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This paper employs predictive regressions to explore the predictability of sovereign Credit Default Swap (CDS) spread dynamics of relevant oil-producing countries. By incorporating oil prices and additional control variables, we predict the rate of CDS spread changes for Brazil, the UK, Malaysia, Norway, Qatar, Russia, Saudi Arabia, the US, and Venezuela. Our findings reveal that (i) the empirical coefficients of determination (R^2) indicate low in-sample predictability for our entire period of analysis (2010-2024), the R^2 increases markedly when dividing the analysis period into more relevant sub-samples (2010-2016 and 2016-2024); (ii) oil prices are not significant predictors for the full period but become significant in many regressions within sub-samples; (iii) for countries where oil prices are significant in both sub-samples, the coefficient sign changes from negative to positive, suggesting that in more recent years, rising (falling) oil prices signal increasing (decreasing) geopolitical risk, positively (negatively) influencing CDS spreads.

Key words: oil prices • fiscal stability • predictive regressions
JEL classification: G17 • H63 • C58 • Q43

1. Introduction

Over the past decade, a growing body of research has investigated the link between oil prices and the sovereign credit risk of oil-producing countries. This literature primarily focuses on how oil price fluctuations impact these nations' sovereign credit risk. Sovereign credit risk is typically assessed through credit ratings (see, for example, Breunig and Chia, 2015), bond yield spreads (see, for example, Filippidis, Filis, and Kizys, 2020), and credit default swap (CDS) spreads (see, for example, Bouri, Shahzad, Raza, and Roubaud, 2018). Understanding the predictability of sovereign CDS spreads in response to oil price fluctuations is crucial for policymakers and investors, as it provides insights into fiscal stability, credit risk management, and the broader implications of commodity price shocks on financial markets. A drop (rise) in oil prices can lead to reduced (increased) government revenues, higher (lower) budget deficits, and increased (decreased) borrowing costs, thus deteriorating (improving) the credit risk profile of these countries. The empirical literature utilizes econometric models to analyze historical data, focusing on the correlation between oil prices and sovereign bond spreads or CDS spreads. Specifically, researchers employ Vector Auto-regressive (VAR) models (see Wegener, Basse, Kunze, and von Mettenheim, 2016, Chen, Huang, and Lin, 2022), quantile regression analysis (see Bouri, Shahzad, Raza, and Roubaud, 2018, Naifar, Shahzad, and Hammoudeh, 2020), and time-varying parameter methods (see Shahzad, Naifar, Hammoudeh, and Roubaud, 2017, Bouri, Kachacha, and Roubaud, 2020).

This paper makes a novel contribution to the existing literature by being the first, to our knowledge, to employ predictive regressions to examine the relationship between oil prices and the sovereign credit risk of oil-producing countries. Specifically, we employ predictive regressions, incorporating oil prices among other variables, to forecast CDS spread dynamics obtained weekly for Brazil, the United Kingdom, Malaysia, Norway, Qatar, Russia, Saudi Arabia, the United States of America, and Venezuela. We select these countries following Wegener, Basse, Kunze, and von Mettenheim (2016) to ensure our results are comparable within the context of existing literature. Building on previous studies that have established a link between oil price movements and sovereign CDS spreads (e.g., Sharma and Thuraisamy, 2013, Bouri, Kachacha, and Roubaud, 2020), this study extends the literature by employing predictive regressions, which allow for a more dynamic assessment of forecastability across different periods and geopolitical contexts, offering new insights into the evolving nature of this relationship.

The primary advantage of predictive regressions lies in the straightforward interpretability of their coefficients of determination, which provide valuable insights into the extent of predictability. Additionally, the method for estimating predictive regressions proposed by Kostakis, Magdalinos, and Stamatogiannis (2015) does not necessitate assumptions regarding the persistence of the regressors. High persistence in regressors can invalidate standard inference procedures, as noted by Stambaugh (1999). To address this issue, we employ the methodologies suggested by Kostakis, Magdalinos, and Stamatogiannis (2015) and Yang, Long, Peng, and Cai (2020), which enable robust inference irrespective of the persistence of the regressors. This is particularly crucial for oil prices, which may be considered either integrated of degree one (i.e., a martingale process) or explosively trending (i.e., integrated of degree infinity or a sub-martingale), according to Figuerola-Ferretti, McCrorie, and Paraskevopoulos (2020) and Kruse and Wegener (2020).

The methodology developed by Kostakis, Magdalinos, and Stamatogiannis (2015) involves the construction of an instrument for the regressor through an appropriate filtering process, thereby eliminating the need for additional data. This instrument, referred to as IVX, relies solely on the regressor itself. The IVX-AR methodology extends the IVX framework by incorporating an autoregressive component to account for serial correlation and heteroscedasticity in predictive regressions.

Developed by Yang, Long, Peng, and Cai (2020), this approach enhances inference robustness by constructing near-stationary instruments that mitigate biases arising from persistent regressors, such as oil prices. By adapting the IVX estimator to autoregressive settings, IVX-AR ensures more reliable coefficient estimates and statistical inference in forecasting models where predictor variables exhibit strong temporal dependencies. Moreover, this approach facilitates the testing of the joint predictive capability of variables in multiple regressions, allowing for the inclusion of control variables within our model. Specifically, in addition to West Texas Intermediate (WTI) oil prices, we incorporate the St. Louis Fed Financial Stress Index (FS) to capture the degree of stress in global financial markets, as well as the foreign exchange rate of our countries of analysis.

We employ an augmented version of the IVX methodology, the IVX-AR. This version accounts for serial correlation and heteroscedasticity in the error terms of the predictive regression model, as proposed by Yang, Long, Peng, and Cai (2020). By utilizing the IVX-AR approach, we ensure robust inference despite the presence of serial correlation and heteroscedasticity, thereby enhancing the reliability and validity of our predictive regression analysis. The IVX-AR methodology improves upon traditional predictive regression models by addressing the challenge of persistent regressors, such as oil prices, through the construction of near-stationary instruments, ensuring valid inference even when predictors exhibit strong temporal dependencies; additionally, its autoregressive adjustment enhances the detection of time-varying predictability, making it particularly suited for capturing structural shifts in the oil price-CDS spread relationship across different economic periods and geopolitical events, as examined in our broader set of oil-producing countries over an extended timeframe.

The IVX approach and its extension have been widely applied in empirical research. Examples include the predictability of US stock returns during the period between 1927 and 2012 (see Kostakis, Magdalinos, and Stamatogiannis, 2015), the predictability of US excess stock returns (the difference between the S&P 500 index and the Treasury bill rate) across different quantiles from 1927 to 2005 (see Lee, 2016), the growth rate of a US house price index from 1975 to 2018 (see Yang, Long, Peng, and Cai, 2020), the predictability of real estate returns and rent growth in 19 OECD countries (see Demetrescu and Rodrigues, 2022), and the use of credit-implied variance as a predictor for the St. Louis Fed Stress Index (see Ammann and Moerke, 2023).

The structure of this paper is organized as follows: Section 2 provides a comprehensive review of the relevant literature, situating our study within the existing research. Section 3 details the data and methodology, focusing on the predictive regressions estimated using the IVX and IVX-AR approaches. In Section 4, we present and analyze the empirical results, highlighting their implications. Finally, Section 5 summarizes the key findings and suggests directions for future research.

