficient for this variable, indicating a somewhat counterintuitive relationship between Chinese liquidity growth and sovereign credit risk in the region.

Keywords: Sovereign CDS, Country Risk, Latin American Markets, DXY, CFETS, VIX, Quantile Regression.

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Objectives and Research Questions

General Objective

In his article titled *How Sovereign Is Sovereign Credit Risk?*, Longstaff investigates CDS spreads in 26 countries and concludes that global variables such as S&P 500 volatility (VIX) and the U.S. Dollar Index (DXY) are the main drivers of CDS spread movements, with local economic indicators playing only a secondary role. Inspired by this framework, the goal of this study is to focus on Latin America and analyze to what extent sovereign CDS spreads in Latin American markets are influenced by global macroeconomic factors compared to local variables. Additionally, it seeks to determine whether Chinese variables—such as the Yuan Index (CFETS) and China's industrial production (IPI China)—can significantly explain CDS spread levels in the Latin American region. Using an Ordinary Least Squares (OLS) regression approach similar to that of Longstaff et al., this thesis aims to assess the relative explanatory power of U.S., Chinese, and local economic indicators in shaping sovereign credit risk perceptions across Latin American countries.

Research Questions

1. Do global factors explain more variability than local ones?
2. Are CDS spreads more correlated with U.S. or Chinese variables?
3. Are there significant differences between countries in the sensitivity of CDS spreads to DXY and CFETS Index?
4. Do Chinese variables have statistical relevance in the behavior of spreads?

Empirical Literature Review

The analysis is supported by a critical review of academic literature and working papers that have examined the relationship between sovereign CDS and country risk.

Relevant Literature

In Damodaran (2024), CDS (Credit Default Swap) spreads are highlighted as a key market-based measure of country risk, offering a real-time reflection of the probability that a sovereign will default on its debt. These spreads are essential in finance because they serve as the foundation for estimating a country's sovereign default spread, which Damodaran uses to adjust the equity risk premium for emerging markets. By subtracting the U.S. CDS spread from a country's CDS, and scaling by the relative volatility of equity to bond markets, he incorporates this risk into discount rates used for valuing investments in different countries. Thus, CDS spreads are widely used by investors and analysts to assess sovereign credit risk, inform bond and equity valuations, and guide capital allocation decisions in international finance.

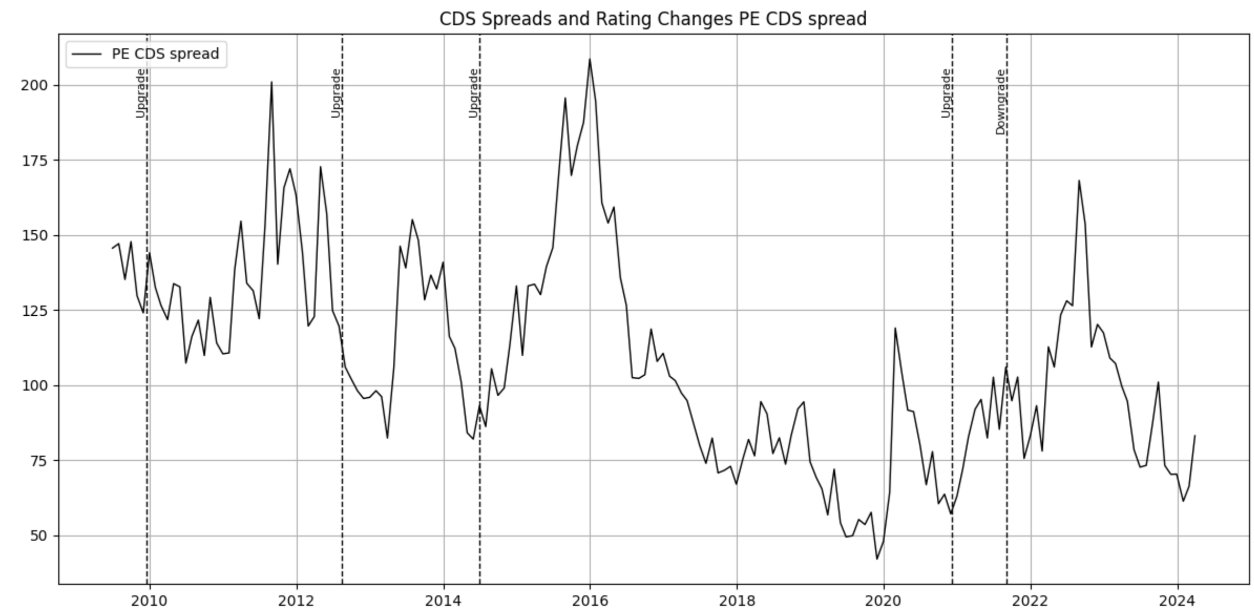

Figure 1:

Ismailescu and Kazemi (2010) examine how sovereign credit default swap (CDS) spreads react to changes in sovereign credit ratings, focusing on emerging markets. They find that CDS spreads respond significantly to both rating changes and outlook revisions, with stronger reactions to downgrades than upgrades. Notably, the market anticipates some rating actions, but actual announcements still move spreads, indicating they are not fully priced in beforehand. This dynamic highlights a two-way relationship: while rating changes impact CDS spreads, the CDS market itself often signals future rating actions. As observed in our chart, a large decrease in peruvian CDS spreads is typically followed by a rating upgrade, and similarly, a sharp increase often precedes a downgrade.

In their paper "How Sovereign Is Sovereign Credit Risk?", Longstaff, Pan, Pedersen, and Singleton (2011) investigate the extent to which sovereign credit risk is driven by local versus global factors. Analyzing CDS spreads for 26 countries using principal component analysis and OLS regressions, they find that global financial variables such as the VIX (a measure of global risk aversion), S&P 500 returns, and global credit conditions—explain a significant portion of the variation in sovereign CDS spreads, while local economic indicators play only a secondary role. Their principal component analysis shows that sovereign risks across countries share common components, meaning that much of the variation in sovereign spreads is due to global factors rather than country-specific fundamentals. Additionally, liquidity conditions in CDS markets are found to be important, with wider bid-ask spreads and lower trading volumes associated with higher CDS spreads. This challenges the notion that sovereign credit risk is primarily determined by a country's own economic health. This master thesis is directly inspired by the approach and findings of Longstaff, Pan, Pedersen, and Singleton (2011) Building on their methodology, this thesis applies a similar framework—using Ordinary Least Squares (OLS) regressions—to investigate whether Chinese or American macroeconomic variables have greater explanatory power over movements in sovereign CDS spreads. While Longstaff et al. focus broadly on global versus local influences, this thesis narrows the lens to compare the influence of two specific economies: China and the United States. By analyzing the sensitivity of CDS spreads to macroeconomic indicators from both countries, the objective is to determine whether the growing influence of China in global financial markets is reflected in credit risk pricing, or whether U.S. variables continue to exert stronger influence. This comparative analysis provides a nuanced extension of Longstaff et al.'s work by shifting the focus from global versus local to a bilateral global influence framework.

Pires, Pereira, and Martins, in their paper "The Complete Picture of Credit Default Swap Spreads – A Quantile Regression Approach" published on January 22, 2010, analyze the determinants of CDS spreads using a quantile regression framework rather than traditional mean-based methods. This approach allows them to assess how various factors influence CDS spreads across different levels of credit risk, offering a more nuanced understanding of the risk structure. Their results show that the impact of explanatory variables such as credit ratings, equity market volatility, and macroeconomic indicators varies across the distribution of CDS spreads. In particular, market variables tend to have a stronger effect in the upper quantiles, where firms are riskier, while fundamental factors play a more prominent role in the lower quantiles. This comprehensive analysis highlights the importance of considering distributional effects when modeling credit risk, as average effects can mask important variations across different credit risk profiles. This method is particularly useful for capturing the non-constant sensitivity of CDS spreads to explanatory variables, meaning that the effect of factors like credit ratings, market volatility, and macroeconomic indicators can vary significantly depending on whether the CDS spread is low, medium, or high. In our research, we adopt this quantile regression approach to better understand how the influence of key variables shifts across different levels of sovereign credit risk. This allows us to identify whether certain drivers are more relevant in times of market stress or during stable periods, offering a more comprehensive view of the dynamics behind CDS spread movements.

Empirical Work

Data

Sovereign CDS spreads: Colombia, Brazil, Mexico, Chile, Argentina. Period: 2015–2024, monthly frequency. Sources: Refinitiv

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
CO CDS spread	111	168.81	62.92	72.70	121.92	156.06	214.65	351.29
BR CDS spread	111	225.17	78.56	99.11	170.54	215.33	258.65	488.99
PE CDS spread	111	97.76	35.35	42.02	73.06	91.64	111.61	208.60
MX CDS spread	111	126.28	31.59	78.45	102.38	118.46	146.49	246.02
CL CDS spread	111	76.36	28.48	35.84	55.12	70.65	90.06	168.05
AR CDS spread	87	3885.70	6554.66	355.84	501.14	1815.64	3393.28	31077.93

Table 1: Descriptive Statistics: Sovereign CDS Spreads (Basis Points)

The sovereign CDS spread data for Colombia, Brazil, Peru, Mexico, Chile, and Argentina from 2015 to 2024 highlights important patterns in country risk across Latin America. As shown in Table 1, Chile and Peru have the lowest average spreads, reflecting stronger macroeconomic fundamentals, lower external vulnerabilities, and greater institutional stability. In contrast, Argentina's CDS spreads are extremely high and volatile, with a mean above 3,800 bps and a maximum exceeding 31,000 bps—indicative of repeated debt crises, high inflation, and episodes of default.

	CO	BR	PE	MX	CL	AR
Colombia	1.00	0.63	0.44	0.57	0.68	0.63
BR	0.63	1.00	0.43	0.58	0.53	0.29
PE	0.44	0.43	1.00	0.58	0.81	0.06
MX	0.57	0.58	0.58	1.00	0.62	0.27
CL	0.68	0.53	0.81	0.62	1.00	0.38
Argentina	0.63	0.29	0.06	0.27	0.38	1.00

Table 2: Correlation matrix of CDS spreads

The correlation matrix reveals relatively high comovement among countries like Chile, Peru, Colombia, and Mexico, for example Chile–Peru with a correlation of 0.81, which reflects shared exposure to global commodity prices, U.S. monetary policy, and regional investor sentiment. Argentina, however, displays weak correlations with most peers such as Argentina–Peru with 0.06, underscoring its idiosyncratic risk profile driven by domestic instability and less synchronized economic cycles. The dataset has fewer observations for Argentina (87 vs. 111 for others), likely due to extended periods of illiquidity or suspended CDS trading during crisis episodes. Given this data discontinuity and Argentina's structural outlier status, it will be excluded from the empirical analysis to avoid distorting regional comparisons.

