ALMA MATER STUDIORUM, UNIVERSITÀ DI BOLOGNA

Statistical Sciences Department
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Financial Risk Management

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Team Work Assignment
Predictive Modeling of CDS Spreads

Group 11

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1 Introduction

Credit Default Swaps (CDS) spreads reflect the cost of insuring against a borrower's default and serve as a key indicator of credit risk in financial markets. These spreads fluctuate based on market perceptions of a country's solvency and macroeconomic conditions, making them a valuable tool for assessing sovereign creditworthiness. The aim of this paper is to analyze how some specific events have affected CDS spreads of some European countries, namely United Kingdom, France, Spain, Italy, Germany, Greece, Turkey, analysing data from 2008 to 2025.
During these years, Europe has experienced several events that affected CDS spreads:

- Global Financial Crisis (2008-2009);
- European Sovereign Debt Crisis (2010-2012);
- Greek Political Crisis (2015);
- Brexit (2016);
- COVID-19 Pandemic (2020);
- Energy Crisis and Inflation (2022-2023);
- Geopolitical Tensions and Economic Uncertainties (2024-2025).

In section 3, a more specific analysis about United Kingdom is presented.

All the scripts utilized for the statistical analysis are attached in the following Github repository: `https://github.com/tommasozeri/Financial-Risk-Management`

Country and Data Selection

The selection of the above mentioned countries was guided by the differences in wealth among these countries, their geographical positioning, and the geopolitical distinctions between them. Additionally, the choice reflects the diverse economic and political events that have impacted these nations over the years. By including countries with varying levels of economic development, from the robust economies of Germany and France to the more volatile situations in Greece and Turkey, we aim to capture a comprehensive picture of the region's financial stability and risk perceptions. The inclusion of both core Eurozone members and non-Eurozone countries like the United Kingdom and Turkey allows for a comparative analysis of how different political and economic frameworks influence CDS spreads. This diverse sample helps in understanding the broader trends and specific shocks that have shaped the European financial landscape from 2008 to 2025.

2 Statistical analysis: an overview

2.1 Time series comparison and Heatmap

To compare the selected countries — United Kingdom, France, Spain, Germany, Greece, Turkey and Italy — we will analyze common statistical data, including historical time series and the correlation matrix, as well as rolling volatility. Time series will show trends and fluctuations in CDS spreads over time, highlighting periods of higher volatility. The correlation matrix will reveal how CDS spreads move together, indicating interconnected risks.
These tools, reported below, provide a clear understanding of credit risk differences and similarities across the countries.

[INSERT FIGURE 1 HERE]

Starting from this **comparison between normalized time series**, it is possible to infer that the CDS spread peaks for these countries reflect key economic events: Italy and Spain were deeply affected by the Eurozone debt crisis, with Spain requiring a € 100 billion banking bailout. France saw moderate increases tied to regional instability. Germany, while stable, faced minor peaks during global stress. Greece's sharp spikes resulted from its severe debt crisis and bailouts. Turkey experienced peaks due to domestic political and economic challenges. The United Kingdom witnessed increases during the 2008 financial crisis and the Brexit referendum, highlighting distinct vulnerabilities for each nation.

[INSERT FIGURE 2 HERE]

The **correlation matrix** of CDS spreads highlights strong positive correlations among Eurozone countries, particularly during periods of shared economic stress. Turkey shows weaker correlations, reflecting its unique economic conditions and lower integration with European markets. United Kingdom's correlations are moderate, influenced by its semi-independent financial context and distinct economic events like Brexit.

Another relevant statistic for CDS spreads is the **rolling volatility**. It measures the historical fluctuations in credit risk perception over different time horizons. For each analyzed country, it has been plotted over different time frames (20, 50 and 100 days).

[INSERT FIGURES 5, 6, 7, 8, 9, 10, 11 HERE]

The 20-day rolling volatility captures short-term fluctuations, making it highly sensitive to recent market shocks and sudden risk perception changes. It is particularly useful for detecting immediate stress periods or abrupt shifts in credit risk.

The 50-day rolling volatility provides a middle-ground measure, balancing responsiveness to short-term movements with a smoother trend over time. It helps in identifying transitional phases in credit risk assessment.

The 100-day rolling volatility reflects long-term stability or instability in CDS spreads. Since it is less sensitive to daily fluctuations and temporary shocks, it is a useful indicator for assessing structural credit risk trends over extended periods.

In practice, an increase in rolling volatility suggests rising uncertainty and heightened credit risk perception. Comparing different rolling windows helps distinguish between temporary market turbulence and longer-term shifts in risk. If short-term volatility (20-day) is significantly higher than long-term volatility (100-day), it may indicate temporary market stress or event-driven disruptions. Conversely, a sustained increase across all time horizons could signal growing systemic risk.

2.2 Time series statistics

In this paragraph, the time series and the most relevant key statistical indicators for each analyzed country are presented.

2.2.1 United Kingdom, France and Spain

[INSERT FIGURE 3 HERE]

Starting with the **United Kingdom**, the CDS spreads exhibit a standard deviation of 25.00, indicating moderate volatility. The skewness of 1.62 suggests a right-skewed distribution, meaning there are occasional high values. The kurtosis of 5.91 indicates a distribution with heavier tails and a sharper peak than a normal distribution, pointing to the presence of outliers. The mean value is 38.10, with a median of 29.20, showing that most data points are clustered around lower values. The maximum value of 165.00 and minimum of 9.41 highlight the range within which the spreads have fluctuated. United Kingdom's CDS spreads are influenced by factors such as economic policies, Brexit-related uncertainties, and global market conditions.

France's CDS spreads exhibit a standard deviation of 41.60, indicating moderate volatility. The skewness of 2.39 suggests a highly right-skewed distribution, with occasional significant high values. The kurtosis of 8.64 indicates a distribution with very heavy tails and a sharp peak, pointing to the presence of notable outliers. The mean value is 48.39, with a median of 32.47, indicating that most data points are around these values. The maximum value of 245.27 and minimum of 15.04 show the range of fluctuations, influenced by France's economic policies, public debt levels, and broader Eurozone stability.

Spain's CDS spreads show a standard deviation of 115.17, reflecting significantly higher volatility compared to the United Kingdom. The skewness of 1.92 indicates a highly right-skewed distribution, with occasional extreme high values. The kurtosis of 6.29 suggests a distribution with even heavier tails and a sharper peak, indicating the presence of significant outliers. The mean value is 121.75, with a median of 77.43, showing that while most data points are around moderate values, there are extreme peaks. The maximum value of 634.35 and minimum of 25.35 underscore the dramatic swings in Spain's CDS spreads, driven by factors such as banking sector stability, public debt, and regional economic disparities.

2.2.2 Germany, Greece, Turkey and Italy

[INSERT FIGURE 4 HERE]

Starting with **Germany**, its CDS spreads exhibit a standard deviation of 20.69, indicating low volatility. The skewness of 2.07 suggests a highly right-skewed distribution, with occasional significant high values. The kurtosis of 7.02 indicates a distribution with very heavy tails and a sharp peak, pointing to the presence of notable outliers. The mean value is 25.30, with a median of 17.32, indicating that most data points are around these values. The maximum value of 118.38 and minimum of 6.26 show the range of fluctuations, influenced by Germany's stable economic environment and strong fiscal policies.

As for **Turkey**, its CDS spreads exhibit a standard deviation of 147.43, indicating much higher volatility in comparison to Germany, but also to the United Kingdom and to France. The skewness of 1.29 suggests a right-skewed distribution, meaning there are occasional high values. The kurtosis of 4.42 indicates a distribution with heavier tails and a sharper peak than a normal distribution, pointing to the presence of outliers. The mean value is 305.41, with a median of 262.76, showing that most data points are clustered around these values. The maximum value of 906.00 and minimum of 109.82 highlight the range within which the spreads have fluctuated. Turkey's CDS spreads are influenced by factors such as political instability, currency fluctuations, and external debt pressures.

Italy's CDS spreads show a standard deviation of 98.27, reflecting moderate to high volatility. The skewness of 1.98 indicates a highly right-skewed distribution, with occasional extreme high values. The kurtosis of 7.15 suggests a distribution with very heavy tails and a sharp peak, indicating the presence of significant outliers. The mean value is 160.96, with a median of 132.76, showing that while most data points are around moderate values, there are extreme peaks. The maximum value of 586.70 and minimum of 43.91 underscore the dramatic swings in Italy's CDS spreads, driven by factors such as high public debt and political uncertainties.

In conclusion, we aim to analyze the situation of **Greece**, which needs a more in-depth analysis due to the distinct behavior of its CDS spreads, which differ significantly from those of other countries. In this regard, attention should be drawn to the very different scale on the vertical axis of Greece's graph. The CDS spreads of this country show a standard deviation of 80455.51, reflecting extremely high volatility. The skewness of 2.66 indicates a highly right-skewed distribution, with occasional extreme high values. The kurtosis of 9.11 suggests a distribution with very heavy tails and a sharp peak, indicating the presence of significant outliers. The mean value is 33966.80, with a median of 381.67, showing that while most data points are around lower values, there are extreme peaks. The maximum value of 370081.41 and minimum of 52.24 highlight the dramatic swings in Greece's CDS spreads, driven by the country's economic instability and debt crisis.

The anomalous results in Greece's CDS spreads, highlighted by an extremely high standard deviation of 80455.51 and a maximum value of 370081.41, can be attributed to several factors. Firstly, the sovereign debt crisis that hit Greece starting in 2010 caused extreme spikes in CDS spreads, reflecting the high risk perceived by investors. During this period, the country faced a severe economic recession, high levels of public debt, and the need for multiple bailout packages from the European Union and the International Monetary Fund.

Secondly, the lack of complete data and the need to interpolate some information may have contributed to anomalous results. Interpolation, a technique used to estimate missing values based on existing data, can sometimes introduce distortions, especially in contexts of extreme volatility like the one that characterizes Greece. This could explain the presence of significant outliers and the heavy-tailed distribution indicated by the high kurtosis of 9.11.

The extreme volatility and anomalous values in Greece's CDS spreads are primarily driven by the country's debt crisis and subsequent bailouts, as well as potential distortions from data interpolation. These factors together create a highly skewed and volatile distribution, reflecting the intense financial instability Greece experienced during the period we analyzed.
A synthetic graphic representation of the above discussed statistics is provided in the *boxplots*.