2. Related Literature

A large body of literature explores the nexus between global risk factors and sovereign credit risk (see, for example, Longstaff, Pan, Pedersen, and Singleton, 2011, Amstad, Remolona, and Shek, 2016, Hibbert and Pavlova, 2017). Energy (and non-energy) commodities represent significant risk factors and thus largely contribute to countries' credit risk, particularly for oil-exporting nations (see Mei, Ma, Liao, and Wang, 2020, Liu, Ma, Tang, and Zhang, 2019). This is especially pertinent at the time of writing, with geopolitical risk at its peak due to numerous global conflicts, such as those between Russia and Ukraine, the US and China over the South China Sea and trade issues, and the Israel-Palestine conflict. These conflicts have substantial spillover effects on energy markets, adding particular salience to this phenomenon. Consequently, numerous studies have sought to contribute to the ongoing debate on the link between commodities and sovereign risk. Our research is linked to at least three key areas of the relevant literature, underscoring its importance and relevance.

First and foremost, we contribute to the debate on the nexus between commodity price dynamics and sovereign risk. This literature highlights the strategic global importance of crude oil, among other commodities (see Barsky and Kilian, 2002, Hamilton, 2003, Kilian, 2008, Kilian and Park, 2009). Specifically, studies have investigated the linkage between crude oil price dynamics and variables such as a country's production costs, price levels, consumption patterns, and exchange rates (see, for example, Filis, 2010, Kilian and Vigfusson, 2011a,b, Hamilton, 2011, Ratti and Vespignani, 2016, Beckmann, Czudaj, and Arora, 2020, Caldara and Iacoviello, 2022). In oil-exporting countries, fluctuations in oil prices are particularly crucial as they can significantly impact export revenues and, consequently, fiscal balances (ibid.). For example, Duffie, Pedersen, and Singleton (2003) conducted a case study on Russia's 1998 default. The authors find that Russian yield spreads vary significantly over time and are negatively correlated with both Russian foreign currency reserves and oil prices. Similarly, Sturzenegger and Zettelmeyer (2007) indicate that the drastic fall in oil prices in the mid-1990s was one of the key factors leading to Russia's default in 1998 (for an interesting investigation of credit defaults by Russia and Venezuela, see Chuffart and Hooper, 2019). Further, Kitous, Saveyn, Keramidas, Vandyck, Rey Los Santos, and Wojtowicz (2016) show that a 60% fall in oil prices could reduce the GDP of Saudi Arabia and Central Asia and the Caucasus by 15%, Kuwait and the UAE by 9%, Sub-Saharan Africa by about 8%, and Russia by 4.4%. Conversely, higher oil prices may significantly improve the public finances of major oil exporters. As a result, several studies have explored the transmission of oil prices to credit risk by analysing Credit Default Swap market prices (or CDS spreads).

The literature has employed a wide range of empirical approaches to study the linkage between oil prices and credit risk. Using a predictability test for daily CDS spread data from eight Asian countries, Sharma and Thuraisamy (2013) document that oil price changes can predict CDS dynamics for three in-sample and six out-sample countries. Further, Wegener, Basse, Kunze, and von Mettenheim (2016), by estimating bivariate VAR-GARCH-in-mean models, show that positive oil price shocks result in lower sovereign CDS spreads for a sample of nine major oil-exporting countries. Utilising the bootstrap rolling window Granger causality algorithm, Shahzad, Naifar, Hammoudeh, and Roubaud (2017) reveal that oil price uncertainty can significantly predict CDS spreads during periods of high oil price volatility.

Another approach is to use quantile-based models to account for the tail dependence feature of financial time series. Naifar, Shahzad, and Hammoudeh (2020), applying quantile regression approaches, show that positive (negative) oil returns reduce (increase) the sovereign CDS spreads of non-Gulf oil-exporting countries but not Saudi Arabia, the UAE, and Norway, with the impacts varying across quantiles. Deploying the cross-quantilogram approach, Bouri, Kachacha, and Roubaud (2020) demonstrate that the CDS spreads of both oil-exporting and importing countries can be predicted by shocks in oil prices and oil volatility, particularly during the price decline between 2014-2016. Similarly, Shahzad, Naifar, Hammoudeh, and Roubaud (2017) use the cross-quantilogram method to verify the strong link between oil prices and CDS spreads.

A few studies have also used sovereign ratings to proxy for sovereign risks under oil price changes instead of credit spreads and found similar results. Breunig and Chia (2015) find that high oil prices are associated with positive changes in the ratings of oil-exporting countries, and these rating premia are unrelated to their macro fundamentals. Using International Country Risk Guide data to measure country risk, Lee, Lee, and Ning (2017) estimate Structural VAR models and find that oil price increases lead to decreased country risk, especially in political and economic aspects, for oil exporters. However, most relevant studies use sovereign CDS spreads to estimate the impacts of oil price dynamics due to their high frequency, unbiased measurement, and long time-series nature.

Second, our paper is linked to the literature exploring the connection between geopolitical risk and oil price dynamics (see, for example, Pavlova, De Boyrie, and Parhizgari, 2018). Crude oil prices have shown significant increases immediately following major geopolitical events such as the 9/11 attacks, the Russo-Ukrainian War, and the recent terrorist attack on Israel. Zhang, Hu, Jiao, and Wang (2024) estimate that more than 50% of the increases in the global crude oil price between October 2021 and August 2022 can be attributed to the Russo-Ukrainian War. Echoing these findings, Bouoiyour, Selmi, Hammoudeh, and Wohar (2019), using a composite indicator of geopolitical risks summarizing all risks arising from tensions such as global trade tensions, US-China relations, US-Iran tensions, Saudi Arabian uncertainty, and the Venezuelan crisis, found that 'acts' affecting geopolitical risk have a strong positive effect on oil prices. In contrast, geopolitical risk 'threats' have rather marginal effects. Various direct and indirect channels can explain the impacts of geopolitical events on crude oil prices: Supply, demand, inventories, the US dollar exchange rate, and sentiment (see, for example, Kilian and Lee, 2014). Nevertheless, geopolitical shocks relevant to major oil producers can undoubtedly lead to significant drops in crude oil supply, affecting oil production and demand, causing volatility in the exchange rate, and driving speculation Cunado, Gupta, Lau, and Sheng (see, for example, 2020). These findings offer a solid foundation for the interpretation of our empirical analysis. Given the strong link between oil prices and geopolitical risks, this provides sufficient grounds to argue that our results can be interpreted as demonstrating the predictive power of both geopolitical risks and energy market dynamics on sovereign credit risk.

Third, our research is linked to the factors influencing sovereign CDS spreads. CDS products have proliferated and garnered significant interest from investors as they facilitate the trading of credit risk (see Kajurova, 2015). The CDS spread signifies the periodic payment a seller receives from a buyer on the notional amount to transfer the risk of a credit event. It reflects market views on the financial health of a sovereign entity (see Annaert, De Ceuster, Van Roy, and Vespro, 2013). Consequently, regulatory authorities can use CDS spreads as early warning indicators of financial stability. According to Ang and Longstaff (2013), CDS spreads offer an advantage over debt spreads in credit risk studies because debt spreads are influenced by numerous factors besides credit risk. Longstaff, Pan, Pedersen, and Singleton (2011) analyzed monthly 5-year CDS data for 26 countries and discovered that global financial market variables largely explain sovereign CDS spreads, whereas local macroeconomic factors have a lower impact. Moreover, Afonso, Alves, and Monteiro (2024) investigate the impact of geopolitical risk and global uncertainty on sovereign CDS spreads of 26 European economies during the period from 1984 to 2022. They find that geopolitical tensions and global uncertainty in neighboring countries, as well as in regions such as South America and Asia, contribute to the rise in sovereign risk for European countries. This effect is especially pronounced during times of crisis, implying that systemic sovereign risk is more closely linked to financial markets, including global energy markets, rather than specific country factors. That said, an extensive literature focuses on the primary determinants of CDS spreads (see, for example, Norden and Weber, 2004, Avramov, Jostova, and Philipov, 2007, Galil, Shapir, Amiram, and Ben-Zion, 2014, Chan and Marsden, 2014, Shen, Feng, and Sun, 2024). These include but are not limited to stock prices, stock market volatility, and interest rates. However, recent studies have incorporated oil prices as an additional determinant of CDS spreads (see, among others, Arouri, Hammoudeh, Jawadi, and Nguyen, 2014, Hammoudeh, Liu, Chang, and McAleer, 2013, Lahiani, Hammoudeh, and Gupta, 2016, Shahzad, Naifar, Hammoudeh, and Roubaud, 2017, Wang, Sun, and Li, 2020, Hammoudeh, Mensi, and Cho, 2022). These studies find that oil prices possess significant explanatory power. Particularly for countries heavily reliant on oil revenues, there is a strong linkage between oil price dynamics and sovereign credit risk (see, for example, Wegener, Basse, Kunze, and von Mettenheim, 2016, Shahzad, Naifar, Hammoudeh, and Roubaud, 2017, Bouri, Shahzad, Raza, and Roubaud, 2018, Naifar, Shahzad, and Hammoudeh, 2020, Bouri, Kachacha, and Roubaud, 2020, Chen, Huang, and Lin, 2022, Cheuathonghua, de Boyrie, Pavlova, and Wongkantarakorn, 2022).

