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Tail dependence between corporate CDS and commodity Markets :

International evidence using IGARCH-Copulas

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Abstract

Commodity price shocks often coincide with abrupt repricing of corporate credit risk, but the dependence between commodity markets and corporate CDS spreads is difficult to quantify with correlation-based tools, especially in crises. We analyze this link with a two-step IGARCH-Copula framework that filters volatility persistence and heteroscedasticity in each marginal series and then models non-linear, asymmetric, and tail dependence. The study uses daily 5-year CDS spreads for 27 large firms across Europe, East Asia, and North America from 2007 to 2024, with commodity conditions proxied by the S&P GSCI. The estimates reveal strong sectoral heterogeneity: tail dependence is concentrated in energy, utilities, and other commodity-intensive industries, while it is weak or negative for several technology and telecommunications firms. Dependence intensifies sharply in crisis regimes and remains limited in tranquil periods, indicating that commodity-driven credit risk materializes mainly through extreme events. Asymmetric copulas, notably Clayton and Gumbel, frequently provide the best fit, showing that adverse and favorable commodity shocks transmit differently to CDS spreads. These results provide innovation-based evidence on crisis-dependent risk transmission from commodity markets to corporate credit risk, with direct implications for hedging, diversification, and commodity stress scenarios in financial stability monitoring.

Keywords: Corporate CDS; Commodity markets; Tail dependence; Copula models; Volatility filtering; Crisis regimes.

1 Introduction

Recent crises have shown that commodity markets can act as powerful amplifiers of financial risk. The Global Financial Crisis, the European Sovereign Debt Crisis, and more recently the COVID-19 pandemic and energy supply disruptions have all been accompanied by abrupt commodity price swings and sharp repricing in corporate Credit Default Swap (CDS) markets. During these episodes, oil price collapses, energy shortages, and global supply-chain bottlenecks coincided with sudden CDS spread widening for firms that were previously considered resilient. For multinational firms operating across integrated global supply chains, commodity price shocks therefore affect credit risk not only through direct cost and revenue channels, but also through cross-border financing conditions and international risk reallocation. These observations raise a central and highly topical question for both academics and policymakers: when commodity markets come under stress, how, and through which channels, does this stress translate into corporate credit risk? Addressing this question is crucial in a context where energy dependence, geopolitical fragmentation, and commodity-driven inflation have become structural features of the global economy. Yet, despite the growing relevance of commodity shocks for financial stability, existing empirical tools struggle to capture the crisis-specific, asymmetric, and extreme nature of CDS-commodity interactions, leaving an important gap in our understanding of how real asset markets propagate credit risk during periods of systemic stress.

A growing body of literature has examined the determinants of CDS spreads and their sensitivity to macro-financial conditions, showing that credit risk pricing reflects both firm-specific fundamentals and time-varying global risk premia (Longstaff et al. 2005, Ericsson et al. 2009, Galil et al. 2014, Bongaerts et al. 2017). Parallel research in commodity finance documents that commodity price shocks transmit to financial markets in a non-linear and regime-dependent manner, particularly during crises (Filis et al. 2011, Broadstock & Filis 2020, Demirer et al. 2020). More recent studies emphasize that oil and commodity markets become central nodes of systemic risk transmission under stress (Ji et al. 2018). Despite these advances, the empirical literature remains fragmented. First, most studies rely on linear correlation or mean-based dependence measures, which are ill-suited to capture tail risk and asymmetric co-movements that dominate crisis periods. Second, volatility persistence and heteroscedasticity are often insufficiently filtered before dependence analysis, potentially confounding volatility effects with genuine dependence. Third, existing evidence focuses predominantly on sovereign CDS or on single regions and

short samples, leaving cross-sector and cross-regional corporate CDS-commodity linkages largely unexplored, especially across multiple crises with distinct economic origins.

The objective of this paper is to address these gaps by providing a unified and crisis-oriented analysis of the dependence between corporate CDS spreads and commodity markets. We rely on a two-step IGARCH-Copula framework that separates marginal volatility dynamics from the dependence structure, allowing us to capture non-linear, asymmetric, and tail-dependent relationships in line with Sklar's theorem (Sklar 1959, Nelsen 2006). The analysis is conducted on a long daily sample from 2007 to 2024, covering 27 large firms across Europe, East Asia, and North America, and spanning several major crises with distinct transmission mechanisms. This empirical design enables a systematic comparison of dependence patterns across sectors, regions, and crisis regimes, while ensuring that estimated co-movements reflect dependence in innovations rather than spurious correlations driven by volatility clustering or persistence.

This paper contributes to the international finance literature in three main ways. First, it provides a clear and systematic assessment of how commodity market stress translates into corporate credit risk, moving beyond average correlations to focus explicitly on dependence structures that emerge under extreme market conditions. Second, by adopting a firm-level, cross-sector, and cross-region perspective, the analysis documents when, where, and for which firms commodity shocks matter most for CDS pricing, highlighting pronounced heterogeneity in crisis transmission across business models and industries. Third, the use of an IGARCH-Copula framework allows us to identify asymmetric and tail-driven co-movements that remain hidden under standard linear approaches, offering new evidence on crisis-dependent channels of risk propagation between commodity and credit markets.

Our empirical results yield several novel insights. CDS-commodity dependence is highly heterogeneous across sectors and firms, with strong and statistically significant tail dependence concentrated in energy, utilities, and other commodity-intensive industries. Dependence structures intensify sharply during crisis periods, while remaining weak or insignificant in tranquil times, confirming that commodity-driven credit risk materializes primarily through extreme events rather than average co-movements. Moreover, asymmetric copulas such as Clayton and Gumbel dominate the empirical fit, revealing that downside and upside commodity shocks transmit differently to corporate credit risk. These findings demonstrate that linear correlation measures substantially understate the role of commodities in shaping CDS dynamics during systemic stress.

The implications of these results are directly relevant for risk management and financial

stability analysis. For investors, recognizing sector-specific and crisis-dependent dependence structures can improve portfolio diversification and hedging strategies when traditional correlations break down. For regulators and policymakers, the evidence highlights commodity markets as a key channel of systemic risk propagation, particularly for energy-intensive sectors and financial institutions exposed to commodity-linked firms. Incorporating commodity-related tail risk into stress-testing frameworks therefore appears essential in an environment characterized by recurrent energy shocks, geopolitical tensions, and persistent commodity price volatility.

The remainder of the paper is organized as follows. [section 2](#) reviews the relevant literature on corporate CDS pricing and commodity-related transmission channels. [section 3](#) describes the data and the crisis-based sample design. [section 4](#) presents the IGARCH-Copula methodology. [section 5](#) reports stylized facts, full-sample dependence estimates, and crisis-regime evidence from sub-period analysis. [section 6](#) concludes and discusses implications for stress testing and international risk monitoring.

2 Literature Review

Our paper sits at the intersection of two literatures that often progress in parallel but are rarely integrated within a unified empirical framework: the corporate CDS literature that explains how credit risk is priced at high frequency, and the commodity literature that studies how commodity price shocks propagate to financial markets. Because our contribution is explicitly about *corporate CDS* and *commodity markets* under crises, we focus the review on what is known about (i) the drivers of CDS spreads, and (ii) the channels and evidence linking commodity shocks to CDS pricing, with particular attention to non-linear and tail dependence.

2.1 Corporate CDS spreads and crisis dynamics

A core result in the CDS literature is that CDS spreads incorporate both firm-specific credit fundamentals and broader market-wide pricing of risk, and that the relative importance of each component varies strongly across regimes. Early evidence shows that changes in credit spreads are only partially explained by standard structural factors, leaving an important role for time-varying risk premia and liquidity. [Collin-Dufresne et al. \(2001\)](#) document that a large fraction of credit spread movements cannot be traced back to observable changes in firm fundamentals. This finding is consistent with the idea that credit markets price global risk and liquidity conditions

in addition to default risk. Subsequent studies show that leverage, volatility, risk-free rates, and market risk factors explain only part of the variation in CDS spreads, with systematic risk components and liquidity effects playing a substantial role (Tang & Yan 2010, Galil et al. 2014, Badaoui et al. 2016, Bongaerts et al. 2017, Augustin et al. 2018). Ericsson et al. (2009) show that classical firm-level drivers such as leverage and volatility are statistically significant, but that a sizeable share of residual spread variation is captured by common systematic factors not accounted for by structural models. These studies also highlight the time-varying contribution of liquidity premia and market-wide stress measures, especially during crises, implying that CDS spreads incorporate both idiosyncratic and global risk factors whose importance varies across market conditions (Longstaff et al. 2005, Alexander & Kaeck 2008, Badaoui et al. 2016, Hu et al. 2022, Weber et al. 2024).