[INSERT FIGURE 12 HERE]

2.3 Linear regressions

For each country in the sample, a linear regression was conducted between the predictive CDS price and the observed CDS price. The purpose of this regression was to analyze the relationship between the predicted values derived from the model and the actual observed values of the CDS prices. This approach allows for the assessment of the accuracy of the model's predictions in comparison to the real market data, providing insights into the potential discrepancies and the overall effectiveness of the predictive model. The regression analysis serves as a key tool in evaluating the performance of the model for each individual country in the sample.
This regression model predicts the Credit Default Swap price based on the following variables: **Oil Price, EUR/GBP Exchange Rate, Gas Price, 10 Years Government Bond-BUND Spread, CISS, and VSTOXX Index**. The model includes spline transformations (using `bs()` for B-splines and `ns()` for natural splines) to capture non-linear relationships. B-splines are piecewise polynomial functions that provide flexibility in modeling complex, non-linear patterns, while natural splines are a type of B-splines that impose additional constraints at the boundaries, ensuring that the fitted curve is linear beyond the range of the data.

2.3.1 United Kingdom

[INSERT FIGURE 13 HERE]

For the United Kingdom, the decrease in oil prices tends to increase CDS prices, possibly indicating concerns about the financial health of the economy. Movements in the EUR/GBP exchange rate influence CDS prices, likely due to their impact on macroeconomic stability. The strong significance of the United Kingdom bond spread suggests that investors use it as a key benchmark for credit risk. As expected, higher systemic risk, captured by the CISS index, leads to higher CDS prices, reflecting increased default risk. However, contrary to typical patterns, higher market volatility is unexpectedly associated with lower CDS prices.

2.3.2 France

[INSERT FIGURE 14 HERE]

For France, oil prices consistently reduce CDS prices, likely because higher oil prices benefit France's diversified economy and foster economic growth. Gas prices increase CDS prices, suggesting that rising energy costs negatively impact credit stability. The bond spread is the strongest factor, with wider spreads significantly increasing France's credit risk. Systemic risk also influences CDS prices, though the effect is moderate. VSTOXX is not significant, indicating that France's CDS prices are less affected by global market risk compared to other countries.

2.3.3 Spain

[INSERT FIGURE 15 HERE]

For Spain, oil prices reduce credit risk, likely because Spain benefits from strong trade, tourism, and economic growth when oil prices rise. Gas prices have no strong impact, as Spain's credit risk is not significantly affected by gas prices. The bond spread has a strong impact, with higher spreads directly increasing CDS prices, indicating that Spain's creditworthiness is tied to investor sentiment in bond markets. Systemic risk is a key driver, as Spain's CDS prices rise significantly when systemic risk increases. VSTOXX is not significant, suggesting that global market volatility does not drive Spain's CDS prices, and domestic factors dominate.

2.3.4 Germany

[INSERT FIGURE 16 HERE]

For Germany, oil prices reduce credit risk, likely because Germany's industrial base benefits from stable oil prices. Gas prices increase credit risk, as energy dependency on imported gas makes Germany vulnerable to price shocks. Bond spread effects are mixed, with unexpected negative coefficients possibly reflecting financial stability measures or strong investor confidence in Germany's debt. Systemic risk has a strong impact, with higher levels of financial instability significantly raising CDS prices. VSTOXX has a negative effect, indicating that Germany's CDS prices do not rise with global volatility, possibly due to its safe-haven status.

2.3.5 Greece

[INSERT FIGURE 17 HERE]

For Greece, oil prices have a non-linear effect: moderate increases lower CDS prices, but very high levels can increase CDS risk. Gas prices have a weak impact, though higher gas prices generally increase risk. The bond spread is the dominant driver, with wider spreads sharply increasing Greece's credit risk. Systemic risk has a weak to moderate effect, contrasting with countries like Turkey, where systemic risk was more influential. VSTOXX is almost significant, suggesting that global market volatility does affect Greece's CDS prices.

2.3.6 Italy

[INSERT FIGURE 18 HERE]

For Italy, oil prices reduce credit risk, likely because Italy benefits from energy-driven economic activity and trade improvements when oil prices are high. Gas prices increase credit risk, as Italy's heavy reliance on gas imports makes it vulnerable to energy price shocks. The bond spread has a dominant impact, with widening spreads reflecting investor concerns about Italy's sovereign risk. Systemic risk shows unexpected negative effects, possibly indicating market interventions that stabilize Italy's credit risk despite rising systemic concerns. VSTOXX is not significant, suggesting that Italy's CDS prices are less influenced by global volatility, with domestic risk factors playing a larger role.

2.3.7 Turkey

[INSERT FIGURE 19 HERE]

Unlike other countries, Turkey's CDS prices are not highly sensitive to oil price changes. As for the gas price influence, there is a stronger but nonlinear relationship, where only large fluctuations in gas prices affect CDS levels. The difference between Turkey's bond yields and the benchmark is a major driver of credit risk perception. The systemic risk has the strongest impact, showing that financial stress and risk aversion are key determinants of CDS levels in Turkey.

3 United Kingdom analysis

In addition to the analysis of the CDS spreads of the seven countries conducted in the previous paragraph, we decided to further discuss the macroeconomic dynamics that have involved the United Kingdom (referred to as UK in the following) in a time frame from 2020 to 2024.

Our analysis was inspired by The United Kingdom mini-budget of September 23, 2022, introduced by Chancellor Kwasi Kwarteng under Prime Minister Liz Truss, aimed to boost economic growth through significant tax cuts and financial incentives. However, it triggered a severe market reaction, leading to a historic drop in the British pound, a surge in government bond yields, and intervention by the Bank of England to stabilize the financial system. The plan faced strong criticism from global institutions, including the IMF, and was largely reversed following Kwarteng's dismissal. The economic turmoil ultimately led to Liz Truss's resignation after just 44 days in office, making her the shortest-serving UK Prime Minister in history. The announcement of the UK mini-budget in September 2022 triggered significant stress in financial markets, as investors reacted negatively to the large-scale unfunded tax cuts and spending measures. The key market impacts were as follows:

Foreign Exchange Market: The British pound (*GBP*) experienced a sharp decline, reaching near parity with the US dollar. The *GBP/USD* exchange rate fell below 1.09 from 1.52, exacerbating inflationary pressures by increasing the cost of imports [1]

Bond Market: The UK government bond market (*gilts*) faced a massive sell-off. Yields on 10-year gilts felt to 94.2 from 104.8, reflecting investor concerns over fiscal sustainability [2].

Credit Default Swaps (CDS): The cost of insuring UK government debt against default, measured through Credit Default Swap (CDS) spreads, saw a dramatic increase to 50.16 from 27.45 b.p. The UK's CDS spread over Germany's and France's doubled, while it quintupled over the US, indicating increased perceptions of sovereign risk [1].

Stock Market: The FTSE 100 index declined, reflecting broader investor uncertainty. On the day of the announcement, the FTSE 100 dropped by 1%, and in a week experienced a loss of about 7% [3].

Consumer Confidence: Consumer confidence reached historic lows, with the GfK Consumer Confidence Index dropping to -49, the lowest since records began in 1974. Confidence in personal finances and economic expectations both plummeted due to the combined effect of inflation and rising interest rates [3].

3.1 Z-score

In this second part of our analysis we decided to use a metric such as the Z-Score in order to complete the previous analysis enriching it by building a predictive model starting from the Z-Scores calculated by all the variables that are available only on an annual basis, which could not have been inserted in the previous regressive models that are made on a daily basis, but which are fundamental for the accuracy and the completeness of the analysis.

The **Sovereign Z-Score** is a financial metric used to assess the credit risk of a country. It helps investors and analysts evaluate a nation's probability of default by analyzing economic and financial indicators. The score is derived from a combination of macroeconomic and market-based factors, providing a quantitative measure of sovereign risk. Mathematically, the Sovereign Z-Score is typically expressed as:

$$Z = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \cdots + \beta_n X_n$$

where:

- α = Intercept of the model, a constant representing the average Z-Score value.
- β_i = Coefficients that measure the impact of each independent variable on the model.
- X_i = Key economic and financial indicators, such as:
- X_1 = Debt-to-GDP ratio: Measures the country's debt burden.
- X_2 = Primary Balance/GDP: government's fiscal health measure.
- X_3 = Inflation rate
- X_4 = Reserves/Imports: measures a country's ability to sustain imports using its reserves.
- X_5 = GDP growth rate: Shows economic strength and stability.

A **higher Z-score** implies lower sovereign risk, while a **lower Z-score** suggests a higher probability of financial distress.
The following criterion is usually utilized:

- $\mathbf{Z > 3}$: Low risk of default, strong economic fundamentals.
- $\mathbf{1 < Z < 3}$: Moderate risk, requiring close monitoring.
- $\mathbf{Z < 1}$: High risk of default, potential financial distress.

To perform the analysis effectively, we developed a Python model consisting of three phases:

- **Phase 1**: Estimating the values of the alpha and beta coefficients to be assigned to the model accurately, in order to quantify the impact of each variable on default risk.

  [INSERT FIGURE 20 HERE]

- **Phase 2**: Computing the Z-scores.

  [INSERT FIGURE 21 HERE]

- **Phase 3**: Implementing a regression model that relates the annual variation of the United Kingdom's CDS as dipendent variable to the Z-score values as an indipendent variable, in order to adjust the z score for the CDS spread. This final phase also includes a predictive model for both the Z-scores and the five-year CDS, calculated using the predicted Z-scores and interpolation with historical CDS prices.

[INSERT FIGURE 22 HERE]

3.2 UK's Sovereign Z-Score Trends

The United Kingdom during the period between 2020-2024 has been characterized by significant events and fluctuations, as reflected in its Sovereign Z-Score. In 2020 the score reflected a relatively strong stability (1.97); despite pandemic, intervention in fiscal policies, and the increasing of the public debt, the country revealed a strong financial stability. Moving into 2021, the UK's economic outlook experienced a sharp decline to 0.82 due to economic shocks after the pandemic, rising inflation, supply chain stress and public debt exceeding 100% of the GDP. Moreover in 2022 we can see the lowest level of -0.32 that can be interpreted as an High Default Risk, due to inflationary pressure, rising interest rates and one of the most significant events of the year, the announcement of Mini-Budget that caused a triggered market panic. In 2023, the financial stability of the UK shows signs of improvement, as reflected by the result of a score of 4.28; the leadership of the new government, the cautious fiscal approach and the full recovery of investor confidence. Looking ahead to 2024 the score stands at 3.13 indicating a continuous path of stabilization.

3.3 Evidences

The most useful information for our analysis came from the incredible increase in the Z scores between 2022 and 2023 which demonstrates that despite the panic caused by the Mini-Budget announcement and the other events happened in 2022, reflected in the calculated Z-Scores, shows a strong stress experienced by the UK. Nevertheless the country has managed the situation in best way possible and the government was able to recover in a a very short time their position of strenght as the next year Z-Score demonstrate a huge increasing, as explained in the previous paragraph, reaching an optimal financial stability as the 2023 Z-Score suggest.