3. Data and Methodology

This section explains the general concept of the IVX approach, introduces the data, explains the general concept of the IVX approach and provides an overview of the stochastic time-trending behavior of CDS spreads in oil-producing countries.

3.1. Data and Initial Data Analysis

We use CDS spreads for Brazil (**BR**), the United Kingdom (**UK**), Malaysia (**MY**), Norway (**NO**), Qatar (**QA**), Russia (**RU**), Saudi Arabia (**SA**), the United States of America (**US**), Venezuela (**VE**). The data was collected weekly from the 25th week of 2010 (June 21-27, 2010, denoted by 2010:25) to the 17th week of 2024 (April 22-28, 2024, denoted by 2024:17), corresponding to end-of-period observations recorded each Friday, and provided by Refinitiv Eikon. Data for this period is fully available for all countries except Venezuela (2010:25 to 2022:18) and Russia (2010:25 to 2022:38). Table 1 below provides a summary of the (sub)sample sizes.

Insert Table 1 here.

Regarding CDS spreads from Venezuela, the US sanctions against Venezuela have imposed restrictions on certain financial services. These sanctions have impacted the CDS market, consequently shortening our observation period. In the case of CDS spreads from Russia, sanctions led to a significant financial event where Russia defaulted on some of its foreign-currency-denominated government debt in June 2022 due to missed bond coupon payments. The motives behind these sanctions have been extensively discussed by Girardone (2022), as well as Quaglia and Verdun (2023). Specifically, Bianchi and Sosa-Padilla (2024) have emphasized that one key objective of the sanctions was to impede Russia's ability to finance its war against Ukraine. They also noted that Russia had already defaulted on some non-ruble-denominated government bonds in April 2022. Despite efforts by Russian authorities to address these issues in April and May 2022, rating agencies quickly identified a technical default. The Russian government asserted its willingness and capability to make the necessary payments to its creditors, yet default became unavoidable. This situation initially caused confusion in the CDS market. In essence, the sanctions against Russia created substantial difficulties and challenges in managing the default on government debt. After several months of uncertainty regarding the resolution of CDS contracts, an auction was held in September 2022 to determine the compensation holders of Russian debt protection would receive from protection sellers. Breydo (2023) has analyzed these events, mainly focusing on the legal aspects. These turbulent occurrences explain our chosen observation period for Russia.

There is an ongoing debate about the stochastic trending behavior of sovereign credit risk and CDS spreads, especially during financial crises, as highlighted by Wegener, Kruse, and Basse (2019) and Phillips and Shi (2019). In light of these issues, we join this debate and choose to employ the proposed algorithm by Smeekes (2015) based on the Bootstrap Sequential Quantile Test (BSQT) to estimate the degree of persistence of a time series, which controls for multiple testing by managing the false discovery rate, referencing Moon and Perron (2012) and Romano, Shaikh, and Wolf (2008). This algorithm determines the degree of integration of CDS spreads, denoted as d. The analysis was conducted using the R-package by Smeekes and Wilms (2023). The findings, presented in Table 2, indicate that all CDS spread series are integrated of order one, i.e., I(1). We further validate our findings by employing the KPSS test (see Kwiatkowski, Phillips, Schmidt, and Shin, 1992), which examines the null hypothesis of stationarity. Our results indicate that we are rejecting the null of stationarity, thereby suggesting that the data series exhibits non-stationary behavior. This outcome corroborates our overall analysis and strengthens our conclusions. Consequently, we use the rate of change in our subsequent analysis.

Insert Table 2 here.

Additionally, we obtained the explanatory variables primarily from the FRED database. However, for the Russian Ruble, we sourced the data from Refinitiv Eikon. For country-specific exchange rates, we utilized appropriate pairings, such as the British pound to the US dollar for the UK. For countries with a fixed exchange rate, such as between Qatar and the USA, we employed the Euro/Dollar exchange rate. Furthermore, for our analysis, we utilized data on Crude Oil Prices: West Texas Intermediate (WTI) – Cushing, Oklahoma, measured in dollars per barrel, on a weekly basis, and not seasonally adjusted.

Additionally, we incorporated the St. Louis Fed Financial Stress Index, which is a not seasonally-adjusted proxy for global market risk. The data is provided by the Federal Reserve Bank of St. Louis. The index is computed on a weekly basis and aims to measure the degree of financial market stress (see, for example, Blot, Creel, Hubert, Labondance, and Saraceno, 2015). The time series aggregates the information from 18 different variables that are of importance in this context, such as interest rates and yield spreads. More specifically, this measure allows for the joint examination of the effective Fed Funds Rate and emerging markets bond data together with several other relevant proxies for financial market risk. While this time series primarily is calculated based on data from the US, it is still considered to be an adequate measure of financial stress in a global context and meanwhile has also been used frequently in empirical studies to do so (see, for example, Dibooglu, Cevik, and Gillman, 2022, examining the global market for precious metals).

Finally, we incorporated the St. Louis Fed Financial Stress Index, which is also measured on a weekly basis and not seasonally adjusted. The St. Louis Financial Stress Index, provided by the Federal Reserve Bank of St. Louis, is computed on a weekly basis and aims to measure the degree of financial market stress (see, for example, Blot, Creel, Hubert, Labondance, and Saraceno, 2015). This index aggregates information from 18 different time series that are pertinent in this context, such as interest rates and yield spreads.

3.2. Methodology

This section outlines the model setup and assumptions of an econometric methodology for testing the predictability of sovereign credit risk, designed to be robust against ambiguity regarding the stochastic properties of the potential predictor variables. This robustness is crucial in this context because the primary predictor of interest, the oil price, is known to be integrated of order one or even (mildly) explosive, meaning it could be integrated of order infinity (see Figuerola-Ferretti, McCrorie, and Paraskevopoulos, 2020, Kruse and Wegener, 2020).

