

Analysis of Credit Default Swaps Before, During, and After the COVID-19 Crisis

Jagat Dave

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Finance Department

Faculty of Business, Economics & Law

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Abstract

In this dissertation, we studied the movement of CDS sector indices due to variables like commodity index and economic policy uncertainty index. We also tested the impact of structural model variables like equity and interest rates on CDS sector indices. The data sample spans seven years, from January 2017 to December 2023, including before, during, and after the COVID-19 period. Panel data regressions were analysed across 10 CDS sector indices sourced from Refinitiv.

The regressions of banking, non-bank financials, manufacturing, service, and sovereign CDS sector indices had positive and statistically significant EPU coefficients for the whole sample period. The commodity index (CRB index) had no statistically significant relationship with CDS sector indices except for the energy, power, and transportation sectors. Crude oil predicts banking, energy, and sovereign CDS sectors better than the CRB index. VIX coefficients were positive with considerable magnitude during COVID-19, and overall, VIX had a statistically significant positive association with CDS for the whole sample period. An exception is a negative association between VIX and CDS before and after COVID-19. VIX is a dominant uncertainty parameter during COVID-19. At the same time, EPU is a more stable indicator of uncertainty's impact on CDS since EPU positively impacts CDS for the entire sample period and sub-periods. The findings of our study confirm that CDS sector indices are negatively associated with the European equity index for the whole sample period and sub-periods. The impact of the US equity index on CDS sector indices differs for sub-periods; there is a positive relationship during the COVID-19 period. In contrast, there is a negative relationship before and after the COVID-19 period. The US 5-year treasury yield positively impacted CDS sector indices, an aberration from a theoretical understanding of structural models.

Our research substantiates previous research reports findings that an increase in EPU increases CDS spread, and we can investigate the relationship between EPU subindices and credit markets. We have used the oil ETF and CRB index to analyze commodity markets' impact on CDS at the global level and all ten sectors of the economy, while in the past, researchers have analyzed specific sectors only.

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List of Abbreviations

Abbreviation	Full Form
AUD	Australian Dollar
BOE	Bank of England
BPS	Basis Points
CSR	Corporate Social Responsibility
CDS	Credit Default Swaps
CDX NA IG	CDX North America Investment Grade
CLN	Credit Linked Notes
COVID	Corona Virus Disease
CRB	Commodity Research Bureau
DD	Distance to Default
ECB	European Central Bank
EPU	Economic Policy Uncertainty
ETF	Exchange Traded Fund
EU	European Union
FDI	Foreign Direct investment
GDP	Gross Domestic Product
GFC	Global Financial Crisis
GICS	Global Industry Classification Standards
GMM	Generalised Method of Moments
IG	Investment Grade
IRF	Impulse Response Function
LLM	Large Language Model
LN	Logarithm Natural
NAV	Net Asset Value
OAS	Option Adjusted Spread
PCA	Principal component Analysis
PHEIC	Public Health Emergency of International Concern
ROA	Return On Assets
SMOVE	Swaption Merrill Lynch Option Volatility Estimate
S&P	Standard and Poor's
TGARCH	Threshold generalised Autoregressive Conditional Heteroskedasticity
TRBC	The Refinitiv Business Classification
TRCCRB	Thomson Reuters/Core Commodity Commodity Research Bureau Index
TRMI	Thomson Reuters MarketPsych Indices
US	United States
USA	United States of America
USO	US Crude oil ETF
VAR	Vector Autoregressive
VECM	Vector Error Correction Model (VECM)
VIX	Chicago Board Options Exchange Volatility Index
WHO	World health Organization
WTI	West Texas Intermediate
WUI	World Uncertainty Index

Attestation of Authorship

I hereby declare that this submission is my work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Signature of the candidate:

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Chapter 1- Introduction

The Corona Virus Disease, also known as the COVID-19 pandemic, is a once-in-a-century global health pandemic. COVID-19 impacted the real economy and the financial economy at a large scale, and companies had to shut down their operations due to government-forced lockdowns. This pandemic has prompted concern in the investment community about the ability of companies to honor their debt obligations. Credit default swaps (CDS) are widely accepted indicators for measuring the probability of default by debt issuers.

Our dissertation focuses on the impact of critical market factors like equity, interest rate, uncertainty, financial volatility, and commodities on CDS for seven years between 2017 and 2023. We will investigate the sign of coefficients for each independent variable in alignment with prevailing financial theories and empirical findings. Our main contribution will be a sectoral analysis of credit default swap indices and the Economic Policy Uncertainty (EPU) index's impact on the movement of all CDS sector indices. We will also compare the relative importance of the economic policy uncertainty and financial uncertainty (VIX) to explain the movement of CDS sector indices. Furthermore, we will consider the FTSE/Core Commodity CRB Index (TRCCRB) and the US Crude oil ETF (USO) and analyse the effectiveness of each one in explaining the CDS sector index movement.