4 Historical Ratings

Since 2008, the UK's credit rating has undergone significant changes, reflecting major economic and political events. From 2008 to 2016, the UK maintained the highest AAA rating from major agencies such as Moody's, S&P, and Fitch. However, the 2016 Brexit referendum marked a turning point. Shortly after the vote, both S&P and Fitch downgraded the UK from AAA to AA, citing concerns over economic uncertainty and fiscal stability. Between 2017 and 2019, Moody's further downgraded the UK's rating from Aa1 to Aa2, reflecting the challenges of Brexit negotiations and slowing economic growth. Fitch and S&P maintained their AA ratings, albeit with negative outlooks. The economic shock of COVID-19 in 2020 led to another downgrade. Moody's cut the rating to Aa3, and Fitch reduced it to AA-, both citing rising public debt and economic contraction. S&P maintained an AA rating but with a negative outlook. In 2022, following the controversial Mini-Budget under Liz Truss's government, market instability caused further concerns. Fitch and S&P revised the UK's outlook to negative, reflecting worries over fiscal discipline and investor confidence. However, by 2024, both agencies improved their outlooks to stable, signaling a more balanced economic recovery. Currently, the UK's ratings stand at Aa3 (Moody's), AA (S&P), and AA- (Fitch), all with a stable outlook, indicating relative economic stabilization after years of volatility.

As part of our analysis, we also incorporated the **Default Risk Proxy**, a key indicator used to assess a country's creditworthiness and the likelihood of default. This metric is typically derived from Credit Default Swaps (CDS) spreads, government bond yields, and other financial risk measures, in this case we have used the metric called **Default Rate** calculated by S&P and available on their website.

The Default Risk Proxy serves as a valuable tool for investors and policymakers, as it provides insights into market perceptions of a nation's fiscal health and stability. A higher value suggests increased default risk and economic uncertainty, while a lower value indicates stronger financial resilience. In our study, this indicator helped us better understand market reactions to significant events, such as the UK's Mini-Budget crisis in 2022, and assess the broader impact on sovereign risk perception.

5 Appendix

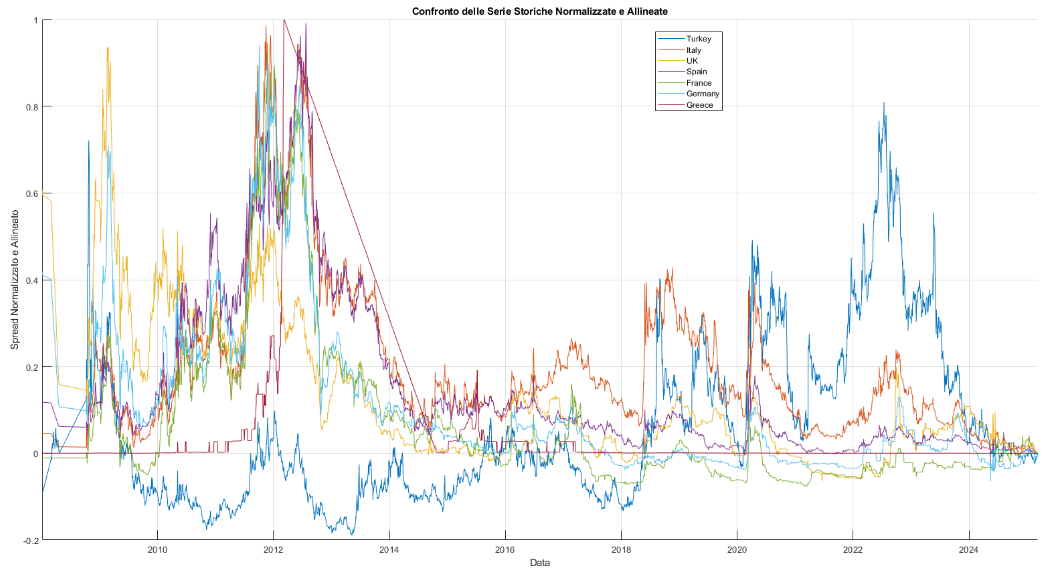

Figure 1: **Comparison between normalized time series of CDS spreads** of the seven analyzed countries: Turkey (dark blue), Italy (orange), United Kingdom (yellow), Spain (purple), France (green), Germany (light blue), Greece (red).

Figure 2: **Correlation matrix of CDS spreads**. It highlights strong positive correlations among Eurozone countries, particularly during periods of shared economic stress. Turkey shows weaker correlations, reflecting its unique economic conditions and lower integration with European markets. The UK's correlations are moderate, influenced by its semi-independent financial context and distinct economic events like Brexit.

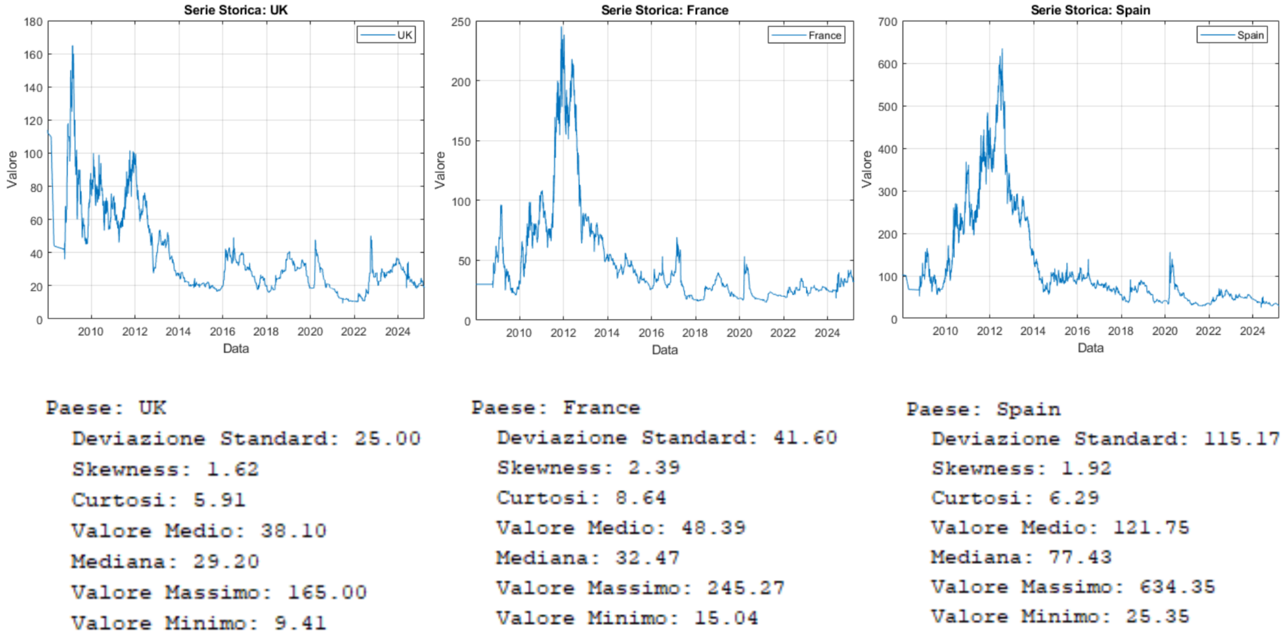

Figure 3: Comparison between the time series of **United Kingdom, France and Spain** respectively. Note the different scale on the vertical axis, related to the value of CDS spreads.

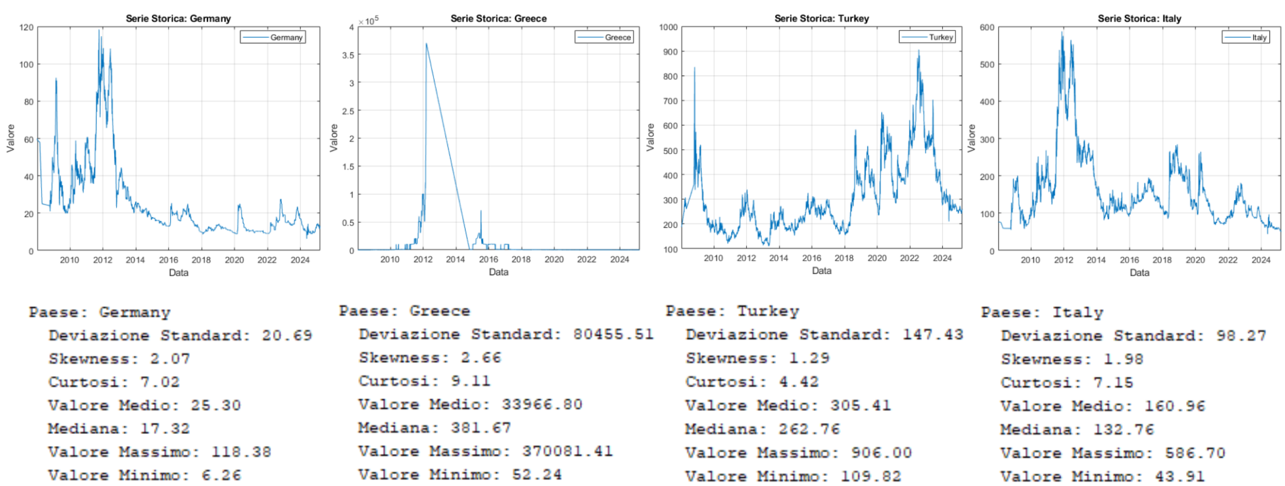

Figure 4: Comparison between the time series of **Germany, Greece, Turkey, Italy** respectively. Note the different scale on the vertical axis, related to the value of CDS spreads, in particular in the case of Greece.