Kostakis, Magdalinos, and Stamatogiannis (2015) consider a multivariate system where the k-dimensional vector of lagged variables, denoted by $x_t = (x_{1,t}, \ldots, x_{k,t})^\top$, exhibit arbitrary degrees of persistence. In this context, this encompasses the price of oil, the corresponding exchange rate, and the St. Louis Fed Financial Stress Index (FS). The linear predictive regression model reads as

$$y_t^{(h)} = \mu + x_{t-h}^\top \beta_h + \varepsilon_t \qquad \text{with} \qquad x_t = \Pi_x x_{t-1} + u_t \qquad \text{for} \qquad t = 1, 2, \ldots, T. \tag{1}$$

Here, $A^\top$ denotes the transpose of the vector or matrix A, β_h is a vector of the associated slope coefficients, u_t follows a stationary linear process, and ε_t is a martingale difference sequence. Note that u_t and ε_t can be correlated. Furthermore, the dependent variable is formulated as the log change on sovereign CDS spreads throughout h (the forecast horizon), i.e.,

$$y_t^{(h)} \equiv \log(CDS_t) - \log(CDS_{t-h}), \tag{2}$$

where $\log(\cdot)$ denotes the natural logarithm. Please note that the definition in Equation (2) is consistent with the literature, as predictive regressions are primarily employed to forecast returns. Furthermore, the autoregressive coefficient matrix Π_x can be decomposed as

$$\Pi_x = I_k + C_k \cdot T^{-\eta_x}, \tag{3}$$

where I_k is the identity matrix, $C_k = \operatorname{diag}(c_1, \ldots, c_k)$ and $0 \leq \eta_x \leq 1$. The specification in Equation (3) encompasses the following scenarios:

1. Stationary regressors, i.e., $c_j < 0$ for $j = 1, \ldots, k$ and $\eta_x = 0$,

2. near-stationary/mildly explosive regressors, i.e., $c_j < 0$ (stationary case) or $c_j > 0$ (explosive case) for $j = 1, \ldots, k$ and $0 < \eta_x < 1$,

3. local-to-unity regressors, i.e., $c_j < 0$ (stationary case) or $c_j > 0$ (explosive case) for $j = 1, \ldots, k$ and $\eta_x = 1$,

4. integrated regressors, i.e., $c_j = 0$ for $j = 1, \ldots, k$.

The approach by Kostakis, Magdalinos, and Stamatogiannis (2015) involves creating near-stationary instruments z_t by differencing the regressors x_t and generating a new process based on an artificially constructed autoregressive coefficient matrix with a defined degree of persistence (which we assess using the BSQT methodology and KPSS test discussed in Section 3.1).

Specifically, we predict the CDS spread dynamics using oil prices, the exchange rate, and the FS. The IVX estimator of the slope coefficient is given by

$$\widehat{\beta}_{j,h}^{IVX} = \frac{\sum_{t=1}^{T} z_{j,t}\tilde{y}_t^{(h)}}{\sum_{t=1}^{T} z_{j,t}\tilde{x}_{j,t}} \qquad \text{with} \qquad j = 1, \ldots, k, \tag{4}$$

where $z_{j,t}$ represents the instrument with a specified degree of persistence with respect to regressor $x_{j,t}$, $\tilde{y}_t^{(h)} \equiv y_t^{(h)} - T^{-1}\sum_{t=1}^{T} y_t^{(h)}$ and $\tilde{x}_{j,t} \equiv x_{j,t} - T^{-1}\sum_{t=1}^{T} x_{j,t}$ for $j = 1, \ldots, k$. Note that since we use demeaned data, our methodology does not provide an estimate for the intercept. Kostakis, Magdalinos, and Stamatogiannis (2015) obtain a mixed Gaussian limiting distribution for the estimated slope coefficient in Equation (4) – a result that holds regardless of the persistence level of the regressors in the model. Consequently, this result enables the formulation of a Wald-type statistic, denoted as W_β, which converges to a standard χ^2 distribution.

Yang, Long, Peng, and Cai (2020) build upon this result by introducing a novel variant known as the IVX-AR statistic. This enhanced approach accounts for both serial correlation and heteroskedasticity in the error terms of linear predictive regression models. Simulation results indicate that the IVX-AR statistic exhibits excellent size control, regardless of the degree of serial correlation in the error terms and the persistence of the predictor variables.[1]

4. Empirical Results

In this section, we present the empirical findings. The results of the predictive regressions for each specific country are detailed in Tables 3 to 11. The number of additional lags included in the predictive regressions is determined based on the Bayesian Information Criterion (BIC). Furthermore, we consider a forecast horizon ranging from $h = 1$ (one week) to $h = 8$ periods (eight weeks).

Insert Table 3 to Table 11 here.

[1] We employ the `ivx` R-package (see Vasilopoulos and Pavlidis, 2020) for estimating the predictive regressions and drawing inference.

Looking across all countries, we obtain the following results. Analyzing the empirical coefficients of determination for the period spanning from 2010:25 to 2024:17, we observe limited in-sample predictability across all countries. Notably, the full sample concludes at 2022:18 for Venezuela and 2022:38 for Russia, respectively. Specifically, for a horizon of $h = 1$, the minimum R^2 value is 0.38%, observed in the case of Saudi Arabia, while the maximum R^2 value is 6.25%, recorded for Russia. For the longer horizon of $h = 8$, the minimum R^2 value is 1.41% for Malaysia, and the maximum is 28.05% for Russia. These values and results for horizons ranging from two to seven suggest overall limited predictability throughout the entire sample period across various horizons. Furthermore, the coefficient for WTI oil is insignificant in most instances, which contrasts with the findings of other methodological approaches prevalent in the majority of the literature.

A notably different picture emerges when the period is divided into two distinct sub-samples, from 2010:25 to 2016:8 and from 2016:9 to 2024:17. Notably, the first sub-sample ends at 2016:8 for all countries. In contrast, the second sub-sample concludes at 2022:18 for Venezuela and 2022:38 for Russia. Within these shorter intervals, the R^2 values increase significantly. This increase suggests that the models demonstrate much stronger in-sample predictability when applied to these specific time frames. Additionally, the coefficients for WTI oil are significantly negative during the first sub-sample for most countries and predictive horizons.

There are two reasons why we divide the sample into two specific sub-samples: before 2016:8 and after 2016:9. First, the periods were deliberately chosen to closely align with the data analyzed by Wegener, Basse, Kunze, and von Mettenheim (2016). Furthermore, the year 2016, which was selected to separate two periods, features different natures of both oil price dynamics and geopolitical situations. While the earlier period witnessed stable oil prices at the beginning and their large drops afterwards (especially in 2014–2016), the oil price dynamics in the later period experienced multiple up-and-down episodes with extreme movements. Regarding geopolitics, the major political disruptions during the first period are mostly regional—the Arab Spring and the conflicts and wars in North Africa and the Middle East—which fade out quickly after the outbreak. In contrast, the later period is characterized by more inter-regional and global relevance and/or long-lasting impacts with the involvement of various parties across multiple fronts and at higher complexity than the previous period, such as terrorist attacks in France, the US embassy in Iraq, or the ongoing Russo-Ukrainian War. Furthermore, together with military or terrorist events, many non-military events that are highly related to geopolitical tensions, such as the China-US trade war or the Corona crisis, have occurred during this period and continue their intertwined impacts. The geopolitical risk index by Caldara and Iacoviello (2022), which separates geopolitical threats (speculative nature) and geopolitical acts (realization or escalation of adverse geopolitical events), proves this difference. The 2010–2016 period shows a similar level of geopolitical threats and realization/escalation, while the 2016–2024 period shows geopolitical threats almost 50% higher than realization/escalation. Notably, previous work on war/conflict-associated geopolitical risk also found evidence of a structural break in geopolitical risk in 2016 (see, for example, Nasir and Spencer, 2025). Because of these distinct features between the two periods, we expect the reaction of CDS spreads to oil price movements in these periods to be very different. Finally, to empirically test the validity of our sample split in 2016, we implemented a Chow test for structural breaks in the data. The Chow test examines whether the coefficients of a regression model are statistically different before and after a specified break date. The null hypothesis assumes that there is no structural break, meaning the same regression model applies to both subsamples. A rejection of the null indicates the presence of a significant break, suggesting a regime shift in the relationship between the variables. We include the p-values of the test for each predictive regression in our result Tables 3-11. Significant structural breaks were detected, as indicated by p-values below the 5% level in multiple time horizons (Tables 5, 6, and 11). These findings further support the validity of our selected sample split.