Series	**ADF Statistic**	**p-value**	**1% Crit.**	**5% Crit.**	**10% Crit.**
CO CDS spread	-2.88	0.048	-3.47	-2.88	-2.58
BR CDS spread	-2.63	0.086	-3.47	-2.88	-2.58
PE CDS spread	-1.83	0.366	-3.47	-2.88	-2.58
MX CDS spread	-4.77	0.00006	-3.47	-2.88	-2.58
CL CDS spread	-3.84	0.003	-3.47	-2.88	-2.58

Table 3: ADF test results for individual series

The ADF test shows us that only Mexico, Chile, and possibly Colombia have stationary CDS series, while Brazil and Peru are non-stationary. Including non-stationary variables in regressions can lead to spurious results. To avoid this, we must difference those series or test for cointegration. Excluding Argentina also helps, as its extreme values and missing data would distort the results and reduce reliability.

Variable	Count	Mean	Std	Min	25%	50%	75%	Max
Latinamerican Variables								
Index Colombia	111.0	1335.75	225.59	890.24	1156.55	1341.32	1515.40	1768.16
COIO=ECI (ECONOMIC)	111.0	2.70	10.85	-35.70	-1.50	1.50	5.15	64.20
COPFX	111.0	3482.28	587.62	2381.00	2991.76	3377.00	3884.75	4929.35
Index Mexico	111.0	9718.64	1876.07	5746.09	8562.80	9448.62	10269.95	15060.31
MXIPY=ECI (ECONOMIC)	111.0	0.95	7.23	-30.00	-1.20	1.00	3.35	37.10
MXNFX	111.0	19.05	1.73	14.95	18.02	19.13	20.12	24.15
Index Brazil	111.0	5874.79	1223.41	2828.86	5095.54	5992.66	6833.33	8228.27
BRIOY=ECI (ECONOMIC)	111.0	-0.98	7.11	-27.70	-4.45	-0.60	1.80	34.80
BRLFX	111.0	4.31	0.88	2.84	3.43	4.05	5.18	5.74
Index Peru	111.0	2957.75	637.82	1563.43	2514.80	3052.10	3435.80	4738.47
aPECINDYG/CA (ECONOMIC)	111.0	1.07	18.11	-52.70	-3.82	-0.04	3.41	121.05
PENFX	111.0	3.50	0.26	3.08	3.28	3.39	3.73	4.12
Index Chile	111.0	4442.76	775.33	2805.26	3934.76	4295.64	4813.26	6632.57
CLMFG=ECI (ECONOMIC)	111.0	-0.03	4.58	-12.70	-2.45	0.10	2.80	14.60
CLPFX	111.0	741.79	97.34	594.74	661.05	712.80	809.42	978.97
Global - US								
US 5T	111.0	2.04	1.17	0.21	1.22	1.77	2.77	4.82
DXY	111.0	97.70	4.75	89.13	94.52	96.95	100.74	112.12
USA Money Supply	111.0	6.88	7.20	-4.53	3.89	5.62	7.23	26.67
VIX	111.0	18.67	7.25	9.51	13.48	16.48	21.10	53.54
Global - China								
CN 5T	111.0	2.91	0.42	1.74	2.59	2.91	3.17	3.96
China Money Supply	111.0	10.12	1.74	7.20	8.52	9.93	11.47	13.92
PMI China	111.0	50.20	1.65	37.31	49.49	50.20	51.18	54.21
CN Industrial Production	111.0	5.77	4.20	-14.77	4.79	5.94	6.66	33.83
CFETS CNY	111.0	97.02	3.75	91.00	94.07	96.74	99.82	105.04
Commodities								
HGc3	111.0	3.15	0.73	2.00	2.60	2.94	3.81	4.67
XAG	111.0	19.30	3.98	13.63	16.13	17.85	23.09	28.09
Brent	111.0	65.46	19.82	18.38	50.16	64.08	78.66	122.71

Table 4: Descriptive Statistics of Explanatory Variables

The dataset used in this analysis covers the period from **January 2010** to **April 2024**, with a **monthly frequency**. This choice reflects the typical reporting intervals of macroeconomic and financial indicators, which are most commonly published on a monthly or quarterly basis. Using monthly data allows for a more granular analysis of the dynamic interactions between sovereign credit risk and global as well as domestic macro-financial conditions.

Domestic Latin American Variables

These variables capture the internal economic conditions of the Latin American countries under study.

Local Stock Market Indices: Represent investor sentiment and expectations regarding the domestic economy. Rising stock indices often correlate with improving economic outlooks and reduced sovereign risk. Index averages vary across countries, such as **1335.75** for Colombia, **5874.79** for Brazil, and **9718.64** for Mexico, with significant dispersion reflecting market-specific dynamics.

Industrial Production Indices: A proxy for domestic economic activity. We include monthly indices for countries such as Colombia, Mexico, Brazil, Peru, Chile, and Argentina. Stronger industrial production implies higher economic growth and tax revenues, lowering default probability. For example, Colombia's industrial production averaged **2.70%**, Mexico's **-0.08%**, and Brazil's **-0.98%**, indicating divergent domestic output patterns across the region.

Exchange Rates (USD per local currency): Exchange rate fluctuations play a critical role in sovereign credit risk, particularly for countries with significant external debt denominated in foreign currency (usually USD). When a country's local currency depreciates against the dollar, the cost of servicing dollar-denominated debt rises in local currency terms. This increases the debt burden and heightens the risk of default, which investors price into the sovereign's credit default swap (CDS) spreads. Higher CDS spreads reflect greater perceived credit risk. For example, the average exchange rates in our sample were **3482.28** for the Colombian peso, **19.05** for the Mexican peso, and **4.31** for the Brazilian real, all showing notable volatility especially during financial stress periods. Sharp depreciation episodes often lead to spikes in CDS spreads, as markets anticipate increased difficulty in meeting external obligations. Therefore, exchange rate dynamics are a key macroeconomic factor influencing sovereign credit risk and must be carefully modeled in CDS spread regressions.

United States of America Financial Indicators

These variables reflect the global financial environment, particularly the influence of the United States, which remains central to international capital flows and investor sentiment.

US 5-Year Treasury Yield: This variable captures the risk-free interest rate in the US for a medium-term horizon. Changes in this yield often signal shifts in global liquidity and monetary policy expectations. Higher US Treasury yields may raise global financing costs, increasing sovereign risk for emerging markets. During the sample period, the yield averaged **2.04%**, with a minimum of **0.28%** and a peak of **4.82%**, reflecting periods of both accommodative and tightening policy stances.

DXY (US Dollar Index): The DXY index measures the value of the US dollar against a basket of major currencies. A stronger dollar can exert pressure on emerging market currencies and sovereign balance sheets, especially for those with dollar-denominated debt. The index exhibited an average of **97.70**, ranging from **88.25** to **112.12**, underscoring substantial currency strength fluctuations over the period.

USA Money Supply (M2): Reflects the liquidity in the US financial system. A rapid increase in US money supply, particularly under expansionary monetary policy, can lead to capital outflows to emerging markets, temporarily reducing their credit spreads. The annual growth rate of US M2 averaged **6.88%**, but ranged widely from a contraction of **-4.53%** to an expansion of **26.67%**, highlighting periods of both monetary easing and tightening.

VIX (CBOE Volatility Index): The VIX is a widely used proxy for global risk aversion. It tends to spike during financial turmoil and global uncertainty. Higher VIX levels are associated with tighter financial conditions and capital outflows from riskier assets, thereby widening CDS spreads for emerging markets. In the sample, it had a mean of **18.67**, with values ranging from a calm **9.14** to a crisis-level **53.54**.

Chinese Macroeconomic and Financial Variables

Given China's increasing economic footprint and trade linkages with Latin America, especially through commodity demand, it is important to incorporate Chinese financial variables.

China 5-Year Treasury Yield: Reflects medium-term interest rates in China, which may influence global capital flows and regional financial conditions, particularly in economies with strong trade ties to China. The yield averaged **2.91%**, with relatively moderate variation between **2.18%** and **3.83%**.

China Money Supply (M2): This is a key measure of domestic liquidity in China, representing the total amount of money available in the economy, including cash, deposits, and easily accessible funds. An expansion in Chinese M2 typically signals stimulative monetary policy aimed at encouraging economic growth. Such growth in liquidity can lead to increased domestic consumption and investment in China, which in turn boosts demand for commodities like metals, energy, and agricultural products—many of which are major exports for Latin American countries. Consequently, higher Chinese M2 growth often translates into stronger trade flows and economic activity in Latin America. During the period studied, the growth rate of Chinese M2 averaged $\mathbf{10}.\mathbf{12}\%$, remaining within a relatively stable range of $\mathbf{8}.\mathbf{06}\%$ to $\mathbf{11}.\mathbf{38}\%$, reflecting consistent monetary expansion efforts by Chinese policymakers.

Purchasing Managers' Index (PMI) – China: A leading indicator of manufacturing activity. A higher PMI suggests strong economic activity, which is closely linked to the demand for Latin American exports, particularly raw materials. The PMI averaged **50.20**, fluctuating from a low of **35.70** during pandemic disruptions to a high of **52.80**, reflecting varying levels of manufacturing strength.

China Industrial Production: This variable reflects the output of the Chinese industrial sector. As China is a major importer of commodities such as copper, oil, and soy, increased production tends to boost demand for Latin American exports and supports sovereign creditworthiness. The year-on-year growth rate averaged **5.77%**, with a minimum of **-13.50%** and a maximum of **33.83%**, indicating strong cyclical volatility.

CFETS CNY Index: The China Foreign Exchange Trade System (CFETS) RMB Index tracks the value of the Chinese yuan against a basket of currencies. Movements in the CFETS index can influence the trade competitiveness of China and signal changes in China's foreign exchange policy stance, indirectly affecting Latin American export volumes and terms of trade. It recorded an average of **97.02**, with relatively contained fluctuations between **91.54**

and **102.93**.

Global Commodity Prices

Since many Latin American economies are commodity exporters, global commodity prices are central to their external accounts and fiscal health.

Copper Prices (HGc3): Copper is a major export for countries like Chile and Peru. Its price is highly sensitive to global industrial demand, especially from China. Higher copper prices can reduce sovereign risk by improving trade balances and fiscal revenues. Copper traded at an average of **3.15 USD/lb**, with a minimum of **2.06** and a maximum of **4.67** during the sample.

Silver Prices (XAG): Silver is another important export commodity, particularly for Peru. Like copper, its price reflects global industrial and investment demand and serves as a barometer of economic conditions. It had an average of **19.30 USD/oz**, with values ranging from **11.77** to **29.59**.

Brent Crude Oil Prices: Oil exports are significant for countries like Colombia and, to a lesser extent, Brazil. The Brent crude price reflects global energy demand and geopolitical dynamics. Higher oil prices generally strengthen sovereign fiscal positions and reduce default risk. Prices averaged **65.46 USD/barrel**, but ranged from a low of **18.38** to a high of **122.71**, illustrating the commodity's volatility.