1.1 Background on credit default swaps (CDS) and their role in financial markets

Credit default swaps are standardized derivatives instruments used by hedgers and speculators. CDS volume has increased significantly after the Global Financial Crisis (GFC) of 2007-2008 due to the standardization and increased regulatory monitoring in the United States of America (USA). CDS became so crucial that the Bank of England (BOE) and the European Central Bank (ECB) added Credit spread changes in their supervisory dashboards. Former Federal Reserve Governor Greenspan and former Treasury Secretary Tim Geithner noted the growth in CDS markets between 2004 and 2009. CDS is the foremost choice for hedgers and risk seekers to keep track of credit risk during high uncertainty periods. CDS are also under the radar of policymakers and market participants due to the general belief that CDS contracts were responsible for exacerbating the effects of the US subprime crisis.

Theoretically, researchers have attempted to understand CDS with structural or reduced-form models. The reduced form models are more mouldable, and they easily fit into various shapes of the term structure of the CDS, while the structural models are more helpful in understanding the economic determinants of the CDS term structure.

Financial researchers have used bond spread as the parameter of a borrower's credit risk before the development of CDS markets. Bond spread is the difference between the corporate bond yield and benchmark bond yield, usually a government bond. The CDS spread is the annual cost (CDS premium), mainly quoted in basis points. The counterparty who wants to transfer the credit risk of the referenced entity-issued bond or loan is a protection buyer who pays the CDS premium to the protection seller. The bond investors can hedge the bond's default risk in CDS markets. Speculators use CDS contracts as part of various credit trading strategies. CDS is a credit component of structured products like Credit Linked Note (CLN), with elements of a bond and a credit derivative.

A Bond may have a feature of a call option or a put option, so researchers adjust the impact of optionality in a bond contract. The spread derived after considering the option feature in a specific bond is called Option-Adjusted Spread (OAS). The credit spread puzzle is the difference between the OAS of the corporate bond and expected loss, which is computed using an (unconditional) one-year rating transition matrix – indicating probabilities of downgrades and defaults with the assumption that recovery rates are a constant share of face value. Corporate bond markets are traditionally used to infer credit spreads. However, empirical research revealed that the expected default losses account for a small portion of observed credit spreads. This phenomenon is known as the credit spread puzzle. Amato and Remolona (2003) concluded that taxes, liquidity, and risk premium are the drivers of credit spread, but these factors do not provide a complete overview of the credit spread. Authors suggested that the largest portion of credit spreads is a result of compensation required by investors for the risk of unforeseen losses from the default. Elton et al. (2001) showed that only 17.8% of the 10-year A-corporate-treasury spread can be assigned to default. Another 36.1% was for tax effects, leaving a residual spread of 46.2%, a puzzle for the researchers. Since CDS are not as widely used for investment purposes as corporate bonds, in relative terms, there is little need to predict the impact of taxes on CDS valuation as much as needed for bonds. Thus, CDS is a better credit instrument for solving the credit spread puzzle than a cash bond.

Norden and Weber (2009) noticed that it was in 2004 that the Basel Committee on Banking Supervision recognized CDS in the new capital adequacy framework of the banks due to the role of CDS as a credit risk transfer mechanism. Norden and Weber (2009) argue that CDS has three main advantages over bonds as a price discovery mechanism. First, the CDS market is less capital-intensive than bond markets. Second, CDS participants can quickly enter long and short positions of credit risk while shorting the bonds can have regulatory and availability issues. Third, CDS is a more

standardized instrument than cash bonds. Hammoudeh, Nandha, et al. (2013) point out that the United States (US) CDS market has grown from \$180 billion in 1997 to \$62.2 trillion in 2007 (in terms of notional amount). Hibbert and Pavlova (2017) have shown year-wise outstanding CDS notional amounts and confirm that the sovereign CDS market rose rapidly between 2004 and 2012, peaking in 2013 with relatively less volume in 2016 than in 2013. The authors also highlighted that the European Union (EU) banned naked trading in sovereign CDS in 2012 due to increased volatility in the European debt market.