With respect to the first sub-sample, the findings in this paper generally support the results of Wegener, Basse, Kunze, and von Mettenheim (2016) and other studies analyzing CDS spread dynamics and oil prices up to 2016. Consequently, we interpret these results to suggest that higher oil prices significantly improved the public finances of major oil-exporting countries during the first sub-sample.

With respect to the second sub-sample, we observe a notable shift in the coefficient sign from negative to positive for countries with significant oil prices in both sub-sample periods. This change suggests a different dynamic in the relationship between oil prices and rates of CDS spread changes across the two periods. Specifically, during the latter period, which is characterized by various crises, an increase in oil prices appears to signal rising geopolitical risk, leading to an increase in CDS spreads. Conversely, a decrease in oil prices during this period signals a reduction in geopolitical risk, leading to a decrease in CDS spreads. This shift indicates that, in the second period, oil prices serve as a risk indicator, with movements in oil prices being interpreted as a measure of geopolitical stability or instability.

4.1. Predictability Across Horizons and Country-Specific Patterns

The empirical results highlight notable variations in the predictability of sovereign CDS spreads across different forecast horizons and reveal distinct country-specific patterns (see Online Appendix 1). The full-sample analysis demonstrates limited overall predictability when considering the entire period from 2010 to 2024. However, when the analysis is conducted within sub-samples, the results indicate significantly improved forecastability, suggesting that the predictability of CDS spreads is time-dependent and influenced by evolving macroeconomic and geopolitical conditions.

The distinction between the two sub-samples, spanning 2010-2016 and 2016-2024, reveals meaningful shifts in the role of oil prices as a predictor of sovereign CDS spreads. In the earlier period, oil prices generally exhibit a negative predictive relationship with CDS spreads, implying that rising oil prices were associated with improving fiscal conditions and declining credit risk in oil-producing nations. This pattern is consistent across several countries, reinforcing the conventional expectation that higher oil revenues strengthen sovereign creditworthiness. However, in the latter period, the predictive coefficient of oil prices changes sign in numerous cases, reflecting an evolving risk environment. The results suggest that, in more recent years, rising oil prices have increasingly been interpreted as a signal of escalating geopolitical risk, contributing to widening CDS spreads rather than reducing them. This shift underscores the dynamic nature of the oil price-credit risk nexus and highlights the importance of considering structural breaks and geopolitical developments when assessing predictability.

In terms of forecast horizons, the results suggest that predictability tends to strengthen at medium-to-long horizons in certain cases, whereas short-term forecastability is generally weaker. For the full sample, the R-squared values remain low across all horizons, indicating weak in-sample predictability. However, within sub-samples, particularly in the 2010-2016 period, the explanatory power of oil prices and control variables becomes more pronounced at longer horizons. This pattern suggests that the impact of oil price fluctuations on sovereign credit risk materialises with some delay, reflecting the gradual transmission of fiscal and economic effects. The increased predictability at longer horizons aligns with the notion that government budgets and sovereign risk perceptions adjust over time in response to sustained oil price trends rather than reacting immediately to short-term fluctuations. In contrast, for certain countries in the 2016-2024 period, significant predictability is observed even at shorter horizons, particularly where geopolitical factors play a dominant role in driving market sentiment. This divergence between periods indicates that different drivers of sovereign CDS spreads may exert influence over distinct timescales, necessitating a nuanced approach to forecasting methodologies.

Country-specific patterns further illustrate the heterogeneity of the oil price-sovereign risk relationship. Russia, for instance, exhibits notably high predictability across various horizons, particularly in the latter sub-sample. This finding reflects Russia's heavy dependence on oil revenues and its exposure to geopolitical tensions, which have intensified in recent years. The results for Russia show a clear transition from a negative to a positive predictive coefficient on oil prices, reinforcing the argument that rising oil prices are now perceived as a risk amplifier rather than a stabilising factor. This shift is largely attributable to sanctions, financial market restrictions, and broader geopolitical instability, which have altered the traditional fiscal implications of oil price movements for Russia's sovereign creditworthiness.

Similarly, Venezuela presents strong predictability in both sub-samples, though the drivers of this relationship differ across periods. During the earlier years, higher oil prices corresponded to lower CDS spreads, consistent with Venezuela's economic reliance on oil exports. However, in the latter period, predictability weakens at shorter horizons, likely due to severe economic distress, hyperinflation, and international sanctions, which introduce additional volatility into sovereign risk assessments. The changing relationship between oil prices and CDS spreads in Venezuela suggests that broader macroeconomic instability can disrupt the predictability of sovereign credit risk, highlighting the limitations of oil prices as a standalone predictor in extreme cases.

In contrast, oil-producing nations with more diversified economies, such as Norway and the United Kingdom, exhibit lower predictability throughout the sample period. For these countries, oil prices do not emerge as consistently significant predictors, and the observed effects vary across sub-samples and forecast horizons. This finding aligns with the expectation that diversified economies are less vulnerable to direct fiscal shocks stemming from oil price fluctuations, thereby reducing the influence of oil prices on sovereign CDS spreads. Norway, in particular, demonstrates limited predictability at shorter horizons, suggesting that the country's strong fiscal buffers and sovereign wealth fund mitigate the impact of oil market volatility on its credit risk profile.

For Middle Eastern producers such as Qatar and Saudi Arabia, predictability varies between periods and across horizons. In the earlier sub-sample, oil prices exhibit moderate predictive power, but the significance of this relationship diminishes in the later period. This reduction in predictability may be attributed to shifts in fiscal policies, the introduction of economic diversification initiatives, and broader structural changes within these economies. However, at longer horizons, some degree of predictability remains, indicating that oil prices continue to play a role in shaping sovereign credit risk perceptions over extended periods, albeit with diminishing immediacy.

The findings also reveal instances where control variables, particularly exchange rates and financial stress indices, contribute to improved predictability. The inclusion of these variables enhances the explanatory power of predictive regressions in certain cases, underscoring the interconnectedness of oil prices, financial markets, and sovereign risk. The foreign exchange rate, for example, appears to be a particularly relevant predictor for countries where oil exports represent a substantial share of GDP, as currency fluctuations can amplify the fiscal effects of oil price changes. Similarly, the financial stress index exhibits stronger predictive significance in the later sub-sample, suggesting that global financial conditions increasingly mediate the relationship between oil prices and sovereign risk.

Overall, the results highlight the complexity of sovereign CDS spread predictability and the necessity of considering both temporal and cross-sectional dimensions. The findings demonstrate that the predictability of sovereign credit risk varies considerably depending on the time period, forecast horizon, and country-specific characteristics. The transition from a stabilising to a risk-amplifying role for oil prices in certain economies underscores the evolving nature of global energy markets and geopolitical dynamics. These insights contribute to a more nuanced understanding of how oil price fluctuations interact with sovereign risk and underscore the need for flexible forecasting models that account for shifting economic and political contexts.

5. Conclusion

In summary, the full sample analysis highlights the limited predictability of CDS spreads using the chosen predictors. However, the subsample analysis reveals periods of significantly improved predictability, particularly in the first subsample, where higher oil prices positively influenced the public finances of oil-exporting countries. The shift in the significance and sign of oil price coefficients between the subsamples underscores the evolving relationship between oil prices and CDS spreads, especially during times of geopolitical instability.

This finding aligns with our initial expectations when dividing the full sample into sub-samples. The shift in impact sign is crucial as it indicates a significant change in the role of oil prices in affecting sovereign risk, a topic that has received limited attention in the literature. This change reflects the evolving nature of geopolitical risks over the two periods, transitioning from regional and local levels with short-term impacts to multi-regional and global outreach with enduring influences. This underscores the close link between geopolitical situations and oil prices, suggesting that both factors may exert significant and time-dependent impacts on CDS spreads.