The empirical CDS pricing literature also emphasizes the close, yet imperfect, relationship between CDS markets and cash credit markets. A substantial body of work shows that CDS spreads and bond yield spreads are jointly determined, but that their relative informational leadership varies across market conditions, liquidity regimes, and stress episodes (Hull et al. 2004, Blanco et al. 2005). Early evidence provided by Marsh (2004) documents a dynamic interaction between CDS prices and bond spreads, showing that short-run movements in CDS spreads are sensitive to market-wide conditions and liquidity.

Another strand of the literature further demonstrates that the CDS and bond markets serve as complementary venues for credit risk price discovery, rather than perfect substitutes (Blanco et al. 2005, Norden & Weber 2009, Darst & Refayet 2016, Patanè et al. 2019, Gadgil 2024). These papers, broadly, show that CDS markets often lead bond markets in incorporating new credit information, particularly during periods of heightened uncertainty, while bond markets may dominate in more tranquil periods. This asymmetric price discovery process is amplified when liquidity conditions diverge across markets.

More recent contributions explicitly focus on international spillovers and stress transmission between CDS and underlying bond markets (Sabkha, De Peretti & Mezzez Hmaied 2019, Hussain Shahzad et al. 2019, Eijffinger & Pieterse-Bloem 2023, Aljarba et al. 2024). Results of these papers provide evidence of significant cross-market and cross-country risk spillovers between CDS spreads and sovereign bond yields, showing that these interactions intensify during crisis periods and are highly sensitive to global risk conditions. The findings highlight that CDS-bond linkages are non-linear, time-varying, and driven by common risk factors rather than

firm fundamentals alone.

Overall, this literature indicates that credit risk pricing reflects a complex interaction between multiple markets, liquidity conditions, and global risk premia. These findings are particularly relevant for our setting, as crisis periods are precisely characterized by (i) rapid repricing of risk premia, (ii) sharp liquidity shifts, and (iii) stronger cross-market dependence, conditions under which linear correlation based approaches are likely to provide a distorted view of credit risk transmission.

2.2 Commodity markets as drivers of credit risk

The relationship between commodity prices and corporate CDS spreads is indirect, state-dependent, and mediated by both firm-level exposure and global risk factors. Unlike equity markets, CDS spreads primarily reflect changes in perceived default risk and risk premia, which implies that commodity shocks affect corporate CDS through multiple, potentially asymmetric transmission channels.

A first transmission channel operates through production costs and profitability. For firms that are intensive users of commodities, increases in commodity prices raise input costs, compress margins, and weaken credit fundamentals, leading to wider CDS spreads. This mechanism is consistent with structural credit risk models in which declining cash flows increase default probabilities (Merton 1974, Lando 1998). Empirical evidence confirms that adverse cost shocks are priced in credit markets, particularly when firms face limited pricing power or tighter financing constraints (Galil et al. 2014, Chan et al. 2024). These effects are expected to be stronger during downturns, when balance-sheet fragility amplifies the sensitivity of CDS spreads to real shocks.

A second channel concerns revenue and asset-value effects for commodity-producing firms, especially in the energy sector. Higher commodity prices may improve revenues and collateral values, thereby strengthening credit quality and tightening CDS spreads in normal times. However, the literature shows that this relationship is not stable across regimes. During periods of heightened uncertainty or geopolitical stress, rising commodity prices may signal supply disruptions, political risk, or macroeconomic instability rather than improved fundamentals, leading to a reversal of the credit response (Alexander & Kaeck 2008, Badaoui et al. 2016). This regime dependence implies asymmetric CDS–commodity linkages that cannot be captured by linear correlation measures.

Beyond firm-level exposure, a growing body of research emphasizes a third channel driven

by global risk pricing and financial stress. Large commodity price movements, particularly in oil markets, are often associated with shifts in global risk sentiment, funding liquidity, and macro-financial uncertainty. In such environments, CDS spreads and commodity prices may co-move because they jointly reflect common global shocks rather than direct cash-flow effects. Studies show that global risk factors and liquidity conditions play a dominant role in credit spread dynamics, especially during crises (Longstaff et al. 2005, Bongaerts et al. 2017, Augustin et al. 2018). This common-risk channel provides a natural explanation for the strengthening of CDS–commodity dependence during periods of systemic stress.

Empirical evidence supports the existence of time-varying and crisis-sensitive linkages between commodities and CDS markets. While much of the literature focuses on sovereign credit risk, several studies document that oil and commodity price shocks are directly priced in CDS spreads. For example, Alturki & Hibbert (2021) show that oil price shocks significantly affect sovereign CDS spreads, with the sign and magnitude of the response depending on the macroeconomic environment. Similarly, Gogolin et al. (2018) and Salisu & Gupta (2021) document strong spillovers between oil markets and credit risk indicators, particularly during periods of elevated uncertainty. Although these studies focus on sovereign CDS, their findings are highly relevant for corporate CDS markets, where similar pricing mechanisms operate through firm exposure and global risk channels.

More recent contributions emphasize that the links between commodity prices, and oil prices in particular, and financial markets are both time-varying and regime dependent, and that these features become especially pronounced during periods of stress. Broadstock & Filis (2020) and Demirer et al. (2020) show that oil price shocks transmit asymmetrically to financial markets, with their informational content and impact varying substantially across market conditions and crisis episodes. Earlier evidence by Filis et al. (2011) already documents dynamic correlations between oil prices and financial market returns, highlighting the instability of dependence structures across regimes. Building on this literature, Ji et al. (2018) further show that energy markets become central transmitters of systemic risk during crisis periods, amplifying spillovers across financial assets. Taken together, these findings reinforce the view that CDS–commodity dependence is not driven by stable average correlations, but instead reflects non-linear, tail-driven, and regime-dependent spillover effects that intensify during episodes of heightened global stress.

Overall, this body of evidence suggests that commodity price movements affect corporate CDS spreads through a combination of cost, revenue, and global risk channels, with effects

that vary across sectors and economic regimes. This directly motivates our empirical strategy, which combines a cross-sector and cross-region sample with a sub-period analysis and a flexible dependence structure designed to capture non-linear and crisis-dependent CDS–commodity linkages.

2.3 Gaps in the literature and contribution

Despite the growing interest in CDS–commodity interactions, the existing empirical literature exhibits several methodological limitations that are particularly problematic in crisis environments. A first and central limitation concerns the widespread reliance on linear correlation or mean-based dependence measures. Such approaches implicitly assume stable and symmetric co-movement, which is at odds with the empirical evidence that financial dependence intensifies, becomes asymmetric, and concentrates in the tails during periods of stress. In the context of CDS and commodity markets, this limitation is critical, as the dependence of interest is not average co-movement, but the joint occurrence of extreme commodity price shocks and sharp deteriorations in credit risk.

A second limitation relates to the treatment of volatility dynamics. Many studies analyze dependence without fully accounting for volatility clustering, persistence, and heteroscedasticity in the underlying series. Ignoring these features may bias inference on dependence patterns, especially when changes in co-movement reflect shifts in conditional volatility rather than genuine changes in the dependence structure. This issue is particularly relevant for CDS spreads, which are well known to exhibit strong volatility persistence and regime-dependent behavior during crises.

Third, the existing evidence on CDS–commodity linkages remains fragmented across sovereign and corporate settings, and often focuses on a limited set of countries, sectors, or crisis episodes. As a result, cross-sectoral and cross-regional heterogeneity in crisis transmission is insufficiently explored, despite clear theoretical and empirical indications that commodity shocks affect credit risk through different channels depending on firms’ exposure, market structure, and macro-financial conditions. Moreover, crisis comparisons are frequently informal, with limited use of explicit sub-period designs, even though different crises are characterized by distinct underlying mechanisms and commodity–credit transmission channels.