Variance Inflation Factor (VIF) Test

Variable	**VIF**
Copper	11.06
USA Money Supply	10.39
USA 5-Year Treasury	9.42
Silver	7.83
DXY	7.38
China Money Supply	5.35
Brent	4.75
China 5-Year Treasury	3.39
VIX	2.90
CFETS CNY	2.57
China Industrial Production	1.99
PMI China	1.93

Table 5: Variance Inflation Factors (VIF) for Selected Features

Note: The VIF coefficient of the i_{th} variable, is computed by regressing it against the other explanatory variables, $X_i = \sum_{j \neq i}^{n} \beta_j X_j$, then taking the coefficient of determination R^2 and computing $\frac{1}{1-R^2}$.

Due to high multicollinearity, we will eliminate variables with a VIF greater than 10 to improve the stability and interpretability of our regression model. In this case, **copper** and **USA money supply** exhibit VIF values exceeding this threshold, indicating they are highly correlated with other explanatory variables like the 5-year Treasury yield and silver. Including such highly correlated variables can inflate the standard errors of coefficient estimates, making it difficult to distinguish their individual effects on CDS spreads. By removing copper and USA money supply, we minimize multicollinearity issues, and enhance the reliability of our coefficient estimates.

Baseline Econometric Model Findings

Explanatory Power of Global vs. Local Factors

A primary objective of this thesis is to determine the relative importance of global versus local factors in driving sovereign risk. The OLS regression results provide a clear and compelling answer. Table 11 (Full Model) shows that the R-squared values are consistently high across all countries, ranging from 0.8003 for Mexico to 0.8637 for Colombia. The data indicates that the combined set of global and local variables explains a substantial portion of the variance in CDS spreads. However, a more nuanced picture emerges when comparing the explanatory power of different variable groups. The 'Global Model' (Table 11), which includes U.S., Chinese, and commodity variables, consistently demonstrates higher R-squared values than the 'Local Model' (Table 6). For instance, in the case of Brazil, the R-squared for the 'Local Model' is 0.7101, while the 'Global Model' has an R-squared of 0.7169, and the 'Full Model' has an R-squared of 0.8172. With the global model outperforming the local model, this hierarchical increase in explanatory power is a consistent pattern across all the countries analysed. The aspect quantitatively substantiates the thesis's central argument: global macroeconomic conditions are the primary drivers of sovereign risk in Latin America.

A large body of academic literature strongly supports the finding. For example, the seminal work of Longstaff et al. (2011) found that a single global factor could explain a significant portion of the variation in sovereign CDS spreads across a wide range of countries. Similarly, other studies (Longstaff et al., 2011; Wang Yao, 2014) have consistently shown that global risk appetite, international liquidity conditions, and significant market volatility are the dominant drivers of emerging market spreads, often dwarfing the impact of domestic fundamentals.

The Influence of U.S. and Chinese Macroeconomic Variables

The OLS analysis reiterates that macroeconomic indicators of the two largest economies of the world, the United States and China, have significant effects. Focusing on the U.S. variables, DXY (U.S. Dollar Index) and VIX (CBOE Volatility Index) are often statistically significant. CDS spreads are also related to stronger DXY, a measure of a stronger U.S. dollar. The rationale is that a stronger dollar aggravates the real burden of dollar-denominated debt characteristic of Latin American economies. Such an observation is in line with a large body of literature that has showcased the adverse impact on the creditworthiness of emerging markets due to the stronger dollar (Pires et al., 2010; Wang et al., 2013). The popular proxy of global risk aversion, VIX, shows a positive correlation with the CDS spreads. Therefore, it implies that when more uncertainties face the world, the investors will likely pull the money out of the riskier emerging economies and switch to safer investments. So, the sovereign risk premiums of these economies are likely to skyrocket. Wang et al. (2013) note that this "flight-to-quality" phenomenon is a well-documented driver of emerging market spreads.

One of the contributions of this thesis is that it is concerned with the increased influence of China. The OLS findings indicate significant influences of the Chinese factors, including the China Money Supply and the CFETS CNY Index. The positive coefficient on China's supply of money indicates that an expansionary policy in China, which may increase the capital flows or raise demand for commodities, has a practical impact on the economies of Latin America. The statistical significance of the CFETS CNY Index indicates the rising role played by the Yuan in the global financial system and its role in the competitiveness of the Latin American commodity exporter countries in their relations with trade. The finding is especially new and introduces a new dimension to the traditional U.S.-centred perspective of involving world factors with the emerging markets. Other researchers, such as Yueh (2014), have explored the concept, noting China's role as a major creditor and its impact on regional debt dynamics.

CDS spreads have long been closely correlated with U.S. macroeconomic variables, particularly the DXY (U.S. Dollar Index) and the VIX (CBOE Volatility Index). A stronger U.S. dollar increases the real burden of dollar-denominated debt in Latin American economies, leading to wider CDS spreads, while higher VIX levels indicate greater global risk aversion, prompting investors to flee riskier emerging markets and seek safer assets, which in turn raises sovereign risk premiums. This relationship is well-documented in the literature and reflects the dominant role of the U.S. in global financial markets. However, this thesis further confirms evidence of a rising influence from Chinese macroeconomic factors, such as the China Money Supply and the CFETS CNY Index. The positive impact of China's expansionary monetary policy suggests increased capital flows and commodity demand that directly affect Latin American economies, while the growing significance of the CFETS CNY Index reflects the Yuan's expanding role in global trade and finance, particularly for commodity-exporting countries. These findings indicate that, although U.S. variables still exert a strong and established effect on CDS spreads, Chinese factors are becoming increasingly important, adding a new dimension to the analysis of emerging market risk and highlighting a shift toward a more multipolar global economic influence.

Commodity Prices

The impact of commodity prices on CDS spreads varies across the countries in the sample, a reflection of their diverse export dependencies. For commodity-exporting nations like Chile and Peru (copper) or Colombia and Brazil (oil), these prices are paramount to their fiscal and external accounts. The negative coefficient for silver (XAG) in the complete model for most countries suggests that higher silver prices are associated with lower CDS spreads, particularly for a major silver exporter like Peru. The findings are consistent with the intuitive expectation that higher export revenues improve a country's ability to service its debt, thus reducing its perceived sovereign risk. That aligns with Naifar's (2024) conclusions, which suggest a significant spillover from commodity markets to the sovereign CDS spreads of commodity-dependent countries.

Local Factors

Surprisingly, in our single block regressions, the US only model often explains less variation in CDS spreads than the local only model, for instance in Brazil and Peru, contradicting Longstaff et al. (2011), who argued that global, particularly US-based, factors overwhelmingly dominate sovereign credit risk pricing. However, our full model results offer a more nuanced picture: Chinese variables, especially the CFETS CNY index and China's money supply, exhibit consistently significant and substantial coefficients across all countries, highlighting China's growing systemic relevance. Meanwhile, local variables, most notably exchange rates and stock market indices, also show strong and statistically significant effects, often more so than US variables like the VIX or US Treasury yields. This suggests not only that local factors retain meaningful, context-dependent influence, especially during stable periods, but also that US financial dominance in Latin American credit risk pricing may be receding in favor of more regionally proximate or directly impactful drivers like China.

The Multiple Ordinary Least Square Regression (OLS)

We model the dependent variable in this case, CDS spreads, denoted as y as a linear function of several explanatory macroeconomic variables $x_1, x_2, \ldots, x_p$. The model takes the form:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots + \beta_p x_{ip} + \varepsilon_i$$

Here, y_i represents the CDS spread for observation at time i, and each x_{ij} is the macroeconomic variable at time i, for example like China Money Supply also. Each coefficient β_j reflects the expected change in the CDS spread resulting from a one standard deviation increase in the macroeconomic variable x_j, holding all other macro variables constant.

These coefficients are estimated jointly using the formula:

$$\hat{\boldsymbol{\beta}} = (\mathbf{X}^T\mathbf{X})^{-1}\mathbf{X}^T\mathbf{y}$$

where $\mathbf{y}$ is the vector of CDS spreads and $\mathbf{X}$ is the matrix of macroeconomic indicators (with a column of ones for the intercept).

Statistical Significance of Coefficients

A p-value is the probability of observing a test statistic as extreme as the one computed from your data, assuming the null hypothesis is true—in regression, this usually tests whether a coefficient $\beta_j = 0$, meaning the corresponding variable has no effect on the dependent variable. It is computed by first calculating the t-statistic for each coefficient:

$$t_j = \frac{\hat{\beta}_j}{\mathrm{SE}(\hat{\beta}_j)}$$

where $\hat{\beta}_j$ is the estimated coefficient and $\mathrm{SE}(\hat{\beta}_j)$ is its standard error. This t_j value is then compared against the t-distribution with $n - p - 1$ degrees of freedom to find the probability (p-value) of observing such an extreme value under the null hypothesis. A low p-value (typically less than 0.05) indicates that the coefficient β_j is statistically significant, suggesting that the corresponding variable has a meaningful effect on the dependent variable. In our table results, the statistically significant variables will be shown in bold to highlight their importance.

The Assumptions of OLS Regression

$$\begin{aligned}
&(1)\quad y_i = \beta_0 + \beta_1 x_{i1} + \cdots + \beta_p x_{ip} + \varepsilon_i \\
&(2)\quad \mathrm{Cov}(\varepsilon_i, \varepsilon_j) = 0 \quad \text{for } i \neq j \\
&(3)\quad \mathrm{Var}(\varepsilon_i) = \sigma^2 \quad \forall i \\
&(4)\quad \mathrm{rank}(\mathbf{X}) = p + 1 \\
&(5)\quad \mathbb{E}[\varepsilon_i \mid \mathbf{x}_i] = 0 \\
&(6)\quad \varepsilon_i \sim \mathcal{N}(0, \sigma^2)
\end{aligned}$$

(1) The model assumes a linear relationship between the dependent variable y_i and the independent variables x_{ij} with error ε_i. (2) Errors are uncorrelated across observations, meaning no error influences another. (3) Errors have constant variance (homoscedasticity), ensuring equal spread of residuals for all data points. (4) There is no perfect multicollinearity; the regressors are linearly independent so that $\mathbf{X}$ has full rank. (5) The errors have zero mean given the predictors, ensuring unbiased coefficient estimates. (6) For valid inference (like hypothesis testing), errors are assumed normally distributed.

Model 1 – Local: includes only local economic variables to estimate their isolated explanatory power on the CDS Spread via OLS.

$$\text{CDS Spread}_{i,t} = \alpha + \beta_1 \textbf{Local IPI}_{i,t} + \beta_2 \textbf{Stock Index}_{i,t} + \beta_3 \textbf{Local FX}_{i,t} + \epsilon_{i,t} \qquad (1)$$

Table 6: Local Models

Variable	**CO**	**BR**	**PE**	**MX**	**CL**
Local Variables					
Local IPI	0.0337	**-0.1279**	0.0024	-0.1873	**-0.2552**
FX	**0.4570**	0.0531	0.0731	0.0715	0.0787
Index	**-0.3018**	**-0.7872**	**-0.7686**	**-0.2686**	**-0.3786**
R^2	0.4362	0.7101	0.5799	0.1803	0.2663

Models focusing only on local variables show much lower R^2 values, especially for Mexico and Chile, this shows the limited explanatory power of domestic factors alone.