However, the mechanisms and extent of this linkage are not fully understood and warrant further investigation. Additionally, the changing role of oil prices on sovereign risk provides new perspectives on understanding this relationship over time. While the literature often states a monotonous link between the two variables, our findings suggest a more complex, time-varying nature. Future research should focus on exploring this dynamic relationship, which is crucial for policymaking and investment decisions given the constantly changing and complex global geopolitical landscape.

To be more specific: Firstly, it would be intriguing to combine predictive and quantile regressions to re-examine the relationship between CDS spread dynamics and oil prices, as the relevant literature on the sovereign credit risk of oil-producing countries frequently employs quantile regressions (see Lee (2016) and Cai, Chen, and Liao (2023) for examples of predictive quantile regressions). Additionally, given the regime-dependent behavior indicated by our results, utilizing a methodology that explicitly accounts for the shift from negative to positive coefficient signs could be highly beneficial. For this, Beckmann, Kerkemeier, and Kruse-Becher (2023) provides a relevant approach.

Moreover, the empirical evidence reported above also seems to have practical implications for investors working in the asset management industry. Most importantly, the existence of a strong relationship between oil prices and the credit risk of oil-producing countries ought to be taken into account by market participants in the strategy asset allocation process. It may, for example, be possible to use oil-related financial instruments to hedge the exposure to sovereign debt of these issuers. Generally speaking, investors should at least be aware of the fact that the fiscal stability of nations which produce oil under certain conditions can profit from positive price shocks to the global oil market. On the other hand, Breunig and Chia (2015), for example, have stressed that with regard to such countries, there is also a risk that significantly falling oil prices could cause sharper sovereign rating downgrades than the deterioration in the economic fundamentals of these nations would in principle suggest. Investors clearly are in need of sophisticated risk management strategies to cope with these issues. The possibility of the existence of structural change in the relationship between oil prices and the CDS spreads clearly does not help to make such efforts easier for financial risk managers.

Tables

Table 1 Summary of the start/end dates and sample sizes for the full sample and subsamples.

Country Code	BR	UK	MY	NO	QA	RU	SA	US	VE
Full sample (T)	721	721	721	721	721	638	721	721	618
Start	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25
End	2024:17	2024:17	2024:17	2024:17	2024:17	2022:38	2024:17	2024:17	2022:18
Subsample 1 (T_1)	296	296	296	296	296	296	296	296	296
Start	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25	2010:25
End	2016:8	2016:8	2016:8	2016:8	2016:8	2016:8	2016:8	2016:8	2016:8
Subsample 2 (T_2)	425	425	425	425	425	342	425	425	322
Start	2016:9	2016:9	2016:9	2016:9	2016:9	2016:9	2016:9	2016:9	2016:9
End	2024:17	2024:17	2024:17	2024:17	2024:17	2022:38	2024:17	2024:17	2022:18

The table summarizes the sample sizes and start and end dates. Country codes are as follows: **BR** for Brazil, **UK** for the United Kingdom, **MY** for Malaysia, **NO** for Norway, **QA** for Qatar, **RU** for Russia, **SA** for Saudi Arabia, **US** for the United States of America, and **VE** for Venezuela.

Table 2 Degree of integration of the CDS spreads.

Country Code	BR	UK	MY	NO	QA	RU	SA	US	VE
Degree of Integration (d)	1	1	1	1	1	1	1	1	1
KPSS $p-$values	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01

The table presents the results from the algorithm developed by Smeekes (2015) based on the Bootstrap Sequential Quantile Test to estimate the degree of persistence in a time series. This analysis was carried out using the R-package created by Smeekes and Wilms (2023). Further, we back up the results by the KPSS test using the R-package `fUnitRoots`.

Table 3 The tables outline the empirical results for Brazil CDS spreads (BR).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.000	0.000	0.000	0.001	0.001	0.001
FS	0.007	0.016	0.026	0.044*	0.039	0.061*	0.096*	0.122**
FXBR	-0.000	-0.001	-0.001	-0.001	-0.001	-0.002	-0.003	0.002
Joint Wald	0.783	0.415	0.556	0.177	0.361	0.254	0.144	0.039*
R^2	0.293%	0.807%	1.313%	2.682%	2.073%	3.457%	6.122%	9.726%
Lags	1	5	4	5	5	5	2	5
Chow	0.375	0.026*	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Subsample 1								
WTI	-0.001	-0.001*	-0.002*	-0.002*	-0.002*	-0.003*	-0.004*	-0.005*
FS	-0.003	-0.006	-0.001	-0.006	-0.011	-0.021	-0.016	-0.013
FXBR	-0.007	-0.014	-0.022	-0.029	-0.020	-0.038	-0.053	-0.056
Joint Wald	0.141	0.138	0.177	0.119	0.017*	0.107	0.129	0.106
R^2	1.959%	3.807%	5.016%	7.849%	12.940%	11.150%	11.740%	14.480%
Lags	5	5	4	5	5	5	5	5
Subsample 2								
WTI	0.000	0.001	0.001	0.002	0.001	0.002	0.003	0.005*
FS	0.010	0.016	0.023	0.057*	0.050	0.088*	0.128**	0.190**
FXBR	-0.001	-0.008	-0.008	-0.007	0.002	-0.007	-0.008	-0.019
R^2	0.795%	1.028%	1.518%	5.626%	4.617%	8.569%	14.730%	22.750%
Lags	4	5	4	5	5	4	4	1

WTI, FS, and FXBR (exchange rate between Brazilian Real and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 4 The tables outline the empirical results for the United Kingdom CDS spreads (UK).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.001	0.001	0.001	0.001	0.001	0.001
FS	0.015*	0.030*	0.052**	0.069**	0.085**	0.087**	0.104**	0.116**
FXUK	-0.023	-0.039	-0.067	-0.067	-0.112	-0.139	-0.183	-0.184
Joint Wald	0.045*	0.050*	0.044*	0.019*	0.003**	0.030*	0.034*	0.055
R^2	1.194%	2.108%	4.111%	5.305%	8.846%	6.954%	8.216%	8.405%
Lags	2	5	4	5	5	5	5	5
Chow	0.091	0.002*	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Subsample 1								
WTI	-0.000	-0.001	-0.001	-0.002	-0.002	-0.002	-0.002	-0.002
FS	0.019	0.046*	0.064	0.086*	0.086*	0.085	0.073	0.097
FXUK	0.053	0.062	0.079	0.228	0.204	0.073	-0.052	0.457
Joint Wald	0.061*	0.028*	0.131	0.048*	0.021*	0.127	0.273	0.176
R^2	2.557%	5.973%	7.745%	8.539%	11.860%	11.210%	9.528%	9.793%
Lags	5	5	4	5	3	4	4	3
Subsample 2								
WTI	0.001**	0.001*	0.002**	0.003**	0.003***	0.004**	0.004**	0.005**
FS	0.018**	0.032*	0.055**	0.076**	0.098***	0.095**	0.102*	0.131**
FXUK	0.001	-0.035	-0.019	-0.114	-0.098	-0.208	-0.356	-0.322
R^2	3.006%	4.122%	7.897%	12.65%	20.57%	17.38%	19.04%	22.96%
Lags	1	5	4	5	5	5	5	5

WTI, FS, and FXUK (exchange rate between Pound Sterling and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 5 **The tables outline the empirical results for Malaysia CDS spreads (MY).**