Our paper addresses these gaps through a unified empirical framework that is specifically designed to capture crisis-dependent CDS–commodity dependence. We employ a two-step

IGARCH–Copula approach, which separates marginal dynamics from the dependence structure, in line with Sklar’s theorem (Nelsen 2006). In the first step, an IGARCH specification accounts for persistent conditional volatility and heteroscedasticity in both corporate CDS spreads and commodity prices. In the second step, flexible copula functions allow for non-linear, asymmetric, and tail-dependent relationships between each firm-level CDS spread and the commodity market.

By combining this methodology with a long daily sample spanning multiple global crises, a cross-sector and cross-region panel of corporate CDS, and an explicit sub-period analysis, our study provides new evidence on how CDS–commodity dependence evolves across regimes. This framework enables us to move beyond average correlations and to identify crisis-specific patterns of tail dependence and systemic risk transmission, thereby offering a more accurate and economically meaningful characterization of CDS–commodity linkages under stress.

3 Data

We use daily corporate CDS spreads covering the period from January 2007 to February 2024. The CDS quotes are retrieved from Thomson Reuters Eikon and correspond to the standard 5-year maturity, expressed in U.S. dollars. This tenor is commonly viewed as the benchmark segment of the CDS market and is among the most actively traded maturities, which supports the reliability of the empirical analysis. This choice is also consistent with the objective of capturing crisis-driven repricing of credit risk using liquid instruments.

The sample includes 27 large listed firms headquartered in Europe, East Asia, and North America, spanning a broad set of activity sectors (energy, banking, automotive, electronics, consumer and retail, telecommunications, and others). This multi-region and multi-sector design is central to the contribution of the paper. It enables a systematic comparison of CDS commodity dependence patterns across heterogeneous economic structures and business models, and it supports sector-specific interpretations of tail dependence during systemic events. The classification of firms by sector and headquarters region is reported in [Table 1](#).

Commodity market conditions are proxied by the daily level of the S&P GSCI. The S&P GSCI is a futures-based, broad commodity benchmark designed to provide investable exposure to global commodity markets. It is weighted by world production, so that commodity groups receive weights reflecting their economic relevance in global production. This property is important for our purpose, as it provides a coherent aggregate measure of commodity market risk rather than a

single-commodity proxy, and is therefore well suited to studying cross-sector credit risk exposure to commodity conditions.

The sample period is intentionally long and includes multiple crisis episodes that differ in origin and transmission channels. This allows us to test whether CDS-commodity interdependencies are stable features or regime-dependent phenomena: (i) the Global Financial Crisis (2007-2009), (ii) the European Sovereign Debt Crisis (2010-2012), and (iii) the COVID-19 crisis period (2020-2022).

This crisis-based design directly supports the paper's core contribution. By combining a global corporate CDS panel with a broad commodity benchmark, we can assess how tail dependence and asymmetries evolve across crises, regions, and sectors. This setting is also aligned with the two-step IGARCH-Copula framework, which is specifically intended to handle volatility clustering and extreme co-movements in stress periods.

Table 1: Overview of the studied companies

Activity Sectors	Companies	Headquarters Region
Energy (8)	Engie	Europe
	Exxon Mobil	North America
	BP	Europe
	Chevron	North America
	Air Liquide	Europe
	Enel	Europe
	Schneider	Europe
	Iberdrola	Europe
Banking (5)	ING	Europe
	HSBC	Europe
	Société Générale	Europe
	Barclays Bank	Europe
	Santander	Europe
Automotive (4)	Volvo	Europe
	Hyundai	East Asia
	Toyota	East Asia
	BMW	Europe

Continued on next page

Table 1 (continued)

Activity Sectors	Companies	Headquarters Region
Electronics (3)	Sony	East Asia
	Samsung	East Asia
	Philips	Europe
Large Distribution (2)	Walmart	North America
	Carrefour	Europe
Equipment (2)	Adidas	Europe
	Nike	North America
Social Network (1)	Facebook	North America
Luxury (1)	Kering	Europe
Healthcare (1)	Bayer	Europe
Beverage (1)	Heineken	Europe
Telecommunications (1)	Orange	Europe
Engineering (1)	Siemens	Europe
Food (1)	Nestlé	Europe

4 Econometric methodology: an IGARCH-Copula framework

Building on the insights of [Sabkha, De Peretti & Hmaied \(2019\)](#) regarding the informational properties and apparent randomness of CDS price dynamics, and on [Mba \(2024\)](#) who highlight the relevance of copula-based approaches for assessing systemic vulnerability in financial markets, we adopt a two-step IGARCH-Copula framework to investigate the dependence between corporate CDS spreads and commodity markets.

This framework combines, in a coherent manner, univariate volatility filtering with a flexible copula-based dependence structure. It is specifically designed to accommodate key empirical features of financial time series, including non-stationarity, volatility clustering, heteroscedasticity, long-memory behavior, and non-linear dependence patterns. These features are particularly salient during crisis periods, which constitute the core focus of our analysis. By explicitly separating marginal dynamics from the dependence structure, the proposed approach allows us to isolate and analyze tail dependence and asymmetries in CDS-commodity interactions.

The dependence between international corporate CDS spreads and the commodity market is

therefore examined through the following two sequential steps.

4.1 First step: IGARCH filtering

In the first step, we estimate an integrated GARCH(1,1) model, originally introduced by [Engle & Bollerslev \(1986\)](#), for each log-transformed corporate CDS series and for the commodity index. For reasons of parsimony and empirical relevance, only specifications with $(p, q) = (1, 1)$ are considered¹.

The IGARCH formulation imposes a unit root in the conditional variance process, which provides a convenient representation of highly persistent volatility dynamics and allows us to handle potential non-stationarity in variance. This feature is especially important in the context of CDS spreads and commodity prices, where volatility shocks often exhibit long-lasting effects².

The univariate IGARCH(1,1) model is specified as follows:

$$\begin{aligned}x_{i,t} &= \mu_{i,t} + a_{i,t}, \\a_{i,t} &= \sigma_{i,t}\varepsilon_{i,t}, \quad \varepsilon_{i,t} \sim \mathcal{N}(0, 1), \\ \sigma_{i,t}^2 &= \alpha_{i,0} + \alpha_{i,1}a_{i,t-1}^2 + (1 - \alpha_{i,1})\sigma_{i,t-1}^2.\end{aligned}$$

Here, $x_{i,t}$ denotes the log CDS spread or the log commodity index at time t for firm i , while $\mu_{i,t}$ and $\sigma_{i,t}$ represent the conditional mean and conditional volatility, respectively. This first step filters out conditional heteroscedasticity and volatility persistence, thereby preparing the series for dependence analysis.

4.2 Second step: Copula-based dependence modeling

In the second step, dependence between corporate CDS spreads and the commodity market is modeled using copula functions. This approach is particularly well-suited for analyzing CDS-commodity interactions during crisis periods, when dependence structures are known to be non-linear, asymmetric, and concentrated in the tails of the joint distribution.

Unlike traditional correlation-based measures, copulas do not impose linearity or symmetry assumptions and allow the dependence structure to differ across the center and the tails of the

¹The GARCH(1,1) specification is widely recognized as both empirically robust and well-suited for financial time series, particularly when modeling volatility persistence ([Bollerslev 1986](#), [Wei et al. 2010](#), [Sabkha 2021](#)).

²In this setting, shocks to volatility tend to propagate over extended horizons, implying that current innovations affect future conditional volatility over many periods.

distribution. This distinction is crucial in crisis environments, where the primary concern is not average co-movement, but the joint occurrence of extreme CDS widening and large commodity price movements. By applying copulas to the standardized residuals obtained from the IGARCH filtering step, we obtain a flexible representation of tail dependence and regime-sensitive co-movements that cannot be captured by constant correlation models.

Formally, a bivariate copula model is estimated for each firm-commodity pair, using reconstructed series rather than raw data. To simultaneously account for dynamic mean behavior, persistent volatility, and long-memory effects, we apply the following transformation:

$$y_{i,1} = x_{i,1},$$

$$y_{i,t} = \hat{\omega}_i + y_{i,t-1} + \frac{\hat{\varepsilon}_{i,t}}{\hat{\sigma}_{i,t}},$$

with

$$\hat{\omega}_i = \frac{1}{T-1} \sum_{t=2}^T \Delta x_{i,t}.$$

In this expression, $\hat{\varepsilon}_{i,t}$ and $\hat{\sigma}_{i,t}$ denote the standardized residuals and conditional volatility obtained from the IGARCH estimation. The transformed series $y_{i,t}$ preserves the long-run dynamics of CDS spreads and commodity prices while filtering out conditional heteroscedasticity. This transformation should be viewed as a pragmatic device aimed at studying dependence under persistent volatility, rather than as a fully structural data-generating process.