Model 2 – United States: focuses exclusively on U.S. macrofinancial variables.

$$\text{CDS Spread}_{i,t} = \alpha + \gamma_1 \mathbf{5Y\ Yield}_t + \gamma_2 \mathbf{VIX}_t + \gamma_3 \mathbf{DXY}_t + \gamma_4 \mathbf{U.S.\ Money\ Supply}_t + \epsilon_{i,t}$$

Table 7: U.S. Model

	CO	**BR**	**PE**	**MX**	**CL**
U.S. Variables					
DXY	**0.6694**	**0.4333**	**0.5174**	**0.5671**	**0.7720**
VIX	**0.2512**	0.0387	-0.0196	**0.2515**	**0.1708**
US 5T	-0.0198	**-0.4896**	**-0.4055**	**-0.4718**	**-0.4562**
R^2	0.52497	0.1547	0.1433	0.3299	0.4190

The U.S.-only model has moderate explanatory power for some countries (e.g., Colombia, Mexico, Chile) but performs poorly for Brazil and Peru. Surprisingly, the U.S only model underperforms the local-only model in most countries, suggesting that domestic economic and financial conditions (such as FX, industrial production, and equity markets) are more influential drivers of CDS spreads than U.S. financial variables alone. This may reflect limited variation in U.S. indicators during the sample period, or that U.S. effects are mediated through other channels like global risk sentiment, China's economy, or commodity prices-rather than acting directly. It also highlights that some countries, like Brazil and Peru, are more insulated from U.S. specific shocks, whereas in more U.S.integrated economies like Mexico, the U.S.only model performs relatively better. This outcome stands in contrast to the findings of Longstaff et al. (2011), who emphasized the dominant role of global—particularly U.S. factors such as the VIX and Treasury yields in driving sovereign credit spreads. The divergence may reflect differences in the sample, time period, or the relative importance of local fundamentals in the countries analyzed, indicating that while global risk sentiment is important, it may not uniformly overshadow domestic conditions in all contexts.

Model 3 – China: includes only macroeconomic and financial indicators from China.

$$\begin{aligned}\text{CDS Spread}_{i,t} = \alpha &+ \delta_1 \mathbf{China\ IPI}_t + \delta_2 \mathbf{China\ 5Y\ Yield}_t \\ &+ \delta_3 \mathbf{China\ M2}_t + \delta_4 \mathbf{CFETS}_t + \delta_5 \mathbf{China\ PMI}_t + \epsilon_{i,t}\end{aligned}$$

Table 8: Chinese Model

	CO	**BR**	**PE**	**MX**	**CL**
Chinese Variables					
CFETS CNY	**0.3370**	0.0630	**0.2762**	**-0.2877**	**0.2378**
CN 5T	**-0.2970**	**0.1482**	**0.1638**	-0.0093	-0.0824
CN Industrial Production	-0.0861	0.0222	-0.0410	-0.0451	**-0.1288**
China Money Supply	**0.4179**	**0.7533**	**0.6813**	**0.6376**	**0.6248**
PMI China	-0.0757	-0.0274	-0.0181	**-0.2634**	-0.0189
R^2	0.721	0.571	0.674	0.433	0.692

The Chinese only model demonstrates that Chinese variables alone explain a substantial portion of CDS spread variation, particularly in countries like Colombia, Peru, and Chile, where R^2 values exceed 0.67. Notably, variables such as China's money supply and the CFETS CNY index are consistently significant across most countries. However, when compared to the full model, where R^2 values rise above 0.80 for all countries, it becomes clear that while Chinese factors are influential, they are not fully sufficient to capture the complexity of sovereign credit risk pricing. The full model benefits from the combined explanatory power of local, US, and commodity variables, suggesting that although China plays a growing systemic role, especially through liquidity and currency channels, its influence complements rather than substitutes for other global and domestic factors.

Model 4 – United States and China: combines the variables from Models 2 and 3.

$$\begin{aligned}\text{CDS Spread}_{i,t} = \alpha &+ \gamma_1 \mathbf{5Y\ Yield}_t + \gamma_2 \mathbf{VIX}_t + \gamma_3 \mathbf{DXY}_t + \gamma_4 \mathbf{U.S.\ Money\ Supply}_t \\ &+ \delta_1 \mathbf{China\ IPI}_t + \delta_2 \mathbf{China\ 5Y\ Yield}_t + \delta_3 \mathbf{China\ M2}_t \\ &+ \delta_4 \mathbf{CFETS}_t + \delta_5 \mathbf{China\ PMI}_t + \epsilon_{i,t}\end{aligned}$$

Table 9: U.S. and China Model

	CO	**BR**	**PE**	**MX**	**CL**
Chinese Variables					
CFETS CNY	**0.260481**	0.125508	**0.313328**	**-0.252025**	**0.260316**
CN Industrial Production	-0.027392	-0.013766	-0.037957	-0.057028	**-0.113763**
China Money Supply	**0.416923**	**0.699383**	**0.630024**	**0.497842**	**0.485852**
PMI China	-0.014420	-0.037889	-0.042186	**-0.166971**	0.060577
CN 5T	**-0.152379**	0.139999	**0.192273**	**0.208382**	**0.153854**
U.S. Variables					
DXY	**0.195845**	0.055990	0.162979	**0.421342**	**0.496660**
VIX	**0.136027**	-0.030726	-0.093849	**0.219664**	**0.154349**
US 5T	**0.190060**	**-0.257812**	**-0.228481**	**-0.322593**	**-0.321129**
R^2	0.803119	0.612301	0.695134	0.522085	0.768956

Model 5 − Global: includes all considered variables except local ones.

$$\begin{aligned}\text{CDS Spread}_{i,t} = \alpha &+ \beta_1\textbf{Local IPI}_{i,t} + \beta_2\textbf{Stock Index}_{i,t} + \beta_3\textbf{Local FX}_{i,t}\\ &+ \gamma_1\textbf{5Y Yield}_t + \gamma_2\textbf{VIX}_t + \gamma_3\textbf{DXY}_t + \gamma_4\textbf{U.S. Money Supply}_t\\ &+ \delta_1\textbf{China IPI}_t + \delta_2\textbf{China 5Y Yield}_t + \delta_3\textbf{China M2}_t\\ &+ \delta_4\textbf{CFETS}_t + \delta_5\textbf{China PMI}_t\\ &+ \kappa_1\textbf{Copper} + \kappa_2\textbf{Silver} + \kappa_3\textbf{Brent} + \epsilon_{i,t}\end{aligned}$$

Table 10: Global Model

Variable	CO	BR	PE	MX	CL
Chinese Variables					
CFETS CNY	**0.2303**	**0.3086**	**0.5181**	-0.0532	**0.2991**
CN 5T	-0.1114	-0.1127	0.0093	-0.1105	0.0626
CN Industrial Production	-0.0413	0.0719	0.0209	0.0524	-0.0817
China Money Supply	**0.4499**	**0.4994**	**0.4082**	**0.2799**	**0.4428**
PMI China	-0.0331	0.0763	0.0616	-0.0324	0.0938
U.S. Variables					
US 5T	**0.1698**	-0.1353	-0.0900	-0.1902	**-0.2958**
VIX	**0.1248**	0.0373	-0.0228	**0.2959**	**0.1707**
DXY	**0.2059**	-0.0075	0.1535	**0.3250**	**0.4599**
Commodities					
XAG	0.0620	**-0.3823**	**-0.2684**	**-0.4860**	**-0.1413**
Brent	0.0213	-0.1253	**-0.2240**	-0.0987	0.0053
R^2	0.8059	0.7169	0.7703	0.6774	0.7803

Model 6 – Full Model: includes all considered variables.

$$\begin{aligned}
\text{CDS Spread}_{i,t} = \alpha &+ \beta_1 \textbf{Local IPI}_{i,t} + \beta_2 \textbf{Stock Index}_{i,t} + \beta_3 \textbf{Local FX}_{i,t} \\
&+ \gamma_1 \textbf{U.S. 5Y Yield}_t + \gamma_2 \textbf{VIX}_t + \gamma_3 \textbf{DXY}_t \\
&+ \gamma_4 \textbf{U.S. Money Supply}_t \\
&+ \delta_1 \textbf{China IPI}_t + \delta_2 \textbf{China 5Y Yield}_t \\
&+ \delta_3 \textbf{China M2}_t + \delta_4 \textbf{CFETS}_t + \delta_5 \textbf{China PMI}_t \\
&+ +\kappa_1 \textbf{Silver} + \kappa_2 \textbf{Brent} \\
&+ \epsilon_{i,t}
\end{aligned}$$

Table 11: Full Models Results

Variable	CO	BR	PE	MX	CL
Local Variables					
IPI	0.0731	0.0097	**-0.3484**	0.1136	-0.0168
FX	**0.4401**	**0.1964**	**0.2658**	**0.6954**	**0.4599**
Index	-0.1004	**-0.6240**	**-0.3484**	**0.2802**	**0.2839**
Chinese Variables					
CFETS CNY	**0.2906**	**0.1617**	**0.3836**	0.1752	**0.3146**
CN 5T	-0.0537	-0.0269	0.0384	-0.0195	0.0877
CN Industrial Production	0.0173	0.0308	0.0493	0.0990	-0.0639
China Money Supply	**0.3639**	**0.2179**	**0.2798**	**0.3991**	**0.5700**
PMI China	-0.0486	0.0249	0.0284	-0.0753	0.1066
U.S. Variables					
DXY	0.1197	0.0810	0.0920	**0.2286**	**0.3251**
US 5T	0.0850	-0.0038	0.1296	0.0044	**-0.4498**
VIX	-0.0440	-0.0775	-0.0203	0.0802	0.1156
Commodities					
Brent	-0.0250	0.0158	**-0.2246**	**-0.3359**	-0.0705
XAG	**-0.2067**	**-0.3112**	**-0.4033**	**-0.6246**	**-0.2134**
R^2	0.8637	0.8172	0.8494	0.8003	0.8085
DW	1.202	1.315	1.478	1.238	1.029

Note: The Full Model and the Global Model (which includes all relevant global variables and commodities but excludes local factors) show the highest explanatory power with $\mathbf{R^2}$ values mostly above 0.8.

Rolling Regression

To visualize the evolution of CDS spread sensitivity over time, we perform rolling regressions using the full model. This approach allows us to capture the dynamic nature of the relationship between CDS spreads and DXY, China Money supply and Foreign Exchange across different periods. By applying a 24 months moving window, we estimate time varying coefficients for each variable, revealing how their influence fluctuates in response to changing economic conditions. The coefficients are then used to plot the evolving sensitivities, providing insights into the temporal dynamics.