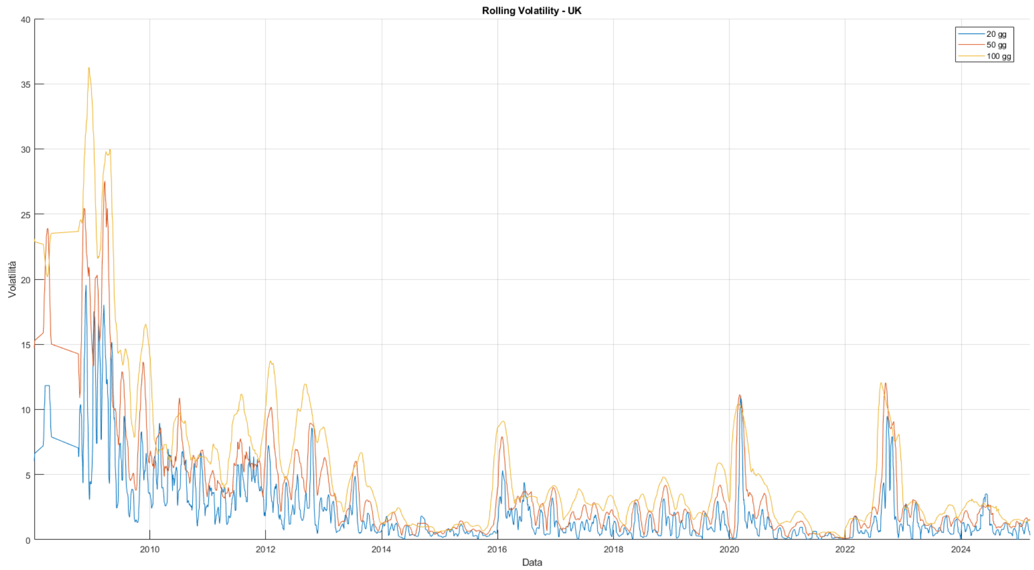

Figure 5: **Rolling volatility of CDS Spreads in the United Kingdom** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

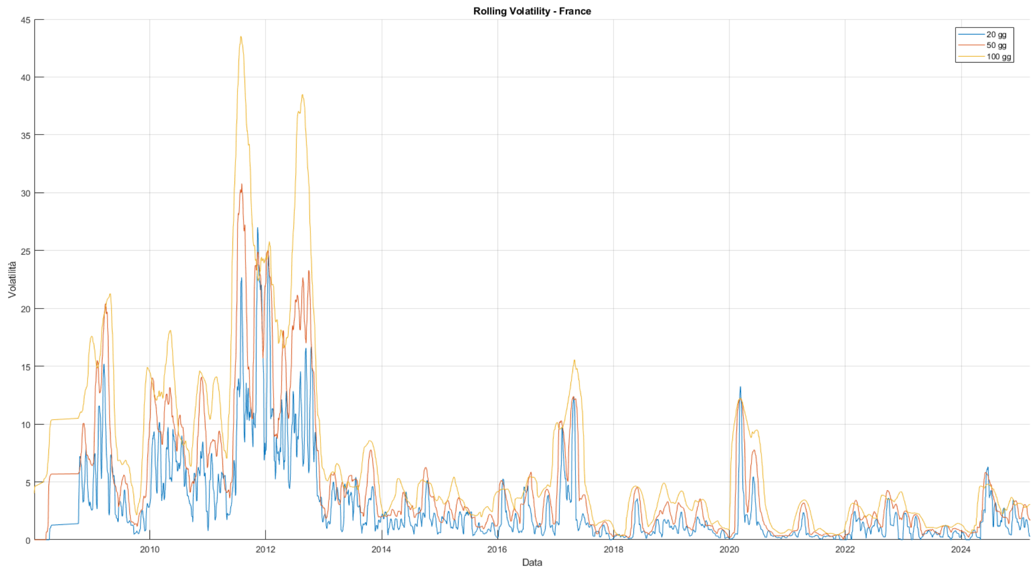

Figure 6: **Rolling volatility of CDS Spreads in France** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

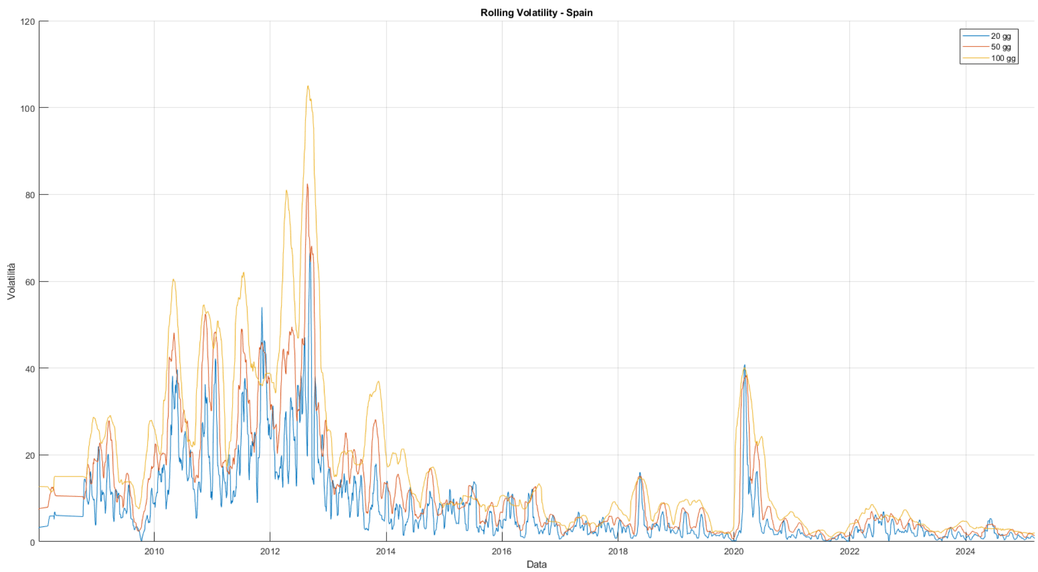

Figure 7: **Rolling volatility of CDS Spreads in Spain** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

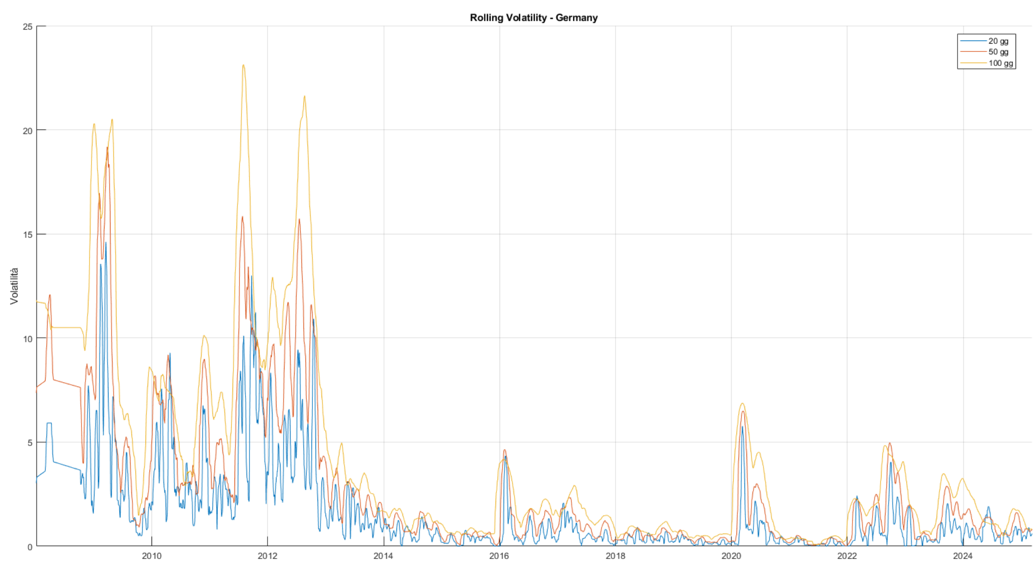

Figure 8: **Rolling volatility of CDS Spreads in Germany** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

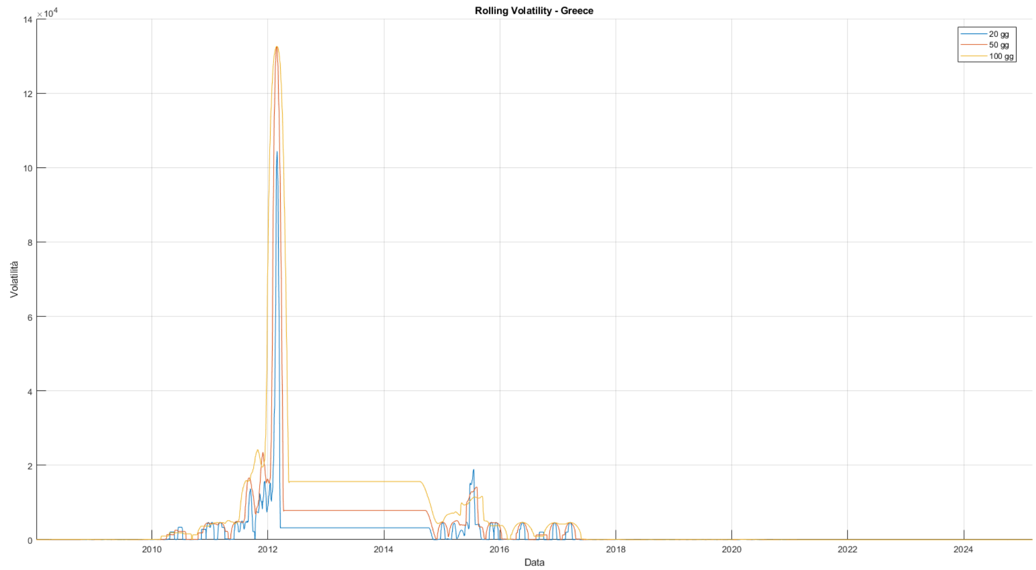

Figure 9: **Rolling volatility of CDS Spreads in Greece** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

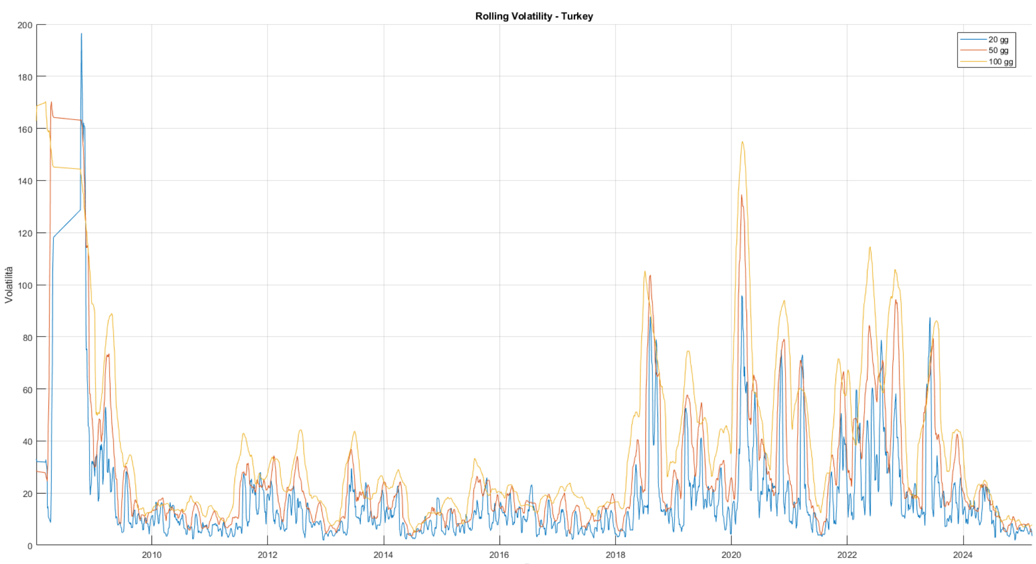

Figure 10: **Rolling volatility of CDS Spreads in Turkey** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