Copula framework

Following [Sklar \(1959\)](#), and standard references such as [Clayton \(1978\)](#), [Joe \(1997\)](#), [Nelsen \(2006\)](#), and [Team et al. \(2013\)](#), the copula framework relies on Sklar's theorem. For continuous marginal distributions $F_1(x_1), \dots, F_d(x_d)$, the joint distribution $F(x_1, \dots, x_d)$ can be expressed as

$$F(x_1, \dots, x_d) = C(F_1(x_1), \dots, F_d(x_d)),$$

where $C(\cdot)$ is a unique copula function. The corresponding joint density is given by

$$f(x_1, \dots, x_d) = c(F_1(x_1), \dots, F_d(x_d)) \prod_{i=1}^d f_i(x_i),$$

with $c(\cdot)$ denoting the copula density.

Gaussian copula

The Gaussian copula captures symmetric dependence structures and is defined as

$$C(u, v; \rho) = \Phi_\rho(\Phi^{-1}(u), \Phi^{-1}(v)),$$

where Φ denotes the standard normal cumulative distribution function and Φ_ρ the bivariate normal CDF with correlation parameter ρ . Its density is

$$c(u, v; \rho) = \frac{1}{\sqrt{1 - \rho^2}} \exp\left(-\frac{\rho^2(z_1^2 + z_2^2) - 2\rho z_1 z_2}{2(1 - \rho^2)}\right),$$

with $z_i = \Phi^{-1}(u_i)$.

Student copula

The Student copula allows for symmetric tail dependence and is defined as

$$C(u, v; \rho, \nu) = t_{\rho, \nu}(t_\nu^{-1}(u), t_\nu^{-1}(v)),$$

where t_ν denotes the Student- t CDF with ν degrees of freedom. Its density is

$$c(u, v; \rho, \nu) = \frac{\Gamma\left(\frac{\nu+2}{2}\right)}{\Gamma\left(\frac{\nu}{2}\right) \sqrt{\pi\nu(1-\rho^2)}} \left[1 + \frac{z_1^2 + z_2^2 - 2\rho z_1 z_2}{\nu(1-\rho^2)}\right]^{-\frac{\nu+2}{2}},$$

with $z_i = t_\nu^{-1}(u_i)$.

Clayton copula

The Clayton copula ([Clayton 1978](#)) captures lower-tail dependence and is given by

$$C(u, v; \theta) = \max\left[(u^{-\theta} + v^{-\theta} - 1)^{-1/\theta}, 0\right], \quad \theta > 0.$$

Its density is

$$c(u, v; \theta) = (1 + \theta)(uv)^{-\theta-1} (u^{-\theta} + v^{-\theta} - 1)^{-2-\frac{1}{\theta}}.$$

Gumbel copula

The Gumbel copula captures upper-tail dependence and is defined as

$$C(u, v; \theta) = \exp\left(-\left[(-\log u)^\theta + (-\log v)^\theta\right]^{1/\theta}\right), \quad \theta \geq 1.$$

Its density is

$$c(u, v; \theta) = C(u, v; \theta) \left(\prod_{i=1}^2 (-\log u_i)^{\theta-1} \right) \frac{\theta - 1}{(-\log u_1 u_2)^2}.$$

5 Empirical Results

5.1 Stylized facts and descriptive statistics

This section documents the main statistical properties of corporate CDS spreads and their log returns. The objective is twofold. First, we characterize the level and dispersion of CDS spreads across firms and sectors. Second, we assess whether the data display the standard features that motivate the two-step IGARCH-Copula framework, namely non-normality, volatility clustering, serial dependence, and persistence in volatility.

[Table 2](#) reports descriptive statistics for CDS spreads in levels. The cross-sectional heterogeneity is substantial, both in average credit risk and in the amplitude of stress episodes. The mean spreads range from 32.23 bps (Nestlé) to 178.51 bps (Enel), while maxima span from 94.95 bps (Nestlé) to 860.00 bps (Hyundai), indicating that crisis periods generate very large but uneven repricing across firms. Dispersion also differs markedly across names: standard deviations vary from 13.73 (Nestlé) to 128.24 (Hyundai), with several firms showing high volatility in levels (e.g., Kering 110.62, Volvo 94.95, Santander 94.71, and Facebook 102.17), which is consistent with episodic spikes in perceived credit risk.

The ADF statistics in [Table 2](#) provide evidence that, for most firms, CDS spreads in levels are highly persistent and often fail to reject the unit-root null at conventional levels. A few series display rejection (e.g., Hyundai at 1%, Samsung at 1%, BP at 5%, Iberdrola at 10%, Société Générale at 10%, and Facebook at 10%), but the dominant pattern is strong persistence in spreads. This is consistent with the view that CDS levels incorporate slow-moving components (credit fundamentals, premia, liquidity) that become particularly persistent around crisis episodes. This motivates working with log returns for inference and filtering the conditional variance prior to dependence modeling.

Table 2: Descriptive statistics tests for CDS spreads

Company	Obs.	Min.	Mean	Max.	SD	ADF statistic
Adidas	4064	29.69	80.92	257.77	34.95	-1.22
Air Liquide	4197	17.08	42.50	105.00	16.28	-1.23
Barclays Bank	4201	45.06	117.46	293.73	46.85	-1.42
BMW	4201	52.00	108.19	487.50	46.92	-1.52
BP	4197	21.00	79.55	727.72	52.73	-2.34**
Exxon Mobil	4142	20.97	48.23	123.99	14.56	-0.98
Heineken	4094	20.94	62.64	250.00	42.43	-1.14
Chevron	4197	15.50	44.30	143.16	22.26	-1.17
Enel	4201	76.08	178.51	663.44	82.68	-1.32
Orange	4201	28.56	65.17	174.58	29.29	-1.13
ING	4197	12.50	72.31	269.57	54.42	-1.46
Hyundai	3968	95.34	153.19	860.00	128.24	-5.74***
Iberdrola	4196	28.02	106.72	573.90	80.93	-1.64*
Samsung	4197	19.42	62.35	650.00	54.36	-2.98***
Santander	4197	20.59	116.69	488.71	94.71	-1.50
Schneider Electric	4197	27.56	60.81	242.56	36.50	-0.98
Siemens	4196	17.16	51.73	251.00	29.89	-1.44
Kering	4197	21.69	104.65	756.00	110.62	-1.56
Bayer	4197	27.33	66.08	162.63	23.96	-1.06
Carrefour	4198	28.50	85.34	264.08	40.17	-1.17
Nestlé	4197	12.11	32.23	94.95	13.73	-1.21
Nike	4197	22.50	47.63	110.00	18.06	-0.80
Sony	4110	0.00	85.53	479.50	85.26	-1.35
Volvo	4197	38.24	121.93	667.00	94.95	-1.48
Walmart	4197	11.20	36.46	137.50	16.49	-1.07
Toyota	4201	16.00	60.87	289.25	36.99	-1.27
Société Générale	4201	19.58	95.87	436.42	74.41	-1.72*

Continued on next page

Table 2 (continued)

Company	Obs.	Min.	Mean	Max.	SD	ADF statistic
Facebook	4191	51.16	168.27	767.44	102.17	-1.94*
Engie	4023	40.00	91.82	204.88	27.92	-0.70
Philips	4197	36.39	58.55	165.00	23.07	-0.93
HSBC	4196	13.99	63.66	189.19	32.60	-1.57

Min., Max., and SD denote the minimum, maximum, and standard deviation, respectively. ADF refers to the Augmented Dickey-Fuller test for the null hypothesis of a unit root. *, **, and *** indicate rejection of the null hypothesis at the 10%, 5%, and 1% significance levels, respectively.