Time-Varying Sensitivity to Global Shocks

The rolling regression results indicate that the explanatory variables' coefficients are not unambiguously stable over time. Instead, they exhibit notable shifts in response to major global events. For instance, during the COVID-19 shock in 2020 and the onset of the war in Ukraine in 2022, the coefficients associated with China's Money Supply, the U.S. Dollar Index (DXY), and local exchange rates (FX) all declined simultaneously. This synchronized drop suggests that Latin American CDS spreads become particularly sensitive to global risk aversion and shifts in international capital flows during periods of heightened uncertainty. Such findings are consistent with the literature, including Giraldo et al. (2023), which emphasizes the time-varying nature of sovereign risk determinants.

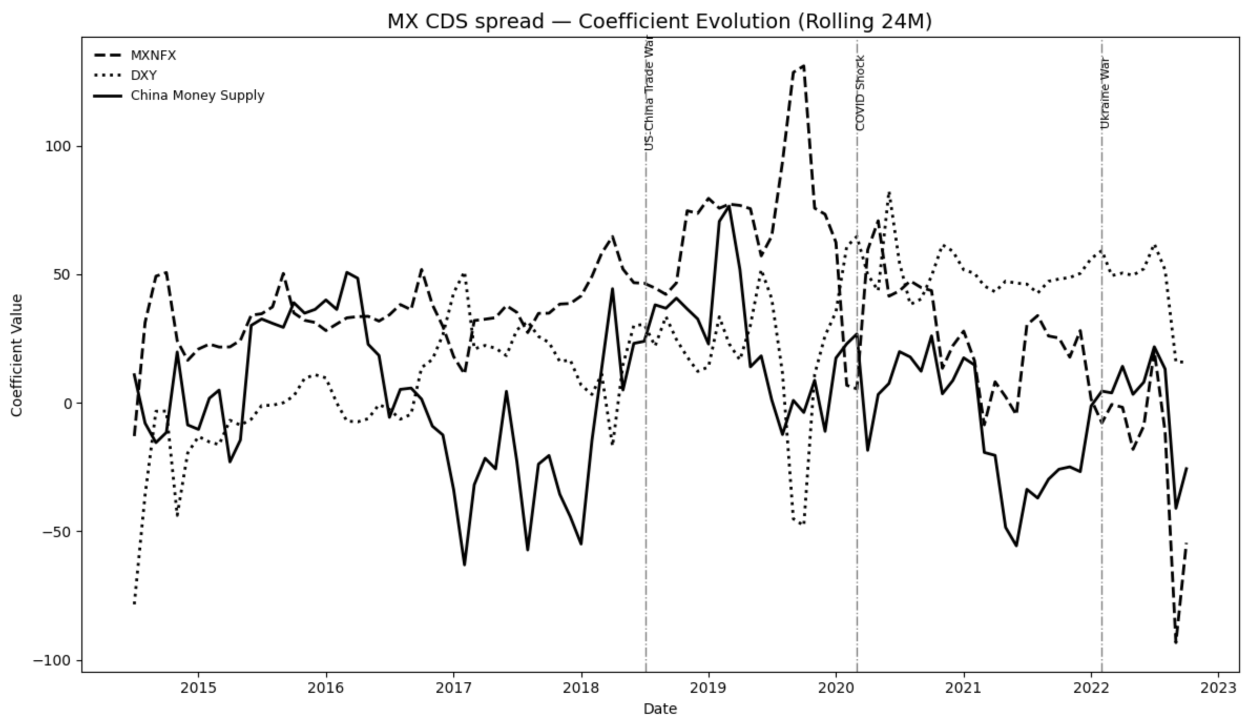

Figure 2:

Quantile Regression

The sensitivities of CDS spreads to macroeconomic variables are clearly not constant over time due to the complex and often nonlinear nature of sovereign debt markets. Traditional Ordinary Least Squares (OLS) regression estimates the average effect of explanatory variables on the dependent variable, assuming a constant relationship across all observations. However, this approach may mask important variations in how macroeconomic factors impact CDS spreads at different points of their distribution. For example, during periods of financial stress, the impact of risk factors on CDS spreads may be significantly stronger than during stable times.

Quantile regression offers a valuable alternative by allowing the estimation of conditional relationships at different quantiles of the CDS spread distribution. This means it can capture how the effects of macro variables vary not just on average, but across low, median, and high levels of sovereign risk. By doing so, quantile regression provides a more comprehensive understanding of the dynamics and heterogeneity in credit risk sensitivity, making it particularly suited for analyzing markets characterized by volatility and structural breaks.

$$Q_{CDS_{i,t}}(\tau) = \alpha(\tau) + \sum_{k} \beta_k(\tau) X_{k,i,t}$$

where $Q_y(\tau \mid \mathbf{x}_{it})$ is the conditional τ-th quantile of the CDS spread y_{it}, and $\beta_j(\tau)$ represents the effect of macroeconomic variable x_j at that specific part of the distribution. This helps capture heterogeneity in how CDS spreads react to macro factors across low-risk and high-risk environments.

Quantile regression provides a more granular and nuanced view of the relationships between the explanatory variables and CDS spreads by examining these relationships at different points (quantiles) of the CDS spread distribution. The concept is particularly valuable for understanding how the determinants of sovereign risk change under different market conditions, such as stable (low spreads), moderate, or high-stress (high spreads) periods

Varying Impact Across CDS Spread Levels

The key insight from the quantile regression analysis, which is visually represented in Figure 3 (Mean Quantile Coefficient Variables), is that the sensitivity of CDS spreads to macroeconomic variables is not constant but varies significantly depending on the level of the spread itself. The finding is significant, hence questioning the uniformity explanation of OLS regression. By observing the coefficient of the VIX across the different quantiles, one would likely see that it increases significantly at higher quantiles. The concept would imply that global risk aversion becomes an even more critical and potent driver of CDS spreads during extreme market stress. The finding agrees with the results of other researchers who employed the quantile regression to examine the sovereign risk and found that the global factors are significantly more influential in the upper tail of the spread distribution (Shahzad et al., 2017). On the other hand, the distribution of coefficients of local variables may reveal that they gain greater significance at lower quantiles. This substantiates the argument of the thesis that the domestic fundamentals become more significant when the macroeconomic conditions are stable and financial markets are not panic-stricken. This non-linear and dynamic relationship is one of the reasons why the traditional OLS regression can only estimate the average difference of a variable. Therefore, quantile regression is a significant methodological contribution that allows for a much more comprehensive and realistic understanding of the complex and multifaceted nature of sovereign risk.

Panel Model

Interpretation of Panel Model Results

The panel regression analysis, presented in Table 12, provides a more robust and statistically powerful assessment of the determinants of CDS spreads by accounting for both cross-sectional and time-series variations across the six Latin American countries.

Significance of Global Variables in our Panel Results

The panel model confirms and strengthens the findings from the OLS regressions regarding the pervasive and dominant influence of global factors. The DXY, VIX, China Money Supply, and CFETS CNY Index all show highly significant coefficients with p-values close to 0.0000, indicating a high degree of statistical confidence. The positive coefficients for DXY (0.2273) and VIX (0.1212) reinforce the conclusion that a stronger U.S. dollar and higher global risk aversion lead to wider CDS spreads in Latin America. The positive coefficients for China Money Supply (0.4161) and CFETS CNY (0.2606) provide strong and compelling evidence of China's substantial and growing role in influencing the region's sovereign risk, likely through trade and financial channels. Interestingly, the U.S. 5-Year Treasury Yield shows a significant negative coefficient (-0.1083). At first glance, this might seem counterintuitive, as higher U.S. interest rates could be expected to increase borrowing costs for emerging markets. However, this could also reflect a 'risk-on' environment, where higher U.S. yields are driven by strong economic growth expectations, increasing investors' appetite for higher-yielding emerging market assets, thus leading to lower CDS spreads.

Commodity Prices in the Panel Model

The panel model also confirms the significant negative impact of silver prices (XAG) on CDS spreads, with a coefficient of -0.2432. This data reinforces that higher commodity prices generally reduce sovereign risk for commodity-exporting nations. However, the Brent crude oil price shows a negative but not statistically significant coefficient (-0.0843 with a p-value of 0.1384). The data suggests a weaker and less consistent impact across the entire panel, likely due to the diverse nature of oil dependence among the selected countries, with some being net exporters (like Colombia) and others being net importers or having more diversified economies (like Chile).

Model Fit and Hypothesis Testing

The panel model has an R-squared of 0.5988 and a highly significant F-statistic of 80.600 (with a p-value of 0.0000). The data indicate that the included global variables are jointly significant and explain a substantial portion of the variation in CDS spreads across the Latin American countries in the panel. The fact that local variables are not explicitly included in the final panel model further supports the thesis's central argument that global factors are the region's primary drivers of sovereign risk. The panel model results allow testing Hypothesis H(fit): $R^2 \leq 0.50$ vs H: $R^2 > 0.50$. With an R-squared of 0.5988, we can confidently reject the null hypothesis and conclude that the model has a good fit and that the included variables explain a significant portion of the variance in CDS spreads. Furthermore, the high statistical significance of the global variables allows us to reject the null hypothesis H: ${}_j = {}_k = {}_l = 0$ (no effect) and accept the alternative hypothesis H_1 : there exists j, k, l such that the coefficient non zero.

Table 12: Panel Regression Results

Variable	Coefficient	Std. Err.	t-stat	p-value	Lower CI	Upper CI
DXY	**0.2273**	**0.0605**	**3.7582**	**0.0002**	**0.1085**	**0.3462**
US 5T	**-0.1083**	**0.0502**	**-2.1595**	**0.0313**	**-0.2068**	**-0.0098**
VIX	**0.1212**	**0.0352**	**3.4397**	**0.0006**	**0.0520**	**0.1904**
China Money Supply	**0.4161**	**0.0475**	**8.7658**	**0.0000**	**0.3228**	**0.5093**
PMI China	0.0332	0.0341	0.9738	0.3306	-0.0338	0.1003
CFETS CNY	**0.2606**	**0.0440**	**5.9269**	**0.0000**	**0.1742**	**0.3469**
CN 5T	-0.0525	0.0469	-1.1210	0.2628	-0.1446	0.0395
CN Industrial Production	0.0045	0.0309	0.1445	0.8852	-0.0562	0.0651
XAG	**-0.2432**	**0.0392**	**-6.2073**	**0.0000**	**-0.3202**	**-0.1662**
Brent	-0.0843	0.0568	-1.4839	0.1384	-0.1959	0.0273
const	0	0.0068	0	1.0000	-0.0134	0.0134

Model Stats: R-squared = 0.5988, F-statistic = 80.600, p-value = 0.0000

Conclusions

Answering Research Questions

Do global factors explain more variability than local ones?
The findings also provide an affirmative answer to the fourth and final research question. The higher R-squared values of the global models compared to the local models and the dominance of global factors in the panel model confirm that global factors are the primary drivers of CDS spread variability in Latin America. Among other researchers, Longstaff et al. (2011) demonstrate this well-established finding in the literature.