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
FS	0.004	0.006	0.013	0.013	0.027	0.027	0.027	0.031
FXMY	-0.003	-0.006	-0.009	-0.015	-0.015	-0.020	-0.024	-0.030
Joint Wald	0.721	0.714	0.727	0.678	0.325	0.520	0.570	0.699
R^2	0.263%	0.431%	0.729%	0.858%	1.908%	1.651%	1.633%	1.407%
Lags	5	5	4	5	5	5	5	2
Chow	0.507	0.014*	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Subsample 1								
WTI	-0.001	-0.001	-0.002	-0.002	-0.002	-0.003	-0.003	-0.005
FS	0.004	0.010	0.018	0.013	0.017	0.062	0.029	0.054
FXMY	-0.018	-0.039	-0.058	-0.085	-0.082	-0.087	-0.105	-0.199
Joint Wald	0.377	0.389	0.445	0.354	0.199	0.308	0.416	0.392
R^2	1.177%	2.183%	2.719%	4.571%	6.234%	7.375%	6.532%	8.630%
Lags	5	5	5	5	5	4	5	2
Subsample 2								
WTI	0.001*	0.001*	0.002**	0.003**	0.003***	0.004**	0.005**	0.006*
FS	0.004*	0.001	0.023*	0.027*	0.063**	0.072**	0.083*	0.066*
FXMY	-0.044*	-0.099	-0.138	-0.191	-0.212**	-0.276*	-0.319**	-0.427*
R^2	1.609%	2.826%	5.793%	6.256%	12.61%	13.04%	12.60%	9.152%
Lags	4	5	5	5	5	5	4	1

WTI, FS, and FXMY (exchange rate between Malaysian Ringgit and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 6 The tables outline the empirical results for Norway CDS spreads (NO).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	-0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000
FS	0.010	0.021*	0.033	0.046*	0.042*	0.064*	0.079*	0.126*
FXNO	-0.001	-0.001	0.001	0.001	0.002	0.002	0.004	0.009
Joint Wald	0.209	0.206	0.230	0.141	0.204	0.199	0.179	0.090*
R^2	0.668%	1.309%	2.088%	3.175%	3.187%	4.178%	5.095%	8.977%
Lags	4	5	4	5	5	5	5	2
Chow	0.616	0.382	0.199	0.048**	0.007***	0.003***	0.001***	0.000***
Subsample 1								
WTI	-0.001	-0.002*	-0.003	-0.004	-0.005*	-0.005	-0.006	-0.005
FS	0.008	0.014	0.028	0.060	0.031	0.049	0.039	0.057
FXNO	-0.016	-0.038	-0.049	-0.067	-0.097*	-0.081	-0.099	-0.083
Joint Wald	0.088*	0.108	0.155	0.101	0.065*	0.286	0.334	0.565
R^2	2.513%	4.363%	5.329%	8.618%	11.180%	7.482%	7.403%	5.332%
Lags	1	5	5	5	5	4	4	2
Subsample 2								
WTI	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.002
FS	0.014*	0.028*	0.041*	0.055*	0.056*	0.081*	0.094*	0.140*
FXNO	-0.004	-0.005	-0.005	-0.005	-0.003	-0.007	-0.006	-0.000
Joint Wald	0.317	0.242	0.239	0.150	0.111	0.150	0.135	0.122
R^2	0.838%	2.062%	3.114%	5.294%	7.343%	8.540%	10.120%	14.150%
Lags	4	5	4	5	5	5	5	2

WTI, FS, and FXNO (exchange rate between Norwegian Krone and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 7 The tables outline the empirical results for Qatar CDS spreads (QA).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.001
FS	0.008	0.014	0.023	0.040*	0.045**	0.054*	0.065*	0.082**
FXQA	-0.003	-0.005	-0.009	-0.008	-0.018	-0.014	-0.005	-0.008
Joint Wald	0.705	0.612	0.557	0.333	0.259	0.357	0.342	0.232
R^2	0.280%	0.484%	0.834%	1.804%	2.504%	2.555%	3.036%	4.362%
Lags	1	5	5	5	5	5	5	5
Chow	0.402	0.014*	0.000*	0.000*	0.000*	0.000*	0.000*	0.000*
Subsample 1								
WTI	-0.000	-0.001	-0.001	-0.002	-0.002	-0.003	-0.002	-0.002
FS	0.013	0.024	0.056*	0.059	0.072**	0.113	0.064	0.102
FXQA	0.034	0.089	0.120	0.140	0.223	0.373	0.143	0.053
Joint Wald	0.083*	0.077*	0.062*	0.077*	0.009**	0.178	0.283	0.142
R^2	2.522%	4.692%	9.738%	9.458%	16.990%	22.230%	10.300%	14.870%
Lags	2	5	4	5	5	1	2	2
Subsample 2								
WTI	0.000	0.001	0.001	0.001	0.001	0.002	0.003	0.004
FS	0.009	0.017	0.028	0.046	0.052	0.077	0.110*	0.184*
FXQA	0.092	0.164	0.247	0.332	0.300	0.462	0.688	1.022
Joint Wald	0.629	0.615	0.536	0.468	0.458	0.356	0.236	0.120
R^2	0.483%	0.484%	1.441%	2.189%	2.742%	4.532%	7.139%	14.760%
Lags	1	5	5	5	5	5	4	1

WTI, FS, and FXUS (exchange rate between Euro and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 8 The tables outline the empirical results for Russia CDS spreads (RU).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.001***	0.004***	0.006***	0.011***	0.009***	0.014***	0.019***	0.016***
FS	0.007	0.015	-0.038	0.053	0.020	0.096	0.212*	0.052
FXRU	0.003***	0.006***	0.009***	0.017***	0.012***	0.021***	0.030***	0.029***
Joint Wald	44.810***	42.140***	40.300***	45.040***	37.850***	41.530***	57.360***	50.380***
R^2	7.632%	14.360%	18.140%	28.720%	26.180%	33.040%	43.630%	36.820%
Lags	5	5	4	5	5	5	5	4
Chow	0.001***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Subsample 1								
WTI	-0.000	-0.001	-0.001	-0.003	-0.001	-0.001	-0.008	-0.004
FS	0.000	-0.007	0.018	0.002	-0.007	-0.016	0.183	-0.024
FXRU	-0.001	-0.002	-0.002	-0.004	-0.002	-0.002	-0.014	-0.006
Joint Wald	0.348	0.493	0.547	0.708	0.215	0.142	0.634	0.494
R^2	0.204%	0.556%	0.996%	1.346%	0.404%	0.337%	14.940%	1.410%
Lags	0	5	4	5	5	5	1	3
Subsample 2								
WTI	0.002***	0.004***	0.005***	0.008***	0.009***	0.014***	0.016***	0.020***
FS	-0.000	-0.012	-0.002	-0.029	-0.149*	-0.128	-0.131	-0.060
FXRU	0.005***	0.012***	0.017***	0.029***	0.024***	0.037***	0.051***	0.069***
Joint Wald	40.600***	38.620***	44.300***	52.590***	31.130***	46.900***	64.710***	55.130***
R^2	11.280%	20.920%	30.280%	42.680%	34.070%	44.740%	52.100%	56.320%
Lags	5	5	4	5	5	5	5	4