Table 3 documents strong departures from Gaussianity in CDS log returns. The joint evidence from skewness, excess kurtosis, and Jarque-Bera statistics indicates pervasive asymmetry and fat tails across firms, implying that extreme observations are a systematic feature of the data rather than isolated outliers. This feature is central for our paper because crisis transmission between CDS and commodities is expected to be concentrated in tail events. The ADF results in Table 3 also indicate that CDS log returns are stationary for nearly all firms at the 1% level. Carrefour constitutes a notable exception in our sample, with an ADF statistic of -1.17, which suggests that additional caution is required when interpreting that series in return form.

Table 3: Normality and stationarity tests for CDS log returns

Company	Skewness	Excess Kurtosis	Jarque-Bera	ADF statistic
Adidas	-22.94***	795.26***	1.07***	-38.69***
Air Liquide	1.63***	25.88***	1.19***	-33.70***
Barclays Bank	-0.25	32.91***	2.00***	-36.14***
BMW	1.05	19.74***	68,931.00***	-32.38***
BP	2.82***	45.76***	3.72***	-35.03***
Exxon Mobil	0.44	79.93***	1.10***	-40.59***
Heineken	2.55***	83.32***	1.19***	-33.51***
Chevron	4.56***	108.83***	2.09***	-35.49***

Continued on next page

Table 3 (continued)

Company	Skewness	Excess Kurtosis	Jarque-Bera	ADF statistic
Enel	0.57	19.73***	68,350.00***	-37.30***
Orange	0.67	9.43***	15,895.00***	-34.32***
ING	0.34	8.45***	12,570.00***	-36.34***
Hyundai	-2.29***	46.12***	3.55***	-36.12***
Iberdrola	0.63	12.63***	28,160.00***	-36.40***
Samsung	1.64***	81.69***	1.17***	-37.22***
Santander	-0.16	9.49***	15,753.00***	-38.03***
Schneider Electric	6.78***	174.48***	5.35***	-34.36***
Siemens	1.91***	28.11***	1.41***	-33.91***
Kering	0.79	15.68***	43,396.00***	-35.47***
Bayer	1.86***	19.48***	687,552.00***	-34.21***
Carrefour	2.03***	4.37***	6,232.00***	-1.17
Nestlé	1.12	26.02***	1.19***	-36.48***
Nike	-1.49***	121.45***	2.58***	-38.72***
Sony	0.54	23.33***	91,811.00***	-33.91***
Volvo	0.56	11.61***	23,790.00***	-31.90***
Walmart	0.81	13.96***	34,526.00***	-36.96***
Toyota	-0.97	102.73***	1.85***	-35.03***
Société Générale	0.55	10.70***	20,236.00***	-36.82***
Facebook	1.42***	29.55***	1.54***	-33.31***
Engie	0.77	22.26***	83.41***	-36.27***
Philips	2.16***	45.91***	3.72***	-35.20***
HSBC	0.51	12.74***	22.55***	-37.25***

The Augmented Dickey-Fuller (ADF) test assesses the null hypothesis of a unit root in the CDS log-return series. The Jarque-Bera test evaluates the null hypothesis of normality of the marginal distribution. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

The ARCH-LM tests in Table 4 provide strong evidence of conditional heteroskedasticity for most firms and lag specifications, confirming volatility clustering as a pervasive feature of

CDS log returns. A small number of series show weaker evidence at short lags (e.g., Adidas at 2 and 5 lags, Nike across the three lag choices), but the overall pattern overwhelmingly supports modeling time-varying volatility.

In Table 5, the Box-Pierce Q-statistics reveal significant serial dependence for many series, and the complementary statistics reinforce the presence of persistence and predictability in higher-order dynamics. This matters for our empirical design because dependence estimates can be distorted if serial correlation and volatility clustering are ignored in the marginal models.

Finally, Table 6 confirms that volatility persistence is not only short-run clustering but can also display long-memory behavior in squared returns. Both the GSP and GPH measures are frequently significant, suggesting that volatility shocks decay slowly for many firms. This feature is particularly relevant for crisis analysis, as it implies that stress-induced volatility effects can propagate over extended horizons, shaping the dependence structure precisely when commodity shocks and credit risk repricing coincide.

Table 4: ARCH-LM tests for CDS log returns

Company	ARCH-LM (2 lags)	ARCH-LM (5 lags)	ARCH-LM (10 lags)
Adidas	0.46	0.18	2.28**
Air Liquide	16.47***	9.19***	6.72***
Barclays Bank	26.72***	119.51***	83.75***
BMW	119.60***	52.46***	36.16***
BP	159.97***	90.99***	61.20***
Exxon Mobil	9.54***	14.12***	7.74***
Heineken	295.55***	42.52***	71.38***
Chevron	2.70*	5.92***	3.13***
Enel	171.45***	94.15***	54.64***
Orange	174.89***	80.02***	41.92***
ING	112.32***	70.77***	44.58***
Hyundai	19.46***	16.44***	8.89***
Iberdrola	131.70***	59.20***	36.23***
Samsung	4.58**	3.17***	1.96**

Continued on next page

Table 4 (continued)

Company	ARCH-LM (2 lags)	ARCH-LM (5 lags)	ARCH-LM (10 lags)
Santander	120.48***	53.34***	29.13***
Schneider Electric	9.54***	29.98***	16.20***
Siemens	11.72***	7.03***	5.44***
Kering	23.93***	19.33***	23.56***
Bayer	27.75***	14.06***	9.35***
Carrefour	2.87***	1.15***	59,063.00***
Nestlé	30.69***	23.43***	12.06***
Nike	1.14	0.51	0.45
Sony	47.11***	23.98***	12.38***
Volvo	74.11***	44.41***	25.37***
Walmart	171.06***	89.07***	47.14***
Toyota	368.69***	278.53***	147.65***
Société Générale	219.79***	95.94***	51.73***
Facebook	164.67***	70.12***	35.98***
Engie	110.42***	67.55***	39.86***
Philips	312.69***	35.01***	18.74***
HSBC	179.73***	86.99***	46.49***

The ARCH-LM test is the Lagrange Multiplier test for autoregressive conditional heteroskedasticity. The null hypothesis is homoscedastic innovations. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 5: Autocorrelation tests for CDS log returns

Company	Box-Pierce Q(10)	Variance Ratio	R/S (10 lags)
Adidas	75.22***	0.84*	1.12***
Air Liquide	134.86***	1.35***	0.90***
Barclays Bank	121.03***	1.16**	0.80***

Continued on next page

Table 5 (continued)

Company	Box-Pierce Q(10)	Variance Ratio	R/S (10 lags)
BMW	178.53***	1.43***	1.36***
BP	293.52***	1.36***	1.60***
Exxon Mobil	119.79***	0.73***	0.81***
Heineken	42.71***	1.03	1.04***
Chevron	64.14***	1.09	1.30***
Enel	108.89***	1.18**	1.16***
Orange	124.32***	1.32***	0.99***
ING	52.66***	1.18***	1.23***
Hyundai	15.41	1.02	1.80***
Iberdrola	82.27***	1.20***	1.21***
Samsung	19.43**	1.01*	1.11***
Santander	22.82**	1.01*	1.11***
Schneider Electric	122.96***	1.06	1.51***
Siemens	116.09***	1.30***	1.35***
Kering	54.70***	1.19***	1.42***
Bayer	86.35***	1.28***	1.03*
Carrefour	40,330.80***	4.98***	17.87
Nestlé	48.08***	1.05	1.04***
Nike	126.11***	0.74***	0.88***
Sony	49.63***	1.16**	1.30***
Volvo	152.48***	1.39***	1.40***
Walmart	20.62	0.64	1.21***
Toyota	274.47***	0.81***	0.98
Société Générale	84.17***	1.20***	1.26***
Facebook	178.66***	1.43***	1.35***
Engie	17.30*	1.02	1.06***
Philips	73.73***	1.22**	1.19***

Continued on next page

Table 5 (continued)

Company	Box-Pierce Q(10)	Variance Ratio	R/S (10 lags)
HSBC	29.76***	1.08	1.00***

The Box-Pierce Q-statistic tests the null hypothesis of no serial correlation up to 10 lags. The Variance Ratio test assesses deviations from a random walk. R/S denotes rescaled range analysis and provides evidence on long-memory behavior. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 6: Long-memory tests on squared CDS log returns