Are CDS spreads more correlated with U.S. or Chinese variables?
The results suggest that both U.S. and Chinese variables are highly significant. While the VIX and DXY are robust and well-established drivers, the growing significance of Chinese variables, such as the money supply and the CFETS index, is a key finding of this thesis. This is consistent with the findings of Aljarba et al. (2024) and Feng et al. (2023), who also highlight the growing importance of Chinese factors.

Are there significant differences between countries in the sensitivity of CDS to VIX and China's industrial production?
The country-specific results presented in Table 13 provide a clear affirmative answer, demonstrating the significant heterogeneity in how individual Latin American countries respond to fluctuations in global risk factors. The findings are supported by research from Ismailescu and Kazemi (2010), who found that the impact of rating changes on CDS spreads varies across emerging markets. For example, a country with a high reliance on commodity exports to China, such as Peru or Chile (in the case of copper), would likely exhibit a stronger negative correlation with China's industrial production. This concept means that a slowdown in Chinese industrial output would lead to a more significant widening of their CDS spreads compared to a country with more diversified trade partners. Similarly, countries with weaker fiscal positions or higher levels of external debt would likely show a greater sensitivity to the VIX, as global risk aversion disproportionately affects their perceived creditworthiness.

While a detailed discussion of each country's specific sensitivity would require a closer examination of the numerical coefficients in Table 13, the methodology confirms that such differences exist and are a critical component of understanding the nuanced impact of global factors across the diverse Latin American sovereign debt landscape. The findings align with studies that have found significant cross-country heterogeneity in the response to global shocks (Gamboa-Estrada Romero, 2024).

Do Chinese variables have statistical relevance in the behaviour of spreads? Yes, the results answer the research question in the affirmative. The statistically significant impact of Chinese variables in both the OLS and panel regression models demonstrates that China plays a measurable and influential role in Latin American countries' economic and financial dynamics. Although this area of research is relatively new, the growing body of literature reinforces the emerging academic consensus that China's presence in the region is not only growing but also shaping key economic indicators (Yueh, 2024).

Further Research

The findings presented in this thesis point towards the idea that the Latin American countries, regardless of their distinctive domestic features and policy systems, are strongly and irreversibly enmeshed with the world financial system. Their sovereign creditworthiness is significantly shaped by external forces, necessitating a proactive and sophisticated approach to managing the risks associated with global economic spillovers. Future research could build upon the findings of this thesis by further exploring the channels through which Chinese macroeconomic variables, particularly China Money Supply impact Latin American CDS spreads and delving deeper into the non-linear relationships identified by the quantile regressions to provide more targeted and actionable policy recommendations for policymakers in the region.

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Appendix

Figure 3: Mean Quantile Coefficient Variables

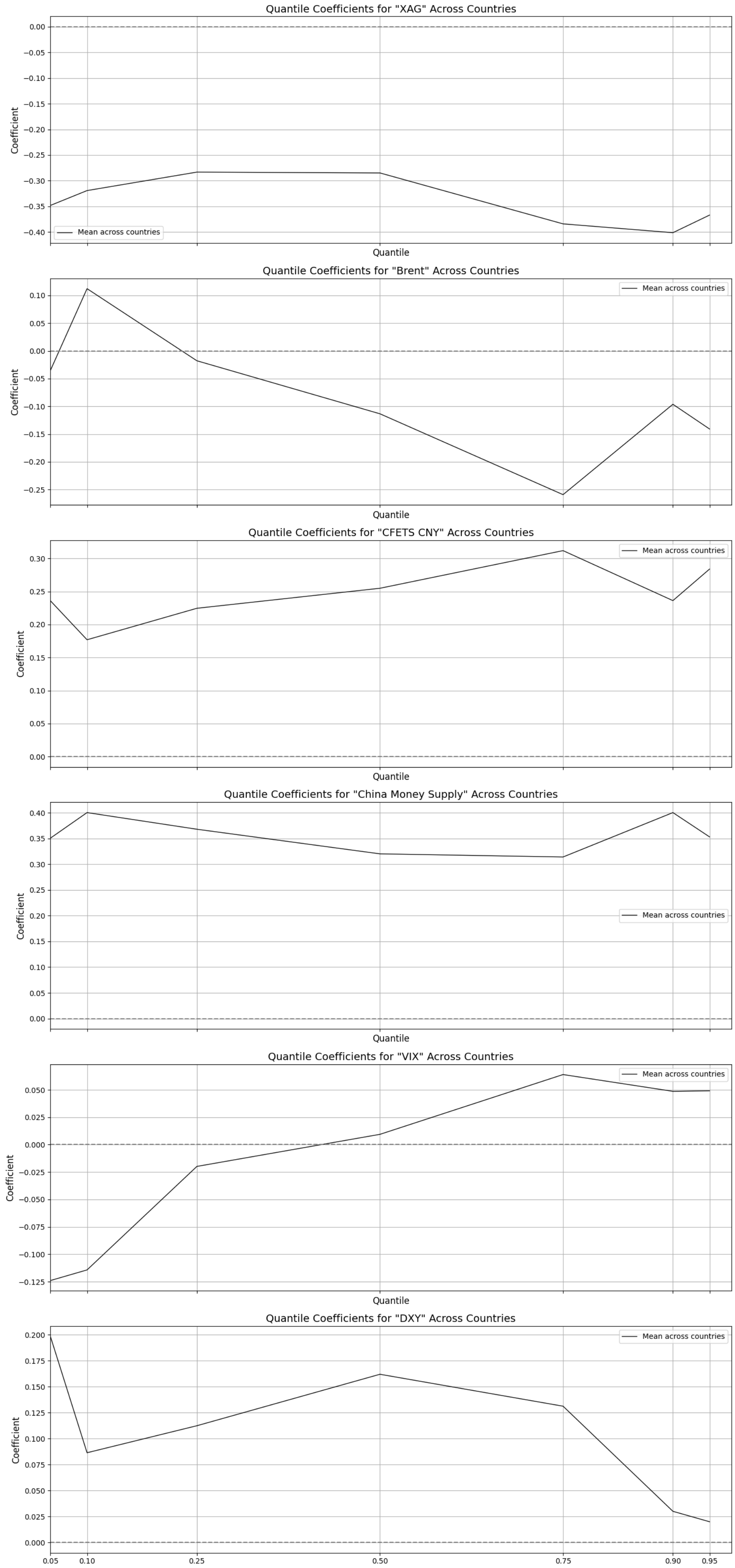
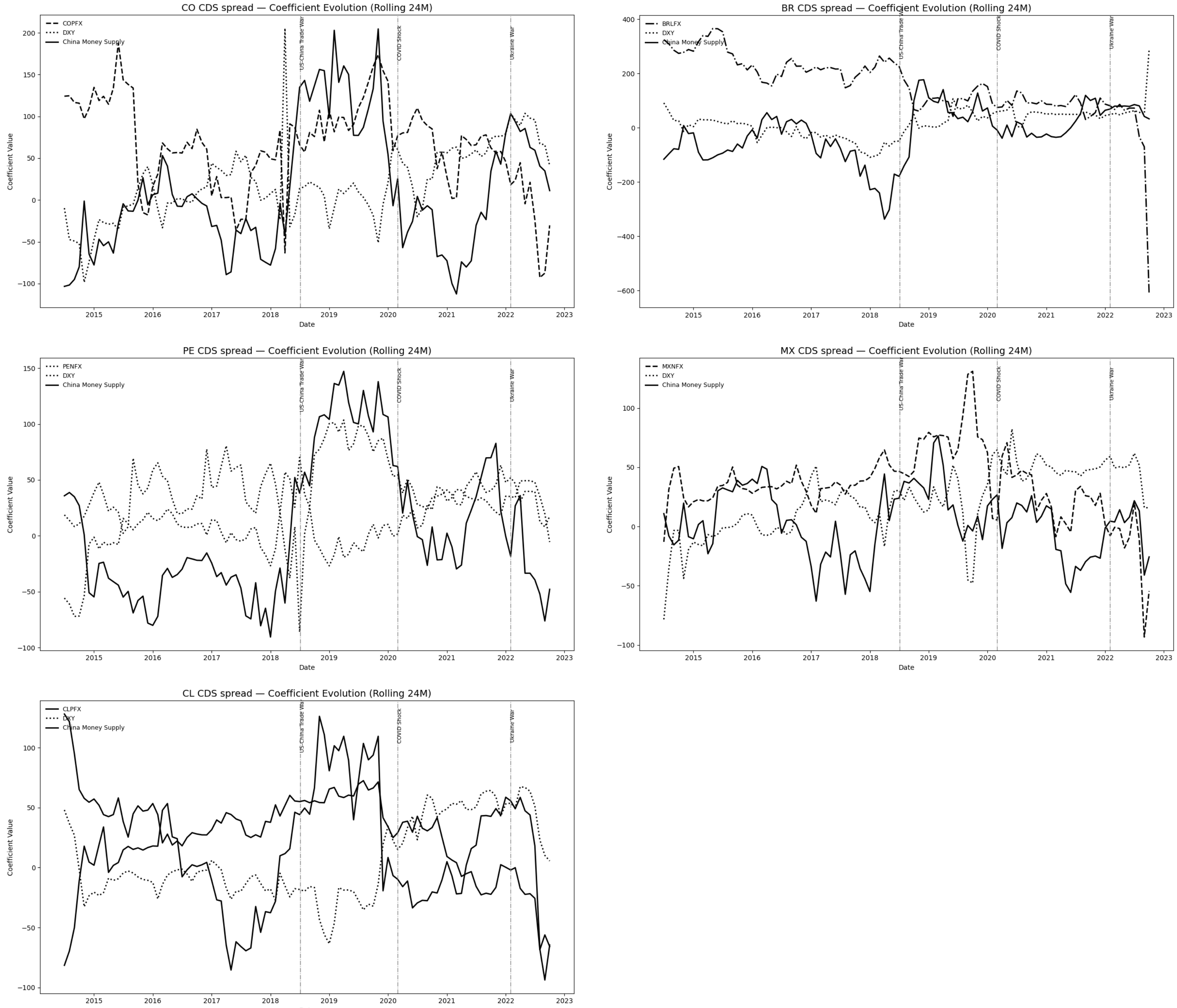