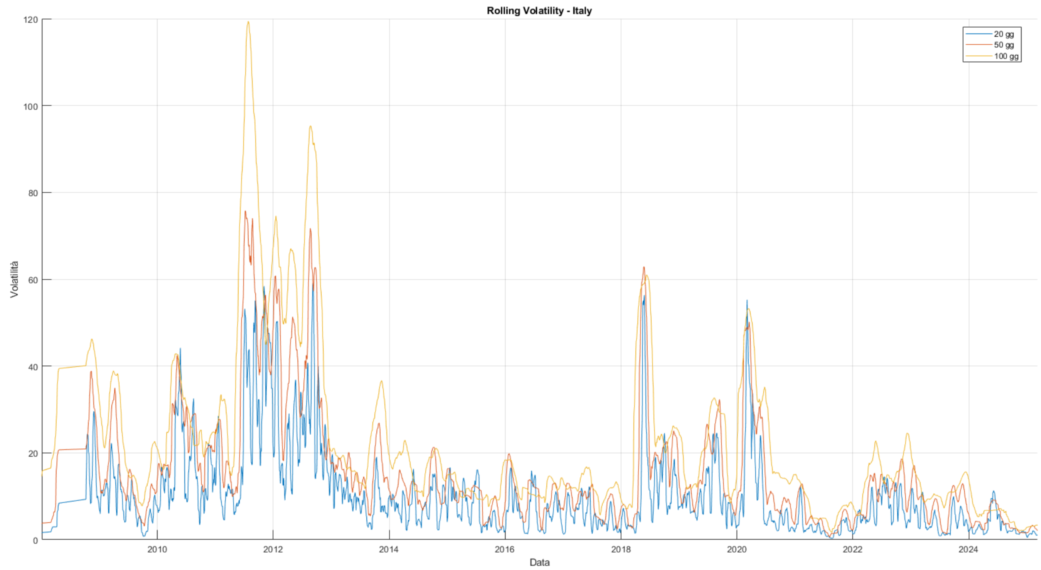

Figure 11: **Rolling volatility of CDS Spreads in Italy** over different time frames: 20-day (blue), 50-day (red), 100-day (yellow).

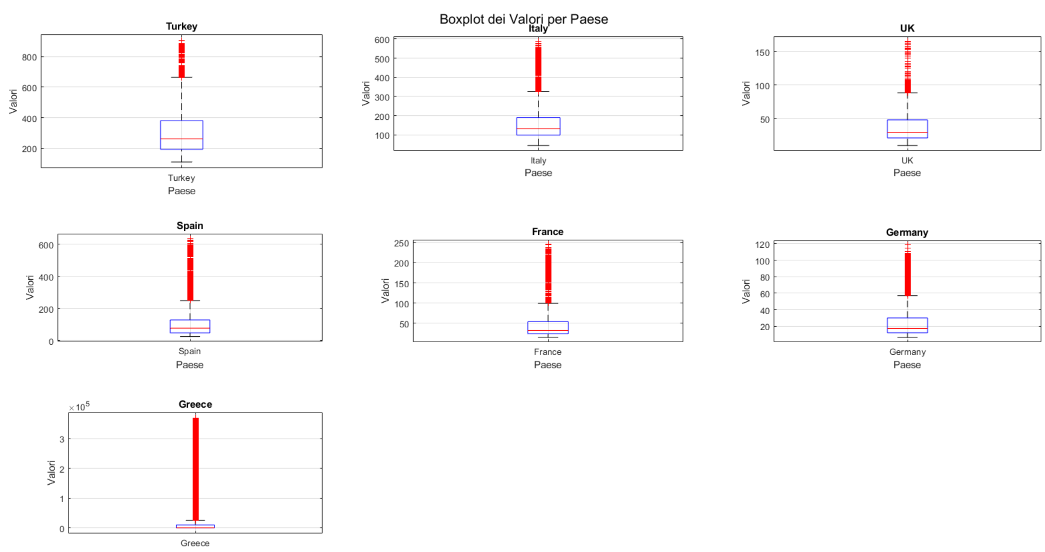

Figure 12: **Boxplots** graphically summarizing the statistics of each country. The red lines represent the outliers.

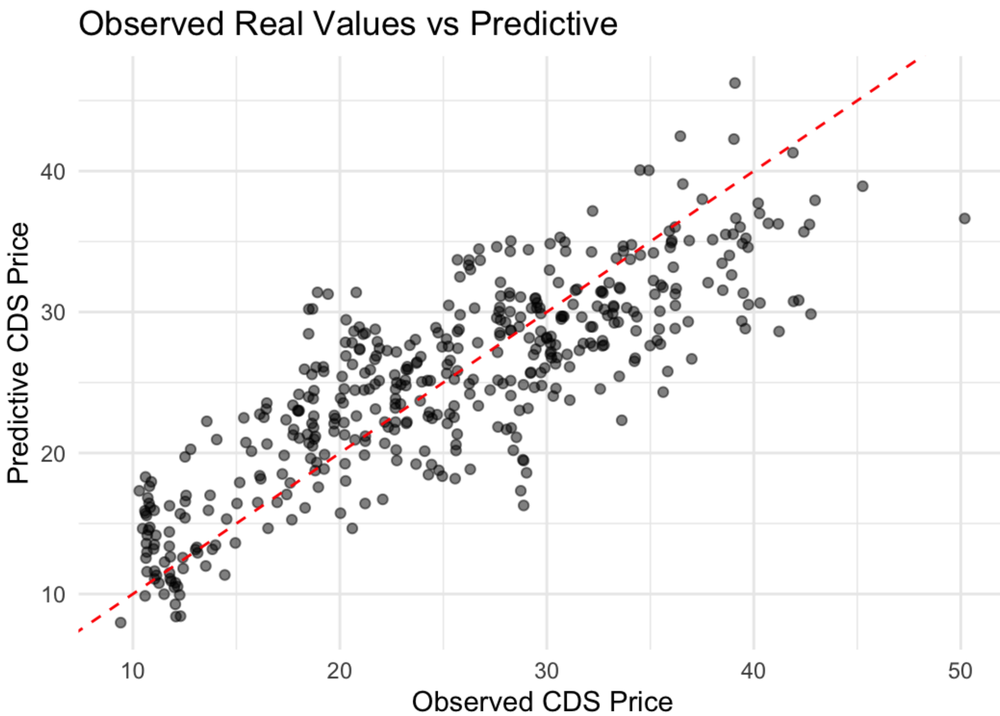

Figure 13: **Linear regression for the United Kingdom**.

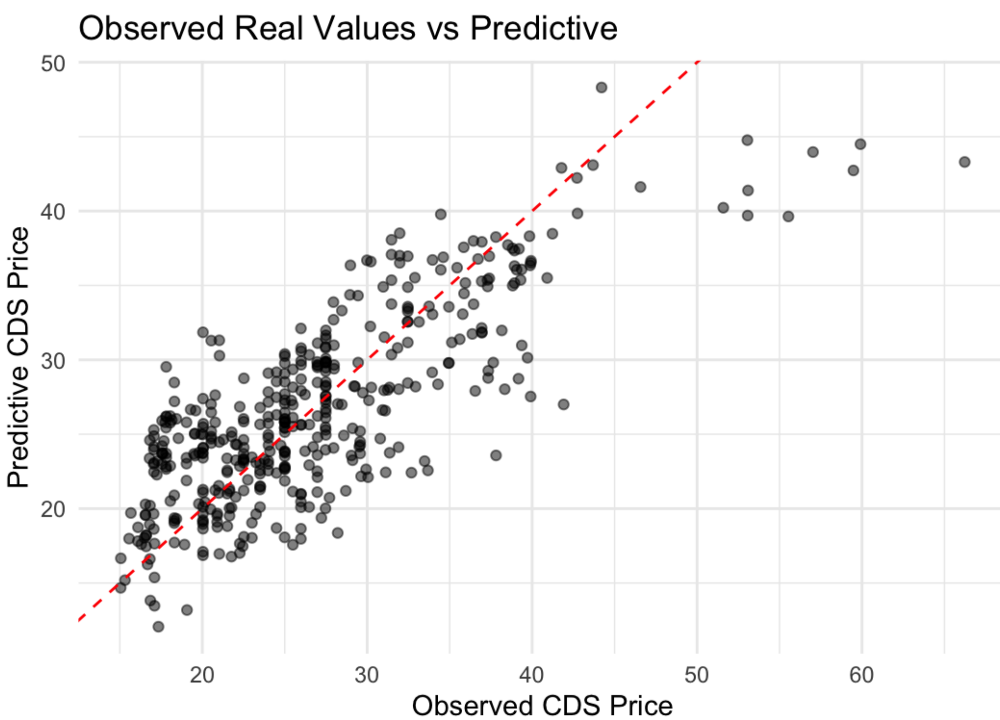

Figure 14: **Linear regression for France**.

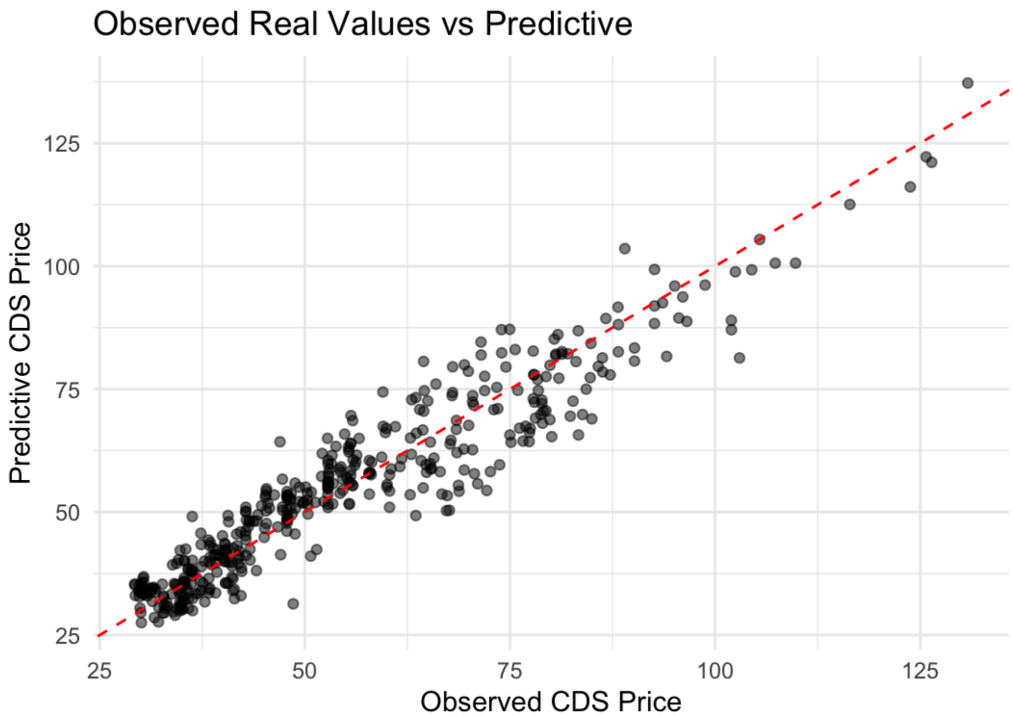

Figure 15: **Linear regression for Spain**.