WTI, FS, and FXRU (exchange rate between Russian Ruble and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 9 The tables outline the empirical results for Saudi Arabia CDS spreads (SA).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.000	0.000	0.000	0.000	0.001	0.001
FS	0.007	0.014	0.025	0.034	0.046	0.043	0.054	0.087
FXSA	-0.015	-0.036	-0.040	-0.101	-0.078	-0.050	-0.205	-0.154
Joint Wald	2.718	2.632	3.417	3.799	6.376	2.618	2.500	4.097
R^2	0.382%	0.704%	1.451%	1.901%	3.689%	2.251%	2.571%	5.395%
Lags	5	5	5	5	5	4	1	2
Chow	0.038**	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
Subsample 1								
WTI	-0.001	-0.002	-0.002	-0.003	-0.003	-0.005	-0.007	-0.004
FS	0.006	0.010	0.030	0.035	0.049	0.052	0.051	0.025
FXSA	0.061	0.153	0.263	0.260	0.294	0.559	0.686	-0.006
Joint Wald	7.912	6.833	8.902	9.939	10.160	5.660	8.081	4.491
R^2	2.689%	4.642%	9.144%	13.330%	15.550%	17.960%	19.540%	13.040%
Lags	5	5	5	5	4	1	4	1
Subsample 2								
WTI	0.000	0.001	0.001	0.002	0.002	0.002	0.003	0.004
FS	0.009	0.020	0.031	0.046	0.057	0.082	0.105	0.111
FXSA	0.053	0.087	0.108	0.158	0.143	0.275	0.285	0.315
Joint Wald	2.996	4.077	4.697	5.771	7.951	7.465	5.663	5.732
R^2	0.831%	1.876%	2.993%	4.369%	7.060%	9.283%	9.859%	10.540%
Lags	4	5	5	5	5	4	2	2

WTI, FS, and FXUS (exchange rate between Euro and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 10 The tables outline the empirical results for the USA CDS spreads (US).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.000	0.000	0.001	0.001	0.001	0.001	0.002	0.002
FS	-0.001	-0.004	-0.006	-0.002	0.015	-0.037	-0.053	-0.050
FXUS	-0.055	-0.117	-0.169*	-0.225*	-0.274	-0.406*	-0.492*	-0.521*
Joint Wald	3.584	3.617	3.835	4.850	6.752*	5.822	0.597	0.615
R^2	0.534%	1.083%	1.639%	2.817%	4.408%	4.441%	6.050%	6.378%
Lags	4	5	4	5	5	5	5	5
Chow	0.997	0.983	0.810	0.502	0.154	0.111	0.098*	0.035*
Subsample 1								
WTI	-0.000	-0.000	-0.000	-0.000	-0.001	0.001	0.001	0.001
FS	-0.001	-0.002	-0.006	-0.001	0.008	-0.024	-0.018	-0.035
FXUS	-0.003	-0.037	-0.022	-0.009	0.043	-0.413	-0.368	-0.410
Joint Wald	0.294	0.288	0.319	0.444	0.737	0.881	0.597	0.615
R^2	0.103%	0.197%	0.318%	0.623%	1.304%	1.689%	1.300%	1.664%
Lags	4	5	4	5	5	5	5	5
Subsample 2								
WTI	0.000	0.001	0.001	0.001	0.002	0.002	0.002	0.003
FS	-0.002	-0.005	-0.006	-0.000	0.018	-0.031	-0.052	-0.076
FXUS	-0.063	-0.124	-0.199	-0.236	-0.279	-0.424	-0.500	-0.559
Joint Wald	3.023	2.974	3.337	4.562	6.503*	4.271	5.066	4.970
R^2	0.782%	1.542%	2.382%	4.590%	7.442%	4.441%	8.648%	10.650%
Lags	4	5	4	5	5	5	5	5

WTI, FS, and FXUS (exchange rate between Euro and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

Table 11 The tables outline the empirical results for Venezuela CDS spreads (VE).

Horizon	1	2	3	4	5	6	7	8
Full Sample								
WTI	0.001	0.001	0.002*	0.003	0.003	0.003*	0.003	0.004*
FS	0.041	0.102***	0.128***	0.226***	0.190***	0.202***	0.229***	0.228***
FXVE	-0.101*	-0.068	-0.216	-0.227	-0.440	-0.339	-0.389	-0.585
Joint Wald	32.250***	41.220***	28.290***	48.870***	26.680***	20.740***	19.870***	16.480***
R^2	5.574%	11.630%	12.510%	22.150%	17.870%	17.540%	17.550%	15.670%
Lags	5	5	5	5	5	5	5	5
Chow	0.071*	0.018**	0.009***	0.006***	0.005***	0.004***	0.003***	0.002***
Subsample 1								
WTI	-0.000	-0.000	-0.001	-0.001	-0.001	-0.002	-0.003	-0.004
FS	-0.001	-0.002	-0.006	-0.001	0.008	-0.024	-0.018	-0.035
FXVE	-0.003	-0.037	-0.022	-0.009	0.043	-0.413	-0.368	-0.410
Joint Wald	0.294	0.288	0.319	0.444	0.737	0.881	0.597	0.615
R^2	0.103%	0.197%	0.318%	0.623%	1.304%	1.689%	1.300%	1.664%
Lags	0	5	5	5	5	5	1	1
Subsample 2								
WTI	0.001	0.003*	0.004*	0.006*	0.008*	0.008*	0.010*	0.010*
FS	0.059*	0.135***	0.187***	0.296***	0.349***	0.351***	0.403***	0.380***
FXVE	0.087	0.207	0.183	0.017	-0.335	0.468	0.571	-0.101
Joint Wald	23.830***	34.300***	26.380***	41.280***	28.500***	21.580***	20.460***	19.680***
R^2	6.990%	17.330%	19.550%	30.520%	31.700%	30.810%	31.100%	27.750%
Lags	1	5	5	5	3	5	5	5

WTI, FS, and FXUS (exchange rate between Euro and US Dollar) correspond to point estimates. Superscripts *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Joint Wald is the p-value of the Joint Wald statistic. R^2 denotes the coefficient of determination in percentages. Lags indicate the number of lags in the predictive regressions.

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6. Online Appendix

6.1. Summary Statistics

This Section further describes our dataset variables by presenting some of the key summary statistics.

The summary statistics displayed in Table 12 provide insights into the key variables used in this study, highlighting the variability in oil prices, financial stress and sovereign CDS spreads. Brent and WTI crude oil prices show substantial volatility, with mean values of \$78.19 and \$71.76 per barrel, respectively, and extreme lows reflecting major market disruptions such as the Covid-19 shock. The financial stress index (FS) has a mean of -0.22, suggesting generally low financial stress, though peaks reaching 5.43 indicate periods of severe market distress.

Sovereign CDS spreads vary widely across countries, reinforcing the paper's argument that oil price movements impact sovereign risk differently depending on fiscal stability and geopolitical exposure. Low-risk economies like Norway, the US, and the UK maintain relatively stable spreads (showing an average CDS spread of 16.54, 23.74, and 32.64, respectively), while oil-dependent and politically volatile countries, such as Russia (455.30), Brazil (197.82), and Venezuela (1685.10), exhibit much higher average CDS spreads. The extreme maximum values for Russia (17,796) and Venezuela (10,000) further emphasize periods of sovereign distress due to geopolitical tensions and economic crises (as emphasized in Section 4).

These statistics underscore the core premise of this paper - that oil price fluctuations interact with sovereign credit risk in a time-varying and country-specific manner. The results justify the use of predictive regressions to assess how this relationship evolves under different economic and geopolitical conditions.

Statistic	BRENT	WTI	FS	MY CDS	BR CDS	SA CDS	QA CDS	NO CDS	RU CDS	US CDS	VE CDS	GB CDS
Obs	721.00	721.00	721.00	721.00	721.00	721.00	721.00	721.00	638.00	721.00	618.00	721.00
Mean	78.19	71.76	-0.22	90.41	197.82	85.49	73.78	16.54	455.30	23.74	1685.10	32.64
Median	76.00	71.81	-0.34	83.38	179.14	75.00	69.67	14.33	162.38	19.50	1490.50	27.83
SD	25.80	22.23	0.57	38.41	77.72	32.54	26.46	7.24	1455.65	12.09	1106.79	18.81
Min	15.87	15.48	-0.93	33.39	92.60	43.33	33.73	3.85	53.54	5.50	451.00	9.67
Max	128.08	120.73	5.43	234.50	502.00	203.35	150.00	55.17	17796.11	65.00	10000.00	103.50

Table 12 Summary Statistics