Table 13: Rolling Regressions Full Model by Country



Code Listings

```
# === 1. Libraries ===
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import statsmodels.api as sm
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.linear_model import ElasticNetCV
from linearmodels.panel import PanelOLS
from statsmodels.tsa.seasonal import seasonal_decompose
from statsmodels.stats.outliers_influence import
    variance_inflation_factor
from statsmodels.stats.diagnostic import het_breuschpagan
from scipy.stats import jarque_bera
from statsmodels.stats.stattools import durbin_watson
```

```
    # === 2. Load Data ===
file_path = "/Users/forrest/Documents/Master Finanzas/TFM/data/"
df = pd.read_excel(file_path + 'HITO3_data.xlsx', parse_dates=['Date
    '])
df.set_index('Date', inplace=True)
# Clean missing values and non-numeric
df.replace('---', np.nan, inplace=True)
df = df.apply(pd.to_numeric, errors='coerce')
# Strip column names (important to avoid later bugs)
df.columns = df.columns.str.strip()
#This allows us to choose the 2015-2024 timeframe
#df = df.loc['2015-01-01':]

# === 3. Standardize Data ===
scaler = StandardScaler()
numeric_cols = df.select_dtypes(include=np.number).columns
df_scaled = pd.DataFrame(scaler.fit_transform(df[numeric_cols]),
    index=df.index, columns=numeric_cols)
# Special interpolation for Argentina CDS Spread (which had missing)
df_scaled['AR CDS spread'] = df_scaled['AR CDS spread'].interpolate(
    method='linear')
```

```
# We destationalize variables known for having strong seasonality
deseasonalize_vars = ["PMI China", "CN Industrial Production", "
    China Money Supply", "USA Money Supply", "HGc3", "XAG"]
# Keep only available ones
deseasonalize_vars = [var for var in deseasonalize_vars if var in df
    .columns]
```

```
# Create empty DataFrame to store deseasonalized series
df_deseasonalized = pd.DataFrame(index=df.index)
# Deseasonalize each variable
for col in deseasonalize_vars:
    series = df[col].dropna()
    try:
        decomposition = seasonal_decompose(series, model='additive',
            period=12)
        trend_resid = decomposition.trend + decomposition.resid
        df_deseasonalized[col] = trend_resid
    except Exception as e:
        df_deseasonalized[col] = series  # fallback to original if
           decomposition fails
# Replace original series in df
df.update(df_deseasonalized)
df_scaled.update(StandardScaler().fit_transform(df[
   deseasonalize_vars]))
```

```
# Updated local variables (by country)
local_vars = {
    'CO': ['Index Colombia', 'COIO=ECI (ECONOMIC)', 'COPFX'],
    'BR': ['Index Brazil', 'BRIOY=ECI (ECONOMIC)', 'BRLFX'],
    'PE': ['Index Peru', 'aPECINDYG/CA (ECONOMIC)', 'PENFX'],
    'MX': ['Index Mexico', 'MXIPY=ECI (ECONOMIC)', 'MXNFX'],
    'CL': ['Index Chile', 'CLMFG=ECI (ECONOMIC)', 'CLPFX'],
    'AR': ['Index Argentina', 'ARIO=ECI (ECONOMIC)', 'ARSFX'],
}

# Global (USA, China, Commodities)
us_vars    = ['US 5T', 'DXY', 'USA Money Supply', 'VIX']
china_vars = ['CN 5T', 'China Money Supply', 'PMI China', 'CN
   Industrial Production', 'CFETS CNY'] #
commodities_vars = ['HGc3', 'XAG', 'Brent']

# Combined global vars
global_vars = us_vars + china_vars + commodities_vars

# Mapping CDS spreads
cds_map = {
    'CO': 'CO CDS spread', 'BR': 'BR CDS spread', 'PE': 'PE CDS
       spread',
    'MX': 'MX CDS spread', 'CL': 'CL CDS spread', 'AR': 'AR CDS
       spread',
}
```

```
# Plot Local Variables + CDS per Country
def plot_local_vars(country_code):
    predictors = local_vars[country_code] + [cds_map[country_code]]
```

```
    available = [var for var in predictors if var in df_scaled.
       columns]

    plt.figure(figsize=(12, 6))
    for var in available:
        lw = 3 if var == cds_map[country_code] else 1
        plt.plot(df_scaled.index, df_scaled[var], label=var,
           linewidth=lw)

    plt.title(f"Standardized Local Variables and {cds_map[
       country_code]}")
    plt.legend(loc="upper left")
    plt.grid(True)
    plt.show()

# Loop through countries
for country in local_vars.keys():
    plot_local_vars(country)
```

```
#VIF computation
# Collect all unique predictors used in any model
all_predictors = set(global_vars)
predictors = [p for p in all_predictors if p in df_scaled.columns]
X = df_scaled[predictors].dropna()

vif_df = pd.DataFrame()
vif_df["feature"] = predictors
vif_df["VIF"] = [variance_inflation_factor(X.values, i) for i in
   range(X.shape[1])]
print(vif_df.sort_values("VIF", ascending=False))
```

```
    # Define which variables belong to each group globally
local_all = []
usa_all = ["USA Money Supply", "US 5T", "DXY", "VIX"]
china_all = ["China Money Supply", "CN 5T", "PMI China", "CN
   Industrial Production", "CFETS CNY"] #
commodities_all = ["HGc3", "XAG", 'Brent']
global_all = usa_all + china_all + commodities_all

df = df.loc['2015-01-01':]
df_scaled = df_scaled.loc['2015-01-01':]
# Initialize structured dictionary
selected_vars_split_grouped = {}


all_selected_vars = {
    'CO': [ 'All variables'],'BR': [],
    'PE': [],'MX': [],'CL': [],'AR': [],}
```

```
for country, selected_vars in all_selected_vars.items():
    # Initialize
    #if 'CFETS CNY' in selected_vars:
    #    selected_vars.remove('CFETS CNY')
    selected_vars_split_grouped[country] = {
        'local': [],
        'usa': [],
        'china': [],
        'commodities': []
    }

    # Assign each selected variable to its group
    for var in selected_vars:
        if var in usa_all:
            selected_vars_split_grouped[country]['usa'].append(var)
        elif var in china_all:
            selected_vars_split_grouped[country]['china'].append(var
               )
        elif var in commodities_all:
            selected_vars_split_grouped[country]['commodities'].
               append(var)
        else:
            selected_vars_split_grouped[country]['local'].append(var
               )


# 4. Define your CDS spreads mapping
latam_countries = {
    'CO': 'CO CDS spread',
    'BR': 'BR CDS spread',
    'PE': 'PE CDS spread',
    'MX': 'MX CDS spread',
    'CL': 'CL CDS spread',
    'AR': 'AR CDS spread'
}

models = {}

def fit_and_store(Y, X, cds, name):
    data = pd.concat([Y, X], axis=1).dropna()
    if data.empty:
        print(f"Skipping {cds} - {name} (not enough data)")
        return
    X2 = sm.add_constant(data.iloc[:, 1:])
    models[(cds, name)] = sm.OLS(data.iloc[:, 0], X2).fit()
```

```
# 5. Loop over each country and fit all model types
for country_code, cds in latam_countries.items():
    if country_code not in selected_vars_split_grouped:
        continue

    Y = df[cds]
    country_vars = selected_vars_split_grouped[country_code]

    # Build the different X matrices
    X_full = df_scaled[
        country_vars['local'] +
        country_vars['usa'] +
        country_vars['china'] +
        country_vars['commodities']
    ]

    X_local = df_scaled[country_vars['local']]
    X_usa = df_scaled[country_vars['usa']]
    X_china = df_scaled[country_vars['china']]
    X_usa_china = df_scaled[country_vars['usa'] + country_vars['
       china']]
    X_usa_china_commod = df_scaled[country_vars['usa'] +
       country_vars['china']+ country_vars['commodities']]
    # Fit and store all models
    fit_and_store(Y, X_full, cds, "Full Model")
    fit_and_store(Y, X_local, cds, "Local Only")
    fit_and_store(Y, X_usa, cds, "U.S. Only")
    fit_and_store(Y, X_china, cds, "China Only")
    fit_and_store(Y, X_usa_china, cds, "U.S. vs China")
    fit_and_store(Y, X_usa_china_commod, cds, "Global Only")

# 6. Print model summaries
for country_code, cds in latam_countries.items():
    for name in ["Full Model", "Local Only", "U.S. Only", "China
       Only", "U.S. vs China", "Global Only"]:
        if (cds, name) in models:
            print(f"\n=== {cds}     {name} ===")
            print(models[(cds, name)].summary())

from collections import Counter

# List of countries for the panel
panel_countries = ['CO', 'BR', 'PE', 'MX', 'CL']  # Excluding AR

# Extract selected variables for each country
selected_variables_by_country = {
    country: (
```

```
        #selected_vars_split_grouped[country]['local'] +
        selected_vars_split_grouped[country]['usa'] +
        selected_vars_split_grouped[country]['china'] +
        selected_vars_split_grouped[country]['commodities']
    )
    for country in panel_countries
}

# Flatten all selected variables across countries
all_selected_vars = [var for vars_list in
   selected_variables_by_country.values() for var in vars_list]

# Count how often each variable appears
var_counter = Counter(all_selected_vars)

# Now pick variables that appear in at least X countries
min_country_appearance = 1  # e.g., selected in at least 2 out of 5
   countries

# Filter variables
most_common_vars = [var for var, count in var_counter.items() if
   count >= min_country_appearance]

print(f"Variables appearing in at least {min_country_appearance}
   countries:")
print(most_common_vars)

# --- Now create the panel DataFrame based on these variables ---

# Prepare list to store country DataFrames
panel_df_list = []

for country in panel_countries:
    cds_name = latam_countries[country]  # Map country code to CDS
       spread name

    # Only keep variables available for this country
    available_vars = [var for var in most_common_vars if var in
       df_scaled.columns]

    # Create a sub-DataFrame
    sub_df = df_scaled[[cds_name] + available_vars].copy()

    # Add 'Country' column
    sub_df['Country'] = country

    # Rename CDS column to common name
```

```
    sub_df = sub_df.rename(columns={cds_name: 'CDS_spread'})

    panel_df_list.append(sub_df)

# Combine into one big DataFrame
panel_df = pd.concat(panel_df_list)
panel_df.index.name = "Date"

# Make MultiIndex: (Country, Date)
panel_df = panel_df.reset_index().set_index(["Country", "Date"])

# Drop missing rows
panel_df = panel_df.dropna()

# --- Run the Panel OLS Regression ---
# Add constant manually
panel_df['const'] = 4

# Define dependent and independent variables
dependent = panel_df['CDS_spread']
independent = panel_df.drop(columns='CDS_spread')

# Fit panel model
panel_model = PanelOLS(dependent, independent, entity_effects=True)
panel_results = panel_model.fit()

# Print results
print(panel_results.summary)
```

```
    # 1. Global events
global_events = {
    'Fed Hiking Cycle': pd.to_datetime('2018-01-01'),
    'COVID Shock': pd.to_datetime('2020-03-01'),
    'Ukraine War': pd.to_datetime('2022-02-01')
}

# 2. Consistent colors for variables
variable_colors = {
    'China Money Supply': 'red',
    'CFETS CNY': 'purple',
    'CN 5T': 'orangered',
    'PMI China': 'chocolate',
    'CN Industrial Production': 'saddlebrown',

    'USA Money Supply': 'blue',
    'US 5T': 'navy',
    'DXY': 'deepskyblue',
    'VIX': 'dodgerblue',
```

```
    'XAG': 'dark gray',
    'Brent': 'black',
}

# 3. Rolling parameters
window_size = 24  # months
step_size = 1

# Storage
models_rolling = {}
coefficients_rolling = {}

# 4. Rolling regressions
latam_countries = {
    'CO': 'CO CDS spread',
    'BR': 'BR CDS spread',
    'PE': 'PE CDS spread',
    'MX': 'MX CDS spread',
    'CL': 'CL CDS spread',
}

for country_code, cds in latam_countries.items():
    if country_code not in selected_vars_split_grouped:
        continue

    country_vars = selected_vars_split_grouped[country_code]

    predictors = (
        country_vars['local'] +
        country_vars['usa'] +
        country_vars['china'] +
        country_vars['commodities']
    )
    if "XAG" not in predictors and "XAG" in df_scaled.columns:
        predictors.append("XAG")
    #if "DXY" not in predictors and "DXY" in df_scaled.columns:
    #    predictors.append("DXY")
    if "USA Money Supply" not in predictors and "USA Money Supply"
       in df_scaled.columns:
        predictors.append("USA Money Supply")
    if "China Money Supply" not in predictors and "China Money
       Supply" in df_scaled.columns:
        predictors.append("China Money Supply")

    Y_full = df[cds]
    X_full = df_scaled[predictors]
```

```
    start_date = pd.to_datetime('2010-01-01')
    end_date = df.index.max()
    window_starts = pd.date_range(start=start_date, end=end_date, freq='MS')

    coeffs_list = []
    dates_list = []

    for window_start in window_starts:
        window_end = window_start + pd.DateOffset(months=window_size) - pd.DateOffset(days=1)

        mask = (df.index >= window_start) & (df.index <= window_end)
        Y_window = Y_full.loc[mask]
        X_window = X_full.loc[mask]

        data = pd.concat([Y_window, X_window], axis=1).dropna()
        if len(data) < 18:
            continue

        X2 = sm.add_constant(data.iloc[:, 1:])
        model = sm.OLS(data.iloc[:, 0], X2).fit()

        models_rolling[(country_code, window_start.strftime('%Y-%m'))] = model

        coeffs = model.params
        coeffs_list.append(coeffs)
        dates_list.append(window_start)

    if coeffs_list:
        coeffs_df = pd.DataFrame(coeffs_list, index=dates_list)
        coefficients_rolling[country_code] = coeffs_df

# 5. Plot coefficients evolution     only selected variables
variables_to_plot = ['China Money Supply', 'COPFX', 'PENFX','BRLFX','CLPFX','MXNFX', 'Brent', 'DXY', 'USA Money Supply', 'CFETS CNY']

for country_code, coeffs_df in coefficients_rolling.items():
    plt.figure(figsize=(16, 9))

    for var in coeffs_df.columns:
        if var not in variables_to_plot:
            continue
```

```
        color = variable_colors.get(var, 'gray')
        lw = 3 if var == 'China Money Supply' else 2

        plt.plot(coeffs_df.index, coeffs_df[var], label=var, color=color, linewidth=lw)

    # Add global event lines
    for event_name, event_date in global_events.items():
        if coeffs_df.index.min() < event_date < coeffs_df.index.max():
            plt.axvline(x=event_date, color='black', linestyle='--', linewidth=1)
            plt.text(event_date, plt.ylim()[1]*0.9, event_name, rotation=90,
                     verticalalignment='center', fontsize=9, color='black')

    plt.title(f"{latam_countries[country_code]}     Coefficient Evolution (Rolling 24M)", fontsize=16)
    plt.xlabel('Date', fontsize=14)
    plt.ylabel('Coefficient Value', fontsize=14)
    plt.grid(True)
    plt.legend(loc='center left', bbox_to_anchor=(1, 0.5), fontsize=10)
    plt.tight_layout()
    plt.show()
```

```
# Make sure latam_countries is defined
latam_countries = {
    'CO': 'CO CDS spread',
    'BR': 'BR CDS spread',
    'PE': 'PE CDS spread',
    'MX': 'MX CDS spread',
    'CL': 'CL CDS spread',
    'AR': 'AR CDS spread'
}

# Quantiles you want to run
quantiles = [0.1, 0.25, 0.5, 0.75, 0.9]

# Dictionary to store results
all_quantile_models = {}

for country_code, cds in latam_countries.items():

    if country_code not in selected_vars_split_grouped:
        print(f"Skipping {country_code}     no selected variables.")
```

```
    continue

# Y = original CDS spread
Y = df[cds]

# X = scaled selected variables
selected_variables = (
    selected_vars_split_grouped[country_code]['local'] +
    selected_vars_split_grouped[country_code]['usa'] +
    selected_vars_split_grouped[country_code]['china'] +
    selected_vars_split_grouped[country_code]['commodities']
)

if len(selected_variables) == 0:
    print(f"Skipping {country_code}     no ElasticNet-selected
       variables.")
    continue

X_full = df_scaled[selected_variables]

# Merge and drop NA
data = pd.concat([Y, X_full], axis=1).dropna()

# Build formula (safe with spaces)
X_formula = ' + '.join([f"Q('{col}')" for col in X_full.columns
   ])

# Dictionary to store results for this country
quantile_models = {}

for q in quantiles:
    mod = smf.quantreg(f"Q('{cds}') ~ {X_formula}", data)
    res = mod.fit(q=q)
    quantile_models[q] = res
    print(f"\n=== {country_code}     Quantile {q} ===")
    print(res.summary())

# Store all quantile models for this country
all_quantile_models[country_code] = quantile_models
```

```
def plot_quantile_coefficients_multiple_countries(country_codes,
    all_quantile_models, variables_to_plot=None):
n_countries = len(country_codes)

fig, axes = plt.subplots(n_countries, 1, figsize=(12, 5 *
   n_countries), sharex=True)
if n_countries == 1:
    axes = [axes]
```

```
# 1. Collect all variables from models (Q('...') format)
all_variables = set()
for country_code in country_codes:
    if country_code in all_quantile_models:
        model = all_quantile_models[country_code][0.5]
        vars_in_model = model.params.index.drop('Intercept',
           errors='ignore')
        all_variables.update(vars_in_model)

def to_q_format(varname):
    return f"Q('{varname}')"  # Single quotes as in your model

if variables_to_plot is not None:
    transformed_vars = [to_q_format(v) for v in
       variables_to_plot]
    filtered_variables = [v for v in transformed_vars if v in
       all_variables]
    all_variables = sorted(filtered_variables)
    label_map = {to_q_format(v): v for v in variables_to_plot}
else:
    all_variables = sorted(all_variables)
    label_map = {v: v for v in all_variables}

color_palette = plt.get_cmap('tab10')
colors = {var: color_palette(i % 10) for i, var in enumerate(
   all_variables)}

for ax, country_code in zip(axes, country_codes):
    if country_code not in all_quantile_models:
        print(f"Skipping {country_code}     not found in models
           .")
        continue

    quantiles = sorted(all_quantile_models[country_code].keys())
    coef_dict = {}
    for q in quantiles:
        model = all_quantile_models[country_code][q]
        coef_dict[q] = model.params.drop('Intercept', errors='
           ignore')

    coef_df = pd.DataFrame(coef_dict).T

    matching_vars = [v for v in all_variables if v in coef_df.
       columns]
    if not matching_vars:
        print(f"No matching variables to plot for {country_code
```