1.2 COVID-19 pandemic and its impact on financial markets and world economy

World Health Organization (WHO) removed COVID-19 from Public Health Emergency of International Concern (PHEIC) on 5th May 2023, while Carter et al. (2022) noted that The WHO accepted the COVID-19 outbreak as a health pandemic on 11th March 2020. Liu et al. (2021) mention that the COVID-19 shock was so severe that S&P500, Standard and Poor's equity index declined 34% within 33 days (from 19th February 2020 to 23rd March 2020). Liu et al. (2021) point out that the US Senate passed two trillion-dollar COVID-19 related aid, relief, and economic security act. The S&P500 rallied 9.38% on 24th March 2020 before the Senate passed the bill. Authors also notice that, by the end of April 2020, The COVID-19 crisis was so widespread in the USA that the US economy lost 20.5 million jobs in April and witnessed a 14.7% unemployment rate, a record for monthly numbers since 1948. Apergis et al. (2022, p. 9) have observed that 65 out of 386 sample firms failed between February 2020 and September 2020, indicating the impact of COVID-19 on the overall world economy.

S&P500, Fitch, and Moody's are the top three ratings agencies in the world. S&P500 and Fitch consider debt rated below BBB- rating as non-investment grade, while BBB- and above-rated debt is called Investment Grade (IG). Moody's has a different rating approach. If the debt is rated by Moody's, then ratings below Baa are considered non-investment grade, while Baa and above rated debt is called Investment Grade (IG). Haddad et al. (2021) document that in the USA, IG bonds, High yield corporate bonds, S&P500, and Municipal Bonds, all four asset classes observed negative returns between 1st February 2020 and 30th April 2020, while treasury bonds were the logical exception having positive return for the period due to reasons being flight to safety as well as anticipated federal reserve rate cuts for 2020. The Federal Reserve made a bond purchase announcement twice. On 23rd March 2020, the Federal Reserve announced the purchase of IG bonds, so IG bonds rallied 7% on 23rd March. Fallen angles are the bonds initially rated as IG bonds but subsequently downgraded to a very low rating category or junk status. The Federal Reserve subsequently announced the purchase of fallen angels and high-yield Exchange Traded Funds (ETF) on 9th April 2020, apart from increasing the corporate credit lines from less than 300US billion dollars to US850 billion, and here again, bond markets replied positively. Although the Federal Reserve did not buy any significant bonds till mid-June 2020, the bond market reaction to the Fed announcement proved the credibility of the Fed as a lender of last resort. US central banks kept announcing various money market liquidity measures and relaxations in reporting requirements. However, bond markets reacted only on the days when the Federal Reserve explicitly announced bond purchases. The large investors kept selling the bonds while bond dealers, primarily market makers, could not function

efficiently as arbitrageurs even though significant arbitrage opportunities arose in the IG bond and IG ETF markets. Haddad et al. (2021) also observe that COVID-19 was a health pandemic while the 2007-2008 subprime crisis was a financial event; both crises witnessed different patterns for IG and high-yield corporate bonds. During the GFC in 2008, high-yield bonds fell almost 40% from the spring of 2008 to January 2009 while IG bonds declined by 15 to 20% only; however, IG bonds were leading the sell-off during the COVID-19 crisis since bond investors were more worried about cash liquidity in the shorter term.

We have analysed major determinants of CDS sector indices for a seven-year period that covers aftershocks of COVID-19, which helps in understanding long-term trends of severe economic shock events in the financial research field. We have investigated the impact of structural models' inputs like equity prices, interest rates, and volatility on CDS. Since our sample contains seven years, it has both a low and high volatility period, which allows us to understand the long-term impact of VIX and EPU on CDS indices. Previously, researchers have studied the impact of the CRB index on specific sectors of the economy. Our study marginally contributes to the existing literature related to the CRB index's impact on CDS since we are the first to analyse the CRB index's impact on all the CDS sector indices before, during, and after COVID-19. Our study also covers the impact of crude oil prices on CDS sector indices.

Chapter 2 of the dissertation discusses the prevailing literature, including theories related to credit risk and market dynamics, as well as the determinants and pricing characteristics of CDS. It also covers event-based and sector-based analysis of credit default swaps. In **Chapter 3**, we will explain the data used in the paper and discuss the summary statistics of each CDS sector indices and independent factors for the whole period and sub-periods. **Chapter 4** will discuss the methodology, introducing the panel data and four-panel regression models. **Chapter 5** provides the empirical findings, showing the regression results of CDS for four-panel regression models and then interpreting the findings at sectoral levels and subperiods of the whole sample data. **Chapter 6** concludes the dissertation.

Chapter 2- Literature Review

CDS-related literature covers two main areas: determinants of CDS and event-specific analysis of CDS, followed by a literature review focusing on EPU and commodities.