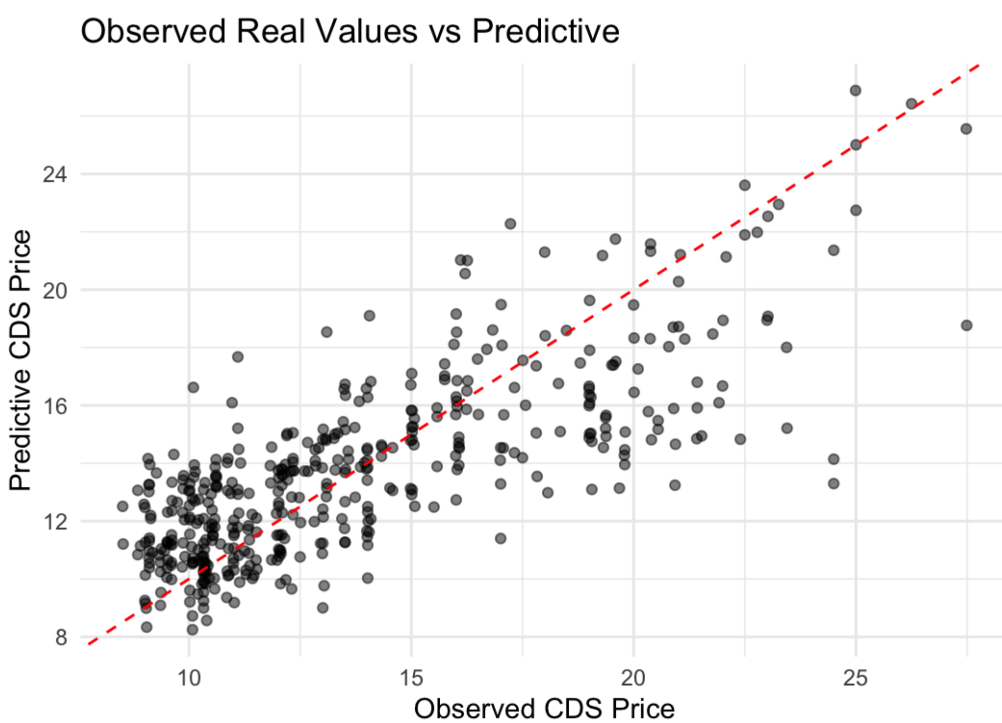

Figure 16: **Linear regression for Germany**.

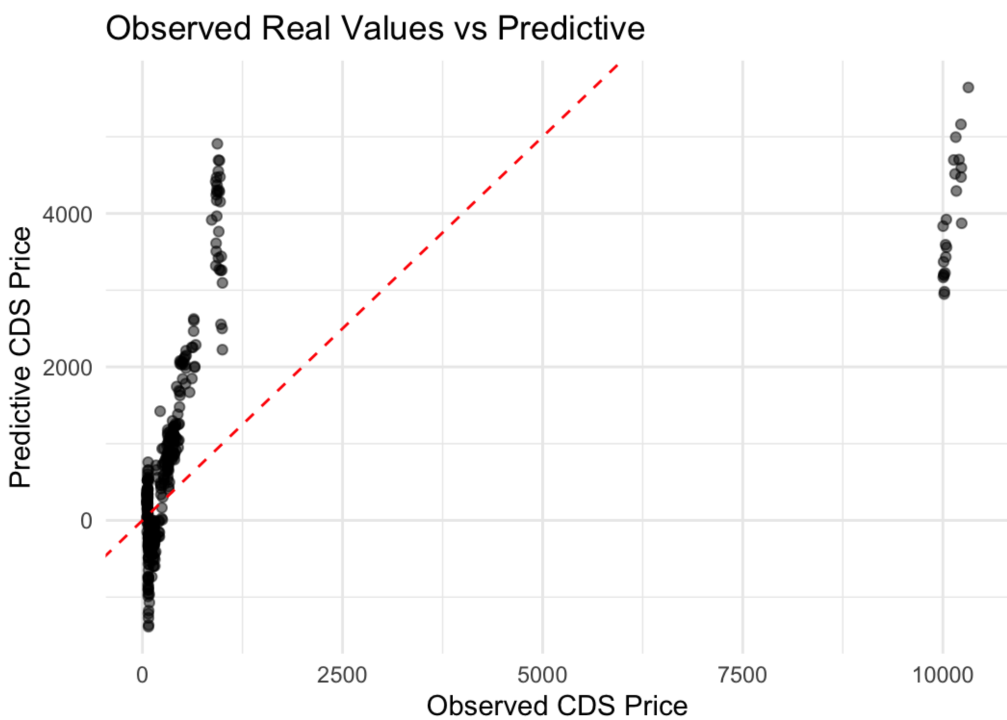

Figure 17: **Linear regression for Greece**.

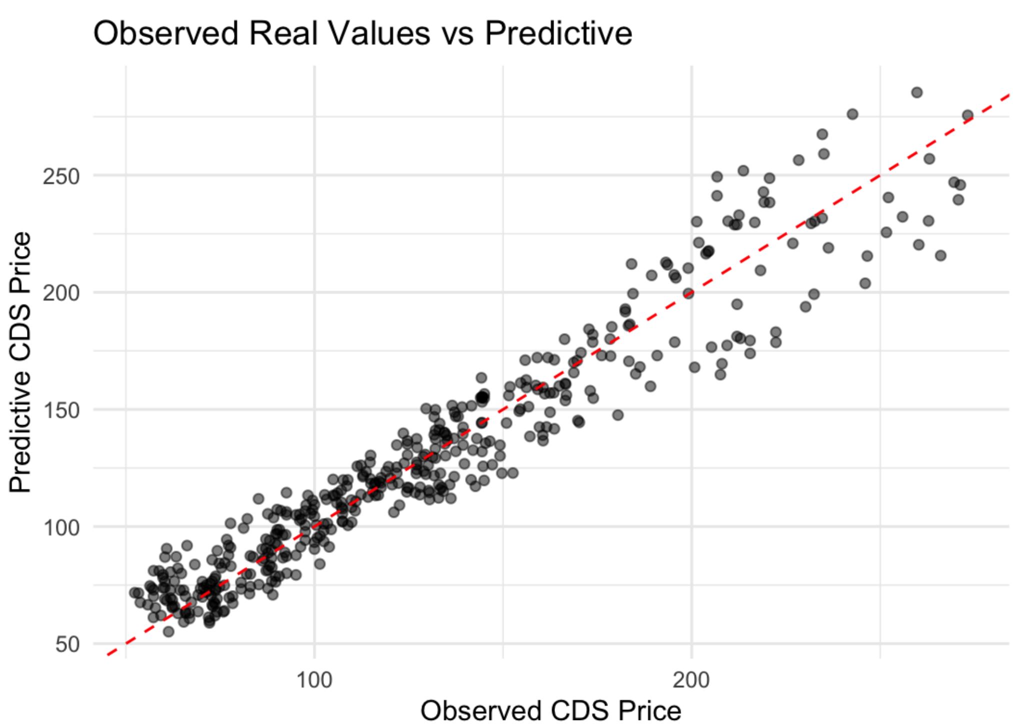

Figure 18: **Linear regression for Italy**.

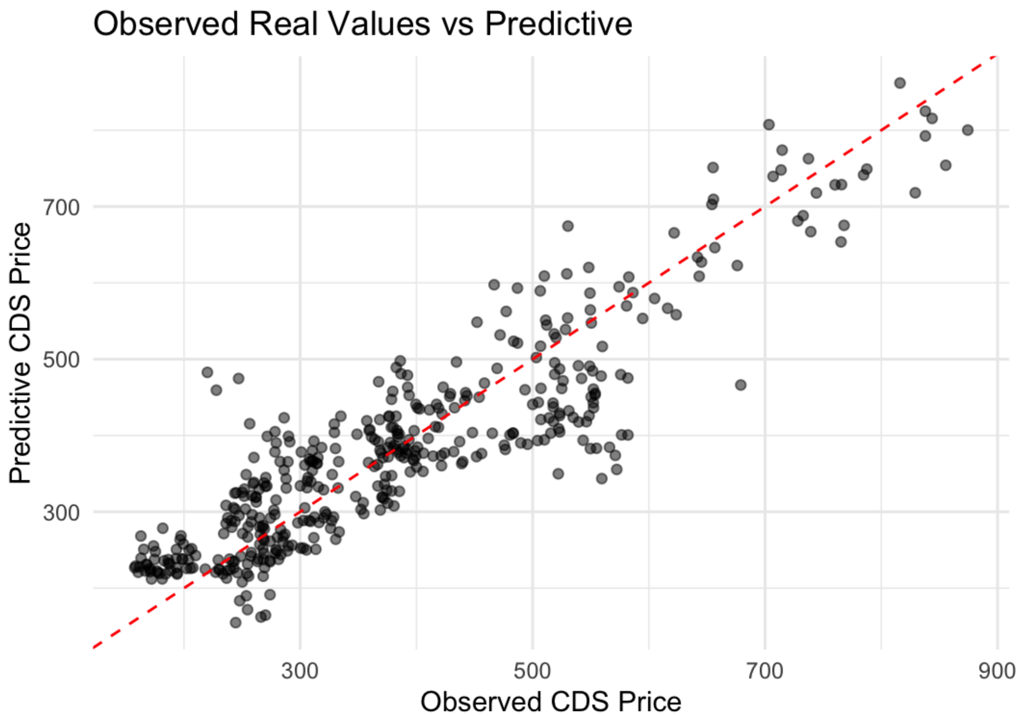

Figure 19: **Linear regression for Turkey**.

const	-0.2951	Reserves/Imports	-2.2179
Debt/GDP	0.0401	Inflation	0.0175
Primary Balance/GDP	0.1145	R-squared:	0.920
GDP Growth Rate	-0.2554	Adj. R-squared:	0.819

Figure 20: **Z-Score coefficient estimation**.