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            }")
            continue

        coef_df = coef_df[matching_vars]

        for var in coef_df.columns:
            label = label_map.get(var, var)
            ax.plot(coef_df.index, coef_df[var], marker='o', label=
               label, color=colors[var])

        ax.set_title(f'Quantile Regression Coefficients     {
           country_code}')
        ax.set_xlabel('Quantile')
        ax.set_ylabel('Coefficient Value')
        ax.axhline(0, color='black', linestyle='--')
        ax.grid(True)
        ax.legend(bbox_to_anchor=(1.05, 1), loc='upper left')

    plt.tight_layout()
    plt.show()



plot_quantile_coefficients_multiple_countries(['CO', 'BR', 'PE', 'MX
   ', 'CL'], all_quantile_models, ['China Money Supply', 'COPFX', '
   PENFX','BRLFX','CLPFX','MXNFX', 'Brent', 'DXY', 'VIX', 'USA Money
    Supply', 'CFETS CNY'])
```

```
    def plot_quantile_coefficients_by_variable(country_codes,
       all_quantile_models, variables_to_plot):
    fig, axes = plt.subplots(len(variables_to_plot), 1, figsize=(14,
        5 * len(variables_to_plot)), sharex=True)
    if len(variables_to_plot) == 1:
        axes = [axes]

    def to_q_format(varname):
        return f"Q('{varname}')"

    for ax, var in zip(axes, variables_to_plot):
        var_q = to_q_format(var)
        line_styles = ['-', '--', '-.', ':']
        line_styles = line_styles * ((len(country_codes) // len(
           line_styles)) + 1)
        style_map = {code: line_styles[i] for i, code in enumerate(
           country_codes)}

        max_quantile = 0  # For x-axis extension
        all_country_values = {}  # Store per-country coefficients
```

```
        for mean calc

    #        LOOP OVER COUNTRIES
    for i, country_code in enumerate(country_codes):
        if country_code not in all_quantile_models:
            continue

        quantiles = sorted(all_quantile_models[country_code].
           keys())
        max_quantile = max(max_quantile, max(quantiles))
        values = []
        for q in quantiles:
            model = all_quantile_models[country_code][q]
            params = model.params
            val = params.get(var_q, None)
            values.append(val if pd.notnull(val) else np.nan)

        if all(np.isnan(values)):
            continue

        all_country_values[country_code] = values




    #     CALCULATE AND PLOT MEAN ACROSS COUNTRIES
    if all_country_values:
        # Turn to DataFrame for easy column-wise mean
        df_vals = pd.DataFrame(all_country_values, index=
           quantiles)
        mean_vals = df_vals.mean(axis=1, skipna=True)

        ax.plot(
            quantiles,
            mean_vals,
            color='black',
            linewidth=1,
            label='Mean across countries'
        )
        ax.legend()

    # Axes formatting
    ax.set_title(f'Quantile Coefficients for "{var}" Across
       Countries', fontsize=14)
    ax.set_xlabel('Quantile', fontsize=12)
    ax.set_ylabel('Coefficient', fontsize=12)
    ax.axhline(0, color='gray', linestyle='--')
```

```
        ax.set_xticks(quantiles)
        ax.grid(True)
        ax.set_xlim(0.05, max_quantile + 0.03)

    plt.tight_layout()
    plt.show()

plot_quantile_coefficients_by_variable(
    ['CO', 'BR', 'PE', 'MX', 'CL'],
    all_quantile_models,
    ['XAG', 'Brent', 'CFETS CNY', 'China Money Supply', 'VIX', 'DXY
       ']
)
```