2.1 Determinants of credit default swaps

Ericsson et al. (2009) attempt to explain credit spread using explanatory variables based on structural models. The authors analysed CDS spread with three main drivers: leverage, volatility, and the term structure of risk-free interest rates. Ericsson et al. (2009) mention that an increase in the risk-free rate will increase the risk-adjusted drift of firm value, which ultimately reduces the firm's default probability. The paper's results align with structural models' expectation of a negative correlation between risk-free rates and CDS. Coefficient estimates for leverage and volatility were higher for lower-rated firms than for higher-rated firms. Principal Component Analysis (PCA) analysis confirmed that theoretical determinants of structural models explained a significant part of the typical variation in CDS. Norden and Weber (2009) analysed the relationship between CDS, bonds, and the stock market. Authors found that mean CDS spreads and mean bond spreads based on swaps are closer for IG bonds, which other researchers have also validated in the past. Norden and Weber (2009) have used a three-dimensional Vector Autoregressive (VAR) model to understand the co-movement of bonds, CDS, and stocks. Norden and Weber (2009) calculated Spearman's rank correlation coefficients and found that CDS spread changes have a significantly negative correlation with stock returns compared to the negative correlation between bonds and stocks. Authors found that lagged stock returns have significant negative effects on CDS and Bond spread changes.

Zhang et al. (2009) focused on equity volatility and jump risk's impact on CDS. The authors calculated the jump's intensity, variance, and mean from the high-frequency equity return data. Zhang et al. (2009) found that volatility could predict 48% of the variations in CDS spread levels, while jump risk alone could anticipate 19% of the CDS spread changes. Hassan et al. (2013) examined the determinants of CDS spread changes with two groups of determinants: firm-specific and macroeconomic variables. As part of the literature review, this paper shows the findings of the previous researchers (in the field of credit markets) in a tabular form, making reading the paper very easy. Hassan et al. (2013) concluded that equity kurtosis and equity skewness did not have a statistically significant effect on CDS spread levels for Europe and the Asia Pacific region. Han and Zhou (2015) analysed drivers of the term structure of CDS. The authors have defined the CDS slope, a dependent variable, as the difference between the 5-year CDS spread and the 1-year CDS spread. This paper analyses monthly observations of 590 US firms between January 2001 and December 2012. Han and Zhou (2015) conclude that the CDS term structure's slope increases with the volatility and leverage

of the company and decreases with the level and slope of the government bond yield curve. Researchers also found that the CDS slope can predict future changes in CDS spreads even after controlling for the structural model's independent variables. The authors conclude that the combined explanatory power of the variables suggested by structural models is low, which signals a missing factor affecting the individual firms' CDS slope.

Pires et al. (2015) used quantile regression to test whether CDS spreads change differently for changes in the explanatory variables depending on whether the firm was in the left tail of the distribution or the right tail of the quantile distribution. The paper validates the well-recognized fact that high-risk firms are more susceptible to changes in explanatory variables than low-risk firms. Pires et al. (2015) used accounting ratios and Distance to Default (DD) as suggested by Moody's KMV Model. Researchers also used put skew as an independent volatility factor to indicate a higher probability of a downside jump in firm value. Put skew was calculated as the difference between 25 and 50 delta volatilities. Pires et al. (2015) have found that the fit of the model increases with the conditional quantile of the CDS spreads, which is in line with the credit spread puzzle that the structural model underestimates CDS spreads of low-risk firms while an underestimation of the CDS spreads of a high-risk firm is at low severity level (compared to low-risk firms). The authors noted that estimated slopes for implied volatility, put skew, ratings, and absolute Bid-Ask spreads were increasing functions of the conditional quantile of the CDS spread. The authors conclude that quantile regression helps in exposing a significant amount of heterogeneity. Hasan et al. (2016) explored the determinants of bank CDS spreads across the globe. The authors found that the model with structural variables explained only around 20% of the CDS spread movement, confirming the credit spread puzzle for the finance firms rather than the industrial firms.

Hibbert and Pavlova (2017) studied the impact of local vs global factors on the sovereign (government) CDS spread changes. The authors built three models, each combining different global factors. Model 1 includes only global factors related to US market conditions, while Model 3 includes global factors related to ex-US market conditions. Model 2 includes global factors related to the US and non-US market conditions. Hibbert and Pavlova (2017) found that Latin American sovereign CDS were driven by global factors like volatility and long-term bond rates, while credit rating changes in the upper quantile of the conditional distribution drove European sovereign CDS. US stock market and bond market changes were highly significant independent variables for all the quantiles. The authors also found that US Fed funds rates did not impact Latin American sovereign CDS.