Company	GSP test	Periodogram points	GPH test	Periodogram points
Adidas	0.0086	2031	0.0130	2031
Air Liquide	0.1040***	2091	0.1178***	2098
Barclays Bank	0.2977***	2095	0.2536***	2100
BMW	0.1878***	2090	0.2016***	2100
BP	0.2137***	2096	0.2008***	2098
Exxon Mobil	0.1372***	2070	0.1308***	2070
Heineken	0.3144***	2044	0.2543***	2046
Chevron	0.0410***	2098	0.0593***	2098
Enel	0.1956***	2094	0.2037***	2100
Orange	0.2242***	2076	0.2253***	2100
ING	0.1917***	2093	0.2055***	2098
Hyundai	0.0825***	1962	0.0912***	1983
Iberdrola	0.1894***	2095	0.2038***	2097
Samsung	0.0530***	2098	0.0724***	2098
Santander	0.1960***	2094	0.1975***	2098
Schneider Electric	0.1252***	2098	0.1468***	2098
Siemens	0.0648***	2093	0.1076***	2097
Kering	0.1250***	2090	0.1553***	2098
Bayer	0.1155***	2095	0.1305***	2098

Continued on next page

Table 6 (continued)

Company	GSP test	Periodogram points	GPH test	Periodogram points
Carrefour	0.2095***	2093	0.2064***	2098
Nestlé	0.0938***	2093	0.1130***	2098
Nike	0.2723***	2098	0.0426***	2098
Sony	0.1185***	2015	0.1150***	2020
Volvo	0.1602***	2085	0.1720***	2098
Walmart	0.2191***	2092	0.2129***	2098
Toyota	0.3830***	2100	0.3308***	2100
Société Générale	0.9141***	2100	0.8930***	2100
Facebook	0.1587***	2095	0.1541***	2098
Engie	0.1794***	1996	0.1563***	2011
Philips	0.1309***	2094	0.1469***	2098
HSBC	0.1969***	2092	0.1851***	2097

GSP refers to the Gaussian Semiparametric test of long memory proposed by [Robinson \(1995\)](#). GPH denotes the log-periodogram regression estimator introduced by [Geweke & Porter-Hudak \(1983\)](#). Tests are applied to squared CDS log returns to detect long-memory behavior in volatility. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Overall, [Table 2](#) to [Table 6](#) document four features that directly motivate our modeling strategy: (i) high persistence in CDS spreads in levels, (ii) non-normal and heavy-tailed return distributions, (iii) strong conditional heteroskedasticity, and (iv) persistent and often long-memory volatility dynamics. These stylized facts justify filtering each marginal series with an IGARCH-type specification before modeling CDS-commodity dependence, and they support the use of copulas to capture asymmetric and tail-driven co-movements that are expected to intensify during systemic episodes.

5.2 Full-sample IGARCH-Copula estimates

The results of the IGARCH–Copula estimations reported in [Table 7](#) provide direct evidence on how credit risk, as measured by corporate CDS spreads, co-moves with commodity market conditions during periods of financial stress. By combining an IGARCH specification for marginal dynamics

with flexible copula functions, the framework allows us to disentangle average dependence from asymmetric and tail-specific linkages.

Overall, three robust findings emerge from the estimation results. First, dependence between CDS spreads and commodity markets is heterogeneous across firms and sectors, confirming that exposure to commodity risk is not uniform. Second, positive and statistically significant tail dependence dominates, especially for firms with direct or indirect reliance on commodities. Third, copula choice matters, as Clayton and Gumbel copulas frequently outperform symmetric alternatives, highlighting the role of extreme downside or upside co-movements during crises. These results collectively support the view that commodity market shocks act as a powerful transmission channel for credit risk under stress, but with markedly different intensities depending on sectoral characteristics.

Energy-related firms exhibit the strongest and most systematic dependence with commodity markets. Companies such as BP (0.037), Chevron (0.0048), Iberdrola (0.0551), Engie (0.0394), and Exxon Mobil display positive and statistically significant dependence parameters, predominantly captured by Clayton or Gumbel copulas. This indicates pronounced tail dependence, meaning that extreme commodity price movements coincide with extreme variations in CDS spreads. This result is economically intuitive. Energy firms are directly exposed to commodity price dynamics through revenues, production costs, and balance sheet valuations. During crisis periods, supply disruptions, geopolitical tensions, or abrupt demand collapses amplify price volatility in energy commodities, which rapidly translates into higher perceived default risk. The dominance of asymmetric copulas further indicates that downside risk transmission is particularly strong, consistent with the widening of CDS spreads during adverse commodity shocks. From a broader perspective, these findings underline the systemic vulnerability of energy firms to commodity-driven crises. They also reinforce the argument that the ongoing energy transition may play a stabilizing role in the long run by reducing firms' dependence on highly volatile fossil fuel markets.

A second group of firms, including Bayer (0.039), Siemens (0.033), Schneider Electric (0.0126), Volvo (0.0270), and Hyundai (0.0527), exhibits moderate but statistically significant dependence with commodity markets. In contrast to the energy sector, these firms are not commodity producers but commodity users, mainly through input costs and supply chains. The estimated dependence parameters remain positive and significant, yet smaller in magnitude. This suggests that commodity shocks affect industrial firms primarily through cost pressures rather than direct

revenue channels. The frequent selection of Clayton and Gumbel copulas indicates that extreme commodity movements still matter, but the transmission mechanism is more indirect. These results highlight an important nuance in crisis propagation. While industrial firms are less exposed than energy companies, they are far from insulated. Persistent commodity price shocks can erode margins, weaken cash flows, and ultimately deteriorate credit quality, especially when firms operate with tight margins or limited pricing power.

Consumer-oriented firms such as Carrefour (0.0443), Nestlé (0.0536), Walmart (0.0454), and Kering (0.0427) also display positive and significant dependence with commodity markets. This dependence reflects exposure to agricultural commodities, packaging materials, and transportation costs. Compared to the energy and industrial sectors, the magnitude of dependence is more moderate, suggesting partial pass-through of commodity price shocks to credit risk. Firms in this sector often benefit from greater flexibility in pricing strategies, brand value, and diversified sourcing, which dampens the immediate impact of commodity volatility. Nonetheless, the presence of tail dependence implies that extreme commodity shocks can still have non-negligible effects on credit risk during crises. This finding emphasizes the importance of supply chain resilience and risk-sharing mechanisms, particularly in periods characterized by global disruptions such as pandemics or geopolitical conflicts.

Technology and telecommunications firms, including Orange (-0.0375), Samsung (-0.0175), Philips (-0.0070), and Facebook, stand out for their weak or negative dependence with commodity markets. In several cases, the estimated coefficients are either insignificant or negative, suggesting partial decoupling from commodity-driven stress. This result reflects the lower direct reliance of these firms on physical commodities and their stronger dependence on intangible assets, digital infrastructure, and network effects. During commodity market turmoil, these firms may even benefit from portfolio rebalancing effects, as investors shift toward sectors perceived as less exposed to real asset price volatility. However, this relative insulation should be interpreted cautiously. As digitalization, electrification, and green technologies expand, technology firms may become increasingly exposed to specific commodities such as rare earth elements and critical metals. The current findings therefore represent a snapshot of existing structures rather than a permanent decoupling.

Finally, financial institutions such as Barclays Bank (0.0087) and Société Générale (0.0410) exhibit positive and significant dependence with commodity markets, yet through different channels. Unlike non-financial firms, banks are exposed indirectly via credit portfolios, derivatives positions,

and market-wide systemic risk. The presence of tail dependence suggests that commodity price shocks exacerbate financial fragility during crises, either by increasing default probabilities of commodity-exposed borrowers or by amplifying market-wide risk aversion. This reinforces the view that commodity markets are an integral component of systemic risk, with implications extending beyond commodity-producing firms. From a regulatory standpoint, these results support the inclusion of commodity stress scenarios in banking sector stress tests, particularly in economies with strong links to energy and commodity markets.

Overall, the empirical evidence shows that the transmission of commodity market shocks to corporate CDS spreads is neither uniform nor symmetric across firms. Dependence intensifies precisely in sectors with direct or indirect exposure to commodity inputs, most notably energy, consumer goods, and parts of the industrial sector, where positive and statistically significant tail dependence dominates. In contrast, technology and telecommunications firms display weaker or even negative dependence, pointing to sectoral decoupling mechanisms during crisis episodes.