2020	3.182	2021	0.483	2022	1.488	2023	2.393	2024	2.339

Figure 21: **UK Z-Score**.

```
   Anno   CDS  Z-score  Z-score Aggiustato
0  2020  22.5    3.182            1.977000
1  2021  17.5    0.483            0.823895
2  2022  12.5    1.488           -0.329209
3  2023  32.5    2.393            4.283209
4  2024  27.5    2.339            3.130105
Coefficiente (Pendenza): 4.3361
Intercetta: 13.9275
MSE (Mean Squared Error): 34.10
R^2 (Coefficiente di determinazione): 0.32
Deviazione standard degli errori: 6.5291
```

```
Previsione dei futuri Z-score per i prossimi 5 anni:
Anno 2025: Z-score previsto = 2.0442
Anno 2026: Z-score previsto = 2.0666
Anno 2027: Z-score previsto = 2.0890
Anno 2028: Z-score previsto = 2.1114
Anno 2029: Z-score previsto = 2.1338

Statistiche modello Z-score:
Coefficiente (Pendenza): 0.0224
Intercetta: -43.3158
MSE (Mean Squared Error): 0.84
```

```
Previsione dei futuri CDS per i prossimi 5 anni:
Anno 2025: CDS previsto = 22.7914
Anno 2026: CDS previsto = 22.8885
Anno 2027: CDS previsto = 22.9856
Anno 2028: CDS previsto = 23.0828
Anno 2029: CDS previsto = 23.1799

Statistiche modello CDS (previsione futura):
Coefficiente (Pendenza): 4.3361
Intercetta: 13.9275
```

Figure 22: **Adjusted Z-Score and CDS predictions**.

5.1 Regression Outputs

```
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    bs(EUR_GBP, degree = 3) + ns(Gas_Price, knots = c(2.5, 5,
    7.5)) + bs(Spread_UK, knots = c(100, 150)) + bs(CISS, knots = c(0.2,
    0.3, 0.4)) + log(VIX), data = combined_data_UK)

Residuals:
     Min       1Q   Median       3Q      Max
-12.4749  -3.2843  -0.1667   3.2204  13.5535

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                              65.530      6.995   9.368  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))1  -21.836      4.937  -4.423 1.25e-05 ***
bs(Oil_Price, knots = c(50, 75, 100))2  -15.420      4.005  -3.850 0.000137 ***
bs(Oil_Price, knots = c(50, 75, 100))3  -43.520      4.048 -10.750  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))4  -31.834      4.519  -7.045 7.80e-12 ***
bs(Oil_Price, knots = c(50, 75, 100))5  -40.024      4.764  -8.402 7.13e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))6  -36.197      5.724  -6.324 6.64e-10 ***
bs(EUR_GBP, degree = 3)1                -15.340      5.175  -2.964 0.003213 **
bs(EUR_GBP, degree = 3)2                 11.915      3.569   3.338 0.000920 ***
bs(EUR_GBP, degree = 3)3                 -5.484      3.441  -1.593 0.111823
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   -3.561      2.108  -1.690 0.091877 .
ns(Gas_Price, knots = c(2.5, 5, 7.5))2    2.981      3.232   0.922 0.356812
ns(Gas_Price, knots = c(2.5, 5, 7.5))3   -2.043      3.550  -0.576 0.565232
ns(Gas_Price, knots = c(2.5, 5, 7.5))4   -6.546      3.159  -2.073 0.038826 *
bs(Spread_UK, knots = c(100, 150))1      -4.122      3.144  -1.311 0.190491
bs(Spread_UK, knots = c(100, 150))2       5.768      2.255   2.559 0.010868 *
bs(Spread_UK, knots = c(100, 150))3      19.019      3.796   5.010 8.09e-07 ***
bs(Spread_UK, knots = c(100, 150))4      13.918      3.380   4.118 4.61e-05 ***
bs(Spread_UK, knots = c(100, 150))5      13.419      3.637   3.689 0.000255 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))1      13.868      2.350   5.903 7.47e-09 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))2       8.077      1.991   4.058 5.93e-05 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))3      15.511      2.366   6.555 1.66e-10 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))4      11.931      3.478   3.430 0.000664 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))5      27.789      5.039   5.515 6.17e-08 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))6      18.519      4.400   4.209 3.15e-05 ***
log(VIX)                                 -8.668      1.298  -6.679 7.80e-11 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 4.905 on 413 degrees of freedom
Multiple R-squared:  0.6865,    Adjusted R-squared:  0.6675
F-statistic: 36.17 on 25 and 413 DF,  p-value: < 2.2e-16
```

(a) **United Kingdom**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_IT, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)) + log(VIX), data = combined_data_IT)

Residuals:
    Min      1Q  Median      3Q     Max
-42.588  -9.876  -1.181   7.772  50.361

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                             94.8370    23.9917   3.953 9.09e-05 ***
bs(Oil_Price, knots = c(50, 75, 100))1  -9.5206    14.7482  -0.646   0.5189
bs(Oil_Price, knots = c(50, 75, 100))2 -13.8485    11.8200  -1.172   0.2420
bs(Oil_Price, knots = c(50, 75, 100))3 -85.2895    12.1800  -7.002 1.04e-11 ***
bs(Oil_Price, knots = c(50, 75, 100))4 -84.9806    13.7006  -6.203 1.36e-09 ***
bs(Oil_Price, knots = c(50, 75, 100))5 -71.3280    14.7537  -4.835 1.89e-06 ***
bs(Oil_Price, knots = c(50, 75, 100))6 -96.8712    17.6229  -5.497 6.81e-08 ***
ns(Gas_Price, knots = c(2.5, 5, 7.5))1  18.3315     6.2800   2.919   0.0037 **
ns(Gas_Price, knots = c(2.5, 5, 7.5))2  22.1493     9.7645   2.268   0.0238 *
ns(Gas_Price, knots = c(2.5, 5, 7.5))3  20.2050    10.3246   1.957   0.0510 .
ns(Gas_Price, knots = c(2.5, 5, 7.5))4   1.7193     9.7356   0.177   0.8599
bs(Spread_IT, knots = c(100, 150))1      5.2269    15.4479   0.338   0.7353
bs(Spread_IT, knots = c(100, 150))2     18.3038    13.5429   1.352   0.1773
bs(Spread_IT, knots = c(100, 150))3     64.0673    15.3204   4.182 3.54e-05 ***
bs(Spread_IT, knots = c(100, 150))4    163.2950    15.1518  10.777  < 2e-16 ***
bs(Spread_IT, knots = c(100, 150))5    190.1667    14.8137  12.837  < 2e-16 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))1      0.4522     7.4029   0.061   0.9513
bs(CISS, knots = c(0.2, 0.3, 0.4))2    -10.2045     6.1371  -1.663   0.0971 .
bs(CISS, knots = c(0.2, 0.3, 0.4))3     -7.8885     7.5745  -1.041   0.2983
bs(CISS, knots = c(0.2, 0.3, 0.4))4     -9.5883    10.9616  -0.875   0.3822
bs(CISS, knots = c(0.2, 0.3, 0.4))5    -20.2752    15.5390  -1.305   0.1927
bs(CISS, knots = c(0.2, 0.3, 0.4))6     -7.7751    13.4712  -0.577   0.5641
log(VIX)                                 5.3420     4.2167   1.267   0.2059
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 15.14 on 410 degrees of freedom
Multiple R-squared:  0.9205,    Adjusted R-squared:  0.9163
F-statistic: 215.9 on 22 and 410 DF,  p-value: < 2.2e-16
```

(b) **Italy**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_GE, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)) + log(VIX), data = combined_data_GE)

Residuals:
    Min      1Q  Median      3Q     Max
-6.5763 -1.7227 -0.2587  1.3615 11.2036

Coefficients: (1 not defined because of singularities)
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                             25.1766     3.3497   7.516 3.34e-13 ***
bs(Oil_Price, knots = c(50, 75, 100))1  -7.5173     2.5728  -2.922 0.003664 **
bs(Oil_Price, knots = c(50, 75, 100))2 -12.2325     2.0658  -5.922 6.55e-09 ***
bs(Oil_Price, knots = c(50, 75, 100))3 -16.2630     2.0960  -7.759 6.34e-14 ***
bs(Oil_Price, knots = c(50, 75, 100))4  -8.3254     2.4860  -3.349 0.000883 ***
bs(Oil_Price, knots = c(50, 75, 100))5 -24.9951     2.5763  -9.702  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))6 -14.5557     3.1182  -4.668 4.08e-06 ***
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   4.2973     1.0946   3.926 0.000101 ***
ns(Gas_Price, knots = c(2.5, 5, 7.5))2  -2.6277     1.7417  -1.509 0.132111
ns(Gas_Price, knots = c(2.5, 5, 7.5))3  -0.7664     1.7740  -0.432 0.665933
ns(Gas_Price, knots = c(2.5, 5, 7.5))4  -5.9236     1.6945  -3.496 0.000522 ***
bs(Spread_GE, knots = c(100, 150))1     -1.3280     1.4655  -0.906 0.365355
bs(Spread_GE, knots = c(100, 150))2     -7.7789     1.6316  -4.768 2.56e-06 ***
bs(Spread_GE, knots = c(100, 150))3      8.2197     1.1544   7.121 4.57e-12 ***
bs(Spread_GE, knots = c(100, 150))4      0.8870     1.9836   0.447 0.655002
bs(Spread_GE, knots = c(100, 150))5          NA         NA      NA       NA
bs(CISS, knots = c(0.2, 0.3, 0.4))1      4.1885     1.2703   3.297 0.001058 **
bs(CISS, knots = c(0.2, 0.3, 0.4))2      6.7726     1.0555   6.416 3.71e-10 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))3     14.2950     1.3354  10.705  < 2e-16 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))4      9.9899     1.9265   5.185 3.33e-07 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))5     20.2879     2.6805   7.569 2.33e-13 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))6     16.0221     2.3655   6.773 4.18e-11 ***
log(VIX)                                -2.3240     0.6963  -3.338 0.000918 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 2.672 on 428 degrees of freedom
  (6 observations deleted due to missingness)
Multiple R-squared:  0.599,     Adjusted R-squared:  0.5794
F-statistic: 30.45 on 21 and 428 DF,  p-value: < 2.2e-16
```

(c) **Germany**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_TKY, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)), data = combined_data_TKY)

Residuals:
     Min       1Q   Median       3Q      Max
-262.578  -48.047   -3.812   42.399  216.858