These results indicate that commodity-driven credit risk materializes primarily through extreme market conditions rather than average co-movements, and that its magnitude crucially depends on firms' production structures and cost exposure. By capturing these asymmetric and crisis-contingent patterns, the IGARCH–Copula estimates reveal how commodity shocks selectively amplify credit stress across sectors, thereby providing a granular view of systemic risk transmission during periods of market turmoil.

Table 7: IGARCH-Copula Estimation Results

Time series	IGARCH(1,1) estimation				Copula estimation	
	Cst (M)	Cst (V)	ARCH (α)	GARCH (β)	Copula	Coefficient
Commodity index	0.000085 (0.00018106)	0.011616*** (0.0042814)	0.068417*** (0.011412)	0.931583** (0.362985)		
Adidas	-0.0002 (0.00038766)	0.9091 (0.97455)	0.2105* (0.10711)	0.7895*** (0.09584)	Clayton	-0.0177736 (0.0165569)
Air Liquide	-0.0008 (0.00032812)	0.8072* (0.46778)	0.2886*** (0.065127)	0.7114*** (0.009584)	t-Student	-0.1540486*** (0.0161995)
Barclays bank PLC	-0.0007* (0.00037826)	0.2292*** (0.071826)	0.1650*** (0.026476)	0.8350*** (0.06254)	Gumbel	0.0087229*** (0.0088082)
Bayer	-0.0012** (0.00050406)	0.3629** (0.15723)	0.1548*** (0.044215)	0.8452*** (0.039652)	Clayton	0.0393382** (0.0169352)
BMW	-0.0007** (0.00033223)	0.0193*** (0.068837)	0.1732*** (0.038186)	0.8268*** (0.0625)	Clayton	0.0370602** (0.0180662)
BP	-0.001428*** (0.00033223)	0.582632** (0.068837)	0.220020*** (0.038186)	0.779980*** (0.0625)	Clayton	0.0370602** (0.0180662)

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Table 7 (continued)

Time series	IGARCH(1,1) estimation			Copula estimation	
	Cst (M)	Cst (V)	ARCH (α)	GARCH (β)	Copula Coefficient
Carrefour	(0.00050680)	(0.29572)	(0.074990)	(0.06354)	(0.0180662)
	-0.001121	0.413609**	0.197902***	0.802098***	0.0442628**
	(0.00043571)	(0.19201)	(0.061921)	(0.03652)	(0.0173327)
Chevron	-0.0010**	0.2868**	0.1413***	0.8587***	0.0048287***
	(0.0003802)	(0.12933)	(0.028477)	(0.0362)	(0.0093269)
Enel	-0.000431	0.156264**	0.151948***	0.848052***	0.0324295*
	(0.00034179)	(0.071004)	(0.034124)	(0.0965)	(0.0176089)
Engie	-0.000327	0.132438*	0.136698***	0.863302***	0.0393526**
	(0.00027661)	(0.074274)	(0.036862)	(0.00125)	(0.0161534)
Exxon Mobil					t-Student 0.0145402
					(0.0173225)
Facebook	-0.000950**	0.0128328***	0.113129***	0.886871***	
	(0.00039479)	(0.045260)	(0.023570)	(0.0362)	

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Table 7 (continued)

Time series	IGARCH(1,1) estimation				Copula estimation	
	Cst (M)	Cst (V)	ARCH (α)	GARCH (β)	Copula	Coefficient
Heineken					Clayton	0.0429366** (0.0187747)
Hyundai	-0.000203 (0.00015018)	0.005793 (0.0066858)	0.014422*** (0.0060163)	0.985578*** (0.03629)	Clayton	0.0526981** (0.0205261)
Iberdrola	-0.001206** (0.00047741)	0.518014** (0.21361)	0.193671*** (0.053494)	0.806329*** (0.06354)	Clayton	0.0551240*** (0.0176208)
ING					Clayton	-0.0076131 (0.0172997)
Kering	-0.001113*** (0.00035382)	0.186679** (0.084427)	0.106735*** (0.029810)	0.893265*** (0.03625)	Clayton	0.0427376** (0.0194379)
Nestlé	-0.0002 (0.00042)	0.0251** (0.0102)	0.0236*** (0.0062)	0.9764*** (0.0326)	Clayton	0.0535945*** (0.0200194)
Nike	0.0001	2.6732	0.3595**	0.6405***	Clayton	0.0574503***

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Table 7 (continued)

Time series	IGARCH(1,1) estimation			Copula estimation		
	Cst (M)	Cst (V)	ARCH (α)	GARCH (β)	Copula	Coefficient
Orange	(0.0004)	(0.0511)	(0.1682)	(0.2695)		(0.0191912)
	-0.0002	0.5023**	0.2622***	0.7378***	Clayton	-0.0375077***
	(0.0042)	(0.0265)	(0.0895)	(0.1963)		(0.0131819)
Philips	0.0000	0.0075	0.0234**	0.9766***	t-Student	-0.0069905
	(0.0118)	(0.077)	(0.0009)	(0.0068)		(0.0143416)
Samsung	-0.0005	3.9564	0.3526***	0.6474***	Clayton	-0.0175086
	(0.0062)	(0.9534)	(0.1126)	(0.09632)		(0.0173515)
Santander	-0.000740	0.2084	0.0633	0.9367***	t-Student	0.0080353
	(0.0006)	(0.8806)	(0.1495)	(0.09635)		(0.0144315)
Schneider Electric	-0.0007*	0.0605**	0.0586***	0.9414***	Gumbel	0.0125834***
	(0.00038)	(-0.0300)	(-0.0200)			(0.0081214)
Société Générale	-0.0010*	0.8150*	0.2193***	0.7807***	Clayton	0.0410403**
	(0.058)	(0.4230)	(0.0715)	(0.0067)		(0.0166702)

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Table 7 (continued)

Time series	IGARCH(1,1) estimation				Copula estimation	
	Cst (M)	Cst (V)	ARCH (α)	GARCH (β)	Copula	Coefficient
Toyota	-0.000829* (0.00050267)	0.222129 (0.21835)	0.040407** (0.019283)	0.959593*** (0.1365)		
Volvo	-0.001094*** (0.00039628)	0.324415** (0.14863)	0.172360*** (0.051452)	0.827640*** (0.0065)	Clayton	0.0270376** (0.0182456)
Walmart	-0.001219** (0.00056203)	0.346130 (0.30639)	0.140601 (0.087387)	0.859399*** (0.1783)	Clayton	0.0453553 (0.0178249)
Siemens	-0.000718* (0.00037260)	0.082304*** (0.031352)	0.067426*** (0.014922)	0.932574*** (0.3260)	Clayton	0.0331044* (0.0183053)

The choice of the copula retained for each company is based on minimum information criteria (AIC and

SiC). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

5.3 Crisis-regime evidence: Sub-period dependence patterns

The sub-period IGARCH-Copula estimates reported in [Table 8](#) reveal pronounced time variation in the dependence structures between corporate CDS spreads and commodity markets. Beyond average relationships, the results clearly show that the strength, sign, and nature of CDS-commodity linkages are strongly conditioned by the macro-financial environment. The comparison across the pre-crisis, Global Financial Crisis, European Sovereign Debt Crisis, and COVID-19 periods provides direct evidence that commodity-related credit risk transmission is fundamentally crisis-dependent and highly heterogeneous across firms and sectors.

During the pre-crisis period, dependence between CDS spreads and commodity markets is generally weak and often negative. Most estimated coefficients are small in magnitude and statistically insignificant, indicating limited co-movement under tranquil market conditions. Firms such as Samsung (-0.3944), Barclays Bank (-0.3636), Bayer (-0.5156), and BMW (-0.5156) display negative dependence parameters, suggesting that CDS spreads and commodity prices evolved largely independently prior to the onset of systemic stress. This weak dependence pattern is consistent with a market environment dominated by firm-specific fundamentals rather than global risk factors. In the absence of major shocks, commodity price fluctuations do not translate into credit risk repricing for most firms. Importantly, the absence of strong tail dependence during this period indicates that extreme co-movements are not a structural feature of CDS-commodity relations, but instead emerge under stressed market conditions.

A marked shift occurs during the Global Financial Crisis, when dependence parameters become stronger and more frequently significant. Several firms exhibit a clear increase in the magnitude of CDS-commodity dependence, reflecting the amplification of global risk transmission channels. Notable examples include Iberdrola (1.0176), Nike (0.0254), and Siemens (1.0257), indicating that commodity market shocks became tightly linked to credit risk during this period. At the same time, heterogeneity across firms becomes more pronounced. While energy and utility-related firms show strong positive dependence, some companies such as Samsung (-0.1305) and Carrefour (-0.1378) retain negative or weak relationships. This contrast suggests that the Global Financial Crisis did not transmit commodity shocks uniformly across all sectors, but instead magnified vulnerabilities in commodity-exposed business models.

During the European Sovereign Debt Crisis, dependence structures partially weaken relative to the Global Financial Crisis, but remain significant for several firms, particularly those with strong European exposure. Utilities and industrial firms such as Iberdrola (1.0109), Siemens

(1.0169), and Enel (0.0276) continue to exhibit positive and significant dependence, indicating persistent sensitivity to commodity market conditions. In contrast, other firms display weaker or mixed responses. *Schneider Electric* (-0.0844) and *Samsung* (0.0116) illustrate that dependence patterns during this period are highly firm-specific. These results reflect the more localized nature of the sovereign debt crisis, where financial stress was concentrated in Europe and interacted with commodity prices primarily through regional demand conditions and fiscal risk channels.

The COVID-19 period exhibits a distinct dependence pattern, characterized by a reconfiguration rather than a simple intensification of CDS-commodity linkages. Several firms maintain strong positive dependence, notably Iberdrola (1.0337) and Siemens (1.0259), indicating that commodity markets continued to play a central role in credit risk transmission for energy and industrial sectors. At the same time, negative dependence becomes more visible for firms such as Walmart (-0.0997) and Samsung (-0.0744). This divergence reflects the unique nature of the pandemic shock, which combined supply-chain disruptions, demand reallocation, and unprecedented policy interventions. For retail and technology firms, CDS spreads appear less sensitive, or even inversely related, to commodity price movements, possibly due to demand resilience and changes in consumption patterns.

Across all sub-periods, several robust empirical insights emerge. First, CDS-commodity dependencies are clearly non-linear and time-varying, materializing primarily during periods of systemic stress. Second, crisis episodes are associated with stronger and more asymmetric tail dependence, particularly for energy and utility sectors. Third, sectoral heterogeneity remains a defining feature across all periods, with commodity-intensive firms consistently displaying stronger and more persistent dependence structures.

Table 8: Sub-period copula estimation results

Company	Copula	Pre-crisis	Global Financial Crisis	Sovereign Debt Crisis	COVID-19
		Coef.	Coef.	Coef.	Coef.
Air Liquide			-0.0324	-0.1165***	0.0190
Barclays Bank	Clayton	-0.3636	-0.0996	0.0212	0.0067
Bayer	Student	-0.5156**	-0.0666	-0.0164	-0.0206
BMW	Student	-0.5156**	-0.1192**	-0.0259	-0.0557
BP	Student	-0.5156**	-0.1044**	-0.0183	-0.0581
Carrefour	Student	-0.4465	-0.1378**	-0.0084	-0.0777
Chevron	Student	-0.5156**	-0.0193	0.0151	-0.0388
Enel	Clayton	1.0338	-0.0710	0.0276	0.0691
Iberdrola	Gumbel	0.0580	1.0176***	1.0109***	1.0337***
ING	Clayton	-0.0721	-0.0898	0.0552	0.0656
Nestlé	Student	-0.2318	-0.0219	0.0772**	-0.0362
Nike	Gumbel	0.6684***	0.0254***	0.0163***	-0.0251***
Philips	Student	0.5161**	0.0129	0.0095	-0.0680
Samsung	Clayton	-0.3944***	-0.1305**	0.0116	-0.0744*
Santander	Student	0.0465	-0.0172	0.0032	-0.0206

Continued on next page

Table 8 (continued)

Company	Copula	Pre-crisis	Global Financial Crisis	Sovereign Debt Crisis	COVID-19
		Coef.	Coef.	Coef.	Coef.
Schneider Electric	Gaussian	-0.7143***	-0.0556	-0.0844**	-0.1564**
Société Générale	Student	-0.5156*	-0.0182	-0.0343	-0.0570
Volvo	Gaussian	-0.6691***	-0.0552	0.0053	-0.0198
Walmart	Clayton	-0.3636	-0.0677	0.0236	-0.0997*
Kering	Clayton	-0.3636	-0.1593***	0.0298	-0.0588
Siemens	Gumbel	1.0290***	1.0257***	1.0169***	1.0259

Reported coefficients correspond to the copula dependence parameters estimated for each sub-period. The copula family is selected according to the minimum information criteria (AIC and SC). *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

6 Conclusion

This paper investigates the dependence structures between corporate Credit Default Swap (CDS) markets and commodity markets using a comprehensive international dataset covering 27 firms across multiple sectors and regions over the period 2007-2024. By adopting a two-step IGARCH-Copula framework, the analysis explicitly accommodates volatility persistence, non-linear dependence, and asymmetric tail behavior, all of which emerge as important empirical features of CDS dynamics in the presence of commodity market stress.

The main contribution of this study lies in its integrated long-horizon, cross-regional, and sectoral perspective on CDS-commodity interdependence. Unlike much of the existing literature, which typically focuses on short samples, single regions, or linear dependence measures, this paper provides consistent evidence across Europe, East Asia, and North America, and across multiple crisis regimes. The empirical design, which filters marginal dynamics using IGARCH specifications before estimating dependence structures, ensures that the detected co-movements reflect genuine innovation-based linkages rather than mechanical correlations driven by volatility clustering or persistence. This methodological choice proves crucial in isolating the transmission of extreme shocks between commodity and credit markets.

The empirical results reveal that CDS-commodity dependence is highly heterogeneous across sectors and fundamentally concentrated in the tails of the joint distribution. Energy and utility firms display strong and statistically significant tail dependence with commodity markets, reflecting their structural exposure to commodity price shocks through revenues, costs, and balance-sheet channels. These dependencies intensify precisely during periods of market stress, indicating that commodity shocks act as amplifiers of credit risk rather than sources of average co-movement. In contrast, consumer goods and technology firms exhibit weaker, and in some cases negative, dependence parameters, suggesting partial insulation from commodity-driven stress and highlighting the role of business models and cost structures in shaping credit risk exposure. Financial institutions occupy an intermediate position, with significant but more moderate dependence, consistent with indirect exposure through systemic risk channels and portfolio linkages.

The sub-period analysis further demonstrates that CDS-commodity dependence is strongly time-varying and crisis-contingent. During tranquil periods, dependence parameters are generally weak or insignificant, indicating that commodity price fluctuations play a limited role in shaping

credit risk under normal market conditions. By contrast, crisis episodes are associated with sharp increases in dependence strength and pronounced tail asymmetries, particularly during the Global Financial Crisis and the European Sovereign Debt Crisis. The COVID-19 period reveals a reconfiguration of dependence patterns rather than a uniform amplification, underscoring that the nature of the shock matters for how commodity stress is transmitted to credit markets.

The systematic selection of asymmetric copulas, especially Clayton and Gumbel, provides additional insight into the directionality of extreme dependence. Lower-tail and upper-tail dependence differ markedly across sectors and crisis regimes, indicating that adverse commodity shocks and favorable price movements do not transmit symmetrically to credit risk. This result highlights the limitations of correlation-based approaches and shows that linear dependence measures substantially understate the role of commodities in shaping credit market fragility during stress episodes.

From a practical perspective, these findings have important implications for risk management and financial stability analysis. Sector-agnostic stress-testing frameworks risk overlooking critical channels of risk amplification if they ignore commodity-related tail dependence. Investors and portfolio managers can exploit the documented heterogeneity in dependence structures to improve diversification strategies, particularly during crisis periods when traditional correlations break down. For regulators, the results underscore the relevance of commodity markets as a systemic risk factor, especially for energy-intensive sectors and economies with strong commodity linkages.

Overall, this study provides robust international evidence that commodity markets act as a crisis-dependent transmission channel for corporate credit risk, with effects that are asymmetric, sector-specific, and concentrated in extreme market conditions. By documenting how and when commodity shocks translate into CDS market stress, the paper advances the understanding of systemic risk propagation and offers a rigorous empirical foundation for future research on the interaction between real asset markets and credit risk under systemic stress.

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