Coefficients: (2 not defined because of singularities)
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                             194.154     47.396   4.096 5.05e-05 ***
bs(Oil_Price, knots = c(50, 75, 100))1   39.394     61.431   0.641  0.52170
bs(Oil_Price, knots = c(50, 75, 100))2  -89.187     49.619  -1.797  0.07300 .
bs(Oil_Price, knots = c(50, 75, 100))3  -26.256     48.585  -0.540  0.58921
bs(Oil_Price, knots = c(50, 75, 100))4  -58.537     55.919  -1.047  0.29580
bs(Oil_Price, knots = c(50, 75, 100))5    9.130     66.418   0.137  0.89073
bs(Oil_Price, knots = c(50, 75, 100))6  -62.393     78.568  -0.794  0.42758
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   48.725     26.599   1.832  0.06770 .
ns(Gas_Price, knots = c(2.5, 5, 7.5))2   95.112     45.906   2.072  0.03890 *
ns(Gas_Price, knots = c(2.5, 5, 7.5))3  112.374     46.659   2.408  0.01646 *
ns(Gas_Price, knots = c(2.5, 5, 7.5))4  139.375     44.227   3.151  0.00174 **
bs(Spread_TKY, knots = c(100, 150))1         NA         NA      NA       NA
bs(Spread_TKY, knots = c(100, 150))2     70.245     36.219   1.939  0.05313 .
bs(Spread_TKY, knots = c(100, 150))3    -53.702     41.111  -1.306  0.19219
bs(Spread_TKY, knots = c(100, 150))4    566.161     52.666  10.750  < 2e-16 ***
bs(Spread_TKY, knots = c(100, 150))5         NA         NA      NA       NA
bs(CISS, knots = c(0.2, 0.3, 0.4))1      -4.223     32.370  -0.130  0.89625
bs(CISS, knots = c(0.2, 0.3, 0.4))2     107.796     27.127   3.974 8.35e-05 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))3     295.267     34.964   8.445 5.27e-16 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))4     274.230     49.051   5.591 4.12e-08 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))5     529.560     69.148   7.658 1.36e-13 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))6     299.389     61.697   4.853 1.73e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 69.28 on 412 degrees of freedom
Multiple R-squared:  0.8038,    Adjusted R-squared:  0.7947
F-statistic: 88.82 on 19 and 412 DF,  p-value: < 2.2e-16
```

(d) **Turkey**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_GK, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)) + log(VIX), data = combined_data_GK)

Residuals:
    Min      1Q  Median      3Q     Max
-4151.8  -695.0    18.7   499.2  6279.8

Coefficients: (2 not defined because of singularities)
                                        Estimate Std. Error t value Pr(>|t|)
(Intercept)                              8171.94    2532.08   3.227 0.001375 **
bs(Oil_Price, knots = c(50, 75, 100))1   -351.85    1822.95  -0.193 0.847069
bs(Oil_Price, knots = c(50, 75, 100))2  -4829.95    1619.86  -2.982 0.003080 **
bs(Oil_Price, knots = c(50, 75, 100))3    682.75    1722.98   0.396 0.692166
bs(Oil_Price, knots = c(50, 75, 100))4  -8907.35    2679.86  -3.324 0.000988 ***
bs(Oil_Price, knots = c(50, 75, 100))5  52366.28   24230.71   2.161 0.031402 *
bs(Oil_Price, knots = c(50, 75, 100))6        NA         NA      NA       NA
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   1496.35    1478.82   1.012 0.312349
ns(Gas_Price, knots = c(2.5, 5, 7.5))2 -12302.15    6414.41  -1.918 0.055987 .
ns(Gas_Price, knots = c(2.5, 5, 7.5))3 252100.57  262791.82   0.959 0.338102
ns(Gas_Price, knots = c(2.5, 5, 7.5))4 374310.85  376229.42   0.995 0.320514
bs(Spread_GK, knots = c(100, 150))1     -2362.65    1212.14  -1.949 0.052123 .
bs(Spread_GK, knots = c(100, 150))2       454.47     820.90   0.554 0.580211
bs(Spread_GK, knots = c(100, 150))3     -5373.42    1351.30  -3.976 8.60e-05 ***
bs(Spread_GK, knots = c(100, 150))4      9815.27    1677.64   5.851 1.18e-08 ***
bs(Spread_GK, knots = c(100, 150))5      3264.34    1417.48   2.303 0.021905 *
bs(CISS, knots = c(0.2, 0.3, 0.4))1      1374.76     962.88   1.428 0.154307
bs(CISS, knots = c(0.2, 0.3, 0.4))2        80.96     967.64   0.084 0.933371
bs(CISS, knots = c(0.2, 0.3, 0.4))3      -965.83    1872.70  -0.516 0.606377
bs(CISS, knots = c(0.2, 0.3, 0.4))4     -7228.28    6432.99  -1.124 0.261989
bs(CISS, knots = c(0.2, 0.3, 0.4))5    101065.44   87007.36   1.162 0.246248
bs(CISS, knots = c(0.2, 0.3, 0.4))6           NA         NA      NA       NA
log(VIX)                                 -949.51     540.79  -1.756 0.080052 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1733 on 330 degrees of freedom
  (87 observations deleted due to missingness)
Multiple R-squared:  0.5084,    Adjusted R-squared:  0.4786
F-statistic: 17.06 on 20 and 330 DF,  p-value: < 2.2e-16
```

(a) **Greece**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_SP, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)) + log(VIX), data = combined_data_SP)

Residuals:
     Min       1Q   Median       3Q      Max
-17.3232  -4.3621  -0.7075   3.7850  21.6326

Coefficients:
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                             92.2801     8.3468  11.056  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))1 -31.8834     6.1098  -5.218 2.85e-07 ***
bs(Oil_Price, knots = c(50, 75, 100))2 -56.1221     5.0283 -11.161  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))3 -63.7363     5.2726 -12.088  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))4 -80.3014     5.6896 -14.114  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))5 -64.7355     6.4639 -10.015  < 2e-16 ***
bs(Oil_Price, knots = c(50, 75, 100))6 -73.3280     7.5081  -9.767  < 2e-16 ***
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   3.9030     2.6965   1.447   0.1485
ns(Gas_Price, knots = c(2.5, 5, 7.5))2   5.7701     4.1890   1.377   0.1691
ns(Gas_Price, knots = c(2.5, 5, 7.5))3  -2.0753     4.4504  -0.466   0.6412
ns(Gas_Price, knots = c(2.5, 5, 7.5))4  -2.9197     4.1473  -0.704   0.4818
bs(Spread_SP, knots = c(100, 150))1     -3.7535     4.1065  -0.914   0.3612
bs(Spread_SP, knots = c(100, 150))2     27.5867     3.0593   9.017  < 2e-16 ***
bs(Spread_SP, knots = c(100, 150))3     42.5937     4.5308   9.401  < 2e-16 ***
bs(Spread_SP, knots = c(100, 150))4     44.7648     4.5577   9.822  < 2e-16 ***
bs(Spread_SP, knots = c(100, 150))5     59.2025     7.0323   8.419 6.22e-16 ***
bs(CISS, knots = c(0.2, 0.3, 0.4))1      6.9705     3.0977   2.250   0.0250 *
bs(CISS, knots = c(0.2, 0.3, 0.4))2      5.3643     2.6265   2.042   0.0417 *
bs(CISS, knots = c(0.2, 0.3, 0.4))3      0.5945     3.2765   0.181   0.8561
bs(CISS, knots = c(0.2, 0.3, 0.4))4     10.2307     4.6587   2.196   0.0286 *
bs(CISS, knots = c(0.2, 0.3, 0.4))5     -1.8602     6.6831  -0.278   0.7809
bs(CISS, knots = c(0.2, 0.3, 0.4))6     12.3059     5.7739   2.131   0.0337 *
log(VIX)                                 0.1663     1.7868   0.093   0.9259
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.531 on 416 degrees of freedom
Multiple R-squared:  0.8985,    Adjusted R-squared:  0.8931
F-statistic: 167.4 on 22 and 416 DF,  p-value: < 2.2e-16
```

(b) **Spain**

```
Call:
lm(formula = CDS_Price ~ bs(Oil_Price, knots = c(50, 75, 100)) +
    ns(Gas_Price, knots = c(2.5, 5, 7.5)) + bs(Spread_FR, knots = c(100,
    150)) + bs(CISS, knots = c(0.2, 0.3, 0.4)) + log(VIX), data = combined_data_FR)

Residuals:
     Min       1Q   Median       3Q      Max
-11.8088  -3.4271  -0.4522   2.7891  22.9338

Coefficients: (2 not defined because of singularities)
                                       Estimate Std. Error t value Pr(>|t|)
(Intercept)                             34.2013     6.1787   5.535 5.50e-08 ***
bs(Oil_Price, knots = c(50, 75, 100))1 -15.7001     4.7211  -3.326 0.000960 ***
bs(Oil_Price, knots = c(50, 75, 100))2  -6.2675     3.9139  -1.601 0.110052
bs(Oil_Price, knots = c(50, 75, 100))3 -27.6971     3.9244  -7.058 7.09e-12 ***
bs(Oil_Price, knots = c(50, 75, 100))4 -25.4656     4.4089  -5.776 1.50e-08 ***
bs(Oil_Price, knots = c(50, 75, 100))5 -30.3830     4.8184  -6.306 7.31e-10 ***
bs(Oil_Price, knots = c(50, 75, 100))6 -28.1557     5.7798  -4.871 1.57e-06 ***
ns(Gas_Price, knots = c(2.5, 5, 7.5))1   6.1894     2.0733   2.985 0.003000 **
ns(Gas_Price, knots = c(2.5, 5, 7.5))2   5.2031     3.2295   1.611 0.107905
ns(Gas_Price, knots = c(2.5, 5, 7.5))3   0.2559     3.3457   0.076 0.939074
ns(Gas_Price, knots = c(2.5, 5, 7.5))4  -2.4413     3.1444  -0.776 0.437958
bs(Spread_FR, knots = c(100, 150))1     13.0631     3.4876   3.746 0.000205 ***
bs(Spread_FR, knots = c(100, 150))2     26.0461     3.2511   8.012 1.14e-14 ***
bs(Spread_FR, knots = c(100, 150))3     26.2936     2.8783   9.135  < 2e-16 ***
bs(Spread_FR, knots = c(100, 150))4          NA         NA      NA       NA
bs(Spread_FR, knots = c(100, 150))5          NA         NA      NA       NA
bs(CISS, knots = c(0.2, 0.3, 0.4))1      7.4428     2.3377   3.184 0.001562 **
bs(CISS, knots = c(0.2, 0.3, 0.4))2      1.9023     1.9773   0.962 0.336570
bs(CISS, knots = c(0.2, 0.3, 0.4))3      7.2680     2.4303   2.991 0.002949 **
bs(CISS, knots = c(0.2, 0.3, 0.4))4      2.0973     3.5459   0.591 0.554529
bs(CISS, knots = c(0.2, 0.3, 0.4))5      4.6688     5.1045   0.915 0.360907
bs(CISS, knots = c(0.2, 0.3, 0.4))6      9.2924     4.4086   2.108 0.035646 *
log(VIX)                                -2.0892     1.3082  -1.597 0.111029
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5.042 on 418 degrees of freedom
Multiple R-squared:  0.6204,    Adjusted R-squared:  0.6022
F-statistic: 34.15 on 20 and 418 DF,  p-value: < 2.2e-16
```

(c) **France**

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