2.2 Event based analysis of credit default swaps

Breitenfellner and Wagner (2012) explored the lead-lag relationship between iTRAXX spread changes and stock returns before, during, and after the 2007-2009 crisis. iTRAXX suite of CDS indices has been owned and managed by S&P Global since 2022, and prior to that, iTRAXX CDS indices were compiled and published by Markit, a financial firm that merged with S&P Global in 2022. The authors examined the behavior of upper and lower quantile credit spread changes. Breitenfellner and Wagner (2012) found that stock market returns had more influence on credit spread than stock market volatility during the financial crisis period. The authors could not confirm a visible lead-lag relationship before the crisis period. During the crisis, stock returns led to CDS spread changes for almost all iTRAXX subindices. A two-sided relationship between CDS spread changes and stock returns occurred after the crisis. Dieckmann and Plank (2011) explored the reasons behind elevated levels of sovereign CDS for Western European countries since the GFC of 2008. Dieckmann and Plank (2011) used panel regression with time-fixed effects of CDS spreads on global and country-specific explanatory variables for a sample period between January 2007 and April 2010. Authors found that stock market index volatility, Debt to Gross Domestic Product (GDP) ratio, forex reserves, and the country's exposure to the financial system impacted the western European sovereign CDS at a 1% significance level. The authors tested the hypothesis of whether high exposure to subprime mortgages impacted a country's sovereign CDS and found that exposure to subprime mortgages at the country level did not impact a country's sovereign CDS at a significant level.

Coro et al. (2013) analysed liquidity drivers of corporate CDS in detail, followed by credit components between January 2006 and July 2009. Researchers used average bid-ask spread and an asymmetric information measure as industry-wide liquidity proxy parameters. The authors calculated asymmetric information measure based on the trade initiation by classifying the trades among the three categories: buyer-initiated, seller-initiated, or undetermined. The authors used novel approaches to define quote imbalance and demand pressure, a strong point of this research paper. The authors found that liquidity risk was more crucial than credit risk drivers of an individual firm regardless of market conditions. Coro et al. (2013) regression results showed that firm-specific and industry-wide bid-ask spreads have the most significant explanatory power, having adjusted R-squared of +34.1% and +13.7%, respectively.

Chiaromonte and Casu (2013) have attempted to cover a complete universe of research conducted in the field of credit risk by splitting their literature review into two groups that are "pricing characteristics of CDS spreads" and "determinants of CDS spreads and their variations." Pricing

characteristics of CDS spreads cover the relationship between CDS and corporate bonds. The authors observed that prior researchers have focused on showing the importance of CDS over corporate bonds in the backward calculation of implied default rates. The authors mention that financial researchers have used either a structural approach or a reduced-form approach for analysing the determinants of CDS. Chiaramonte and Casu (2013) analysed the determinants of bank CDS during the financial crisis. This paper is unique because the authors used quarterly balance sheet data of eight accounting variables from four categories: asset quality, operations, capital, and liquidity. The authors have provided tables showing predicted signs of the coefficient of independent variables before conducting regression analysis. Chiaramonte and Casu (2013) found that the balance sheet variables explained nearly 64% of CDS spread changes. The authors noticed that the loan loss reserve to gross loans ratio was the only significant variable for all three sub-periods of crisis: pre-crisis, during, and post-crisis. Leverage and tier 1 capital ratios were no significant determinants of bank CDS for any of the three sample periods.

Annaert et al. (2013) analysed the European bank CDS for the pre and post-GFC crisis, considering 2nd April 2007 as a breakpoint since US subprime lender New Century Financial Corporation filed chapter 11 bankruptcy that day. Annaert et al. (2013) found that individual CDS liquidity measured by Bid-Ask spread was essential through the sample period and became more critical during the crisis. The authors also proved that the risk-free rate and leverage explained a substantial part of CDS spread changes during the crisis; however, equity volatility was unrelated to CDS spread changes during the GFC crisis period. Annaert et al. (2013, p. 16) concluded that credit risk was not the only source of CDS spread changes; however, structural variables mentioned in Merton (1974) became necessary when the credit status of the bank was under pressure.

Haddad et al. (2021) documented US debt market events during the most critical period of COVID-19, which was between January 2020 and June 2020. The authors have run regression models with bond spread changes as dependent variables while using ratings, crisis period, liquidity, and maturity of the bonds as independent variables. After observing regression results, Haddad et al. (2021) found that IG bonds were traded at a discount to credit default swaps. The authors compared the Bond-CDS basis spread for IG and non-IG bonds, and they found significant differences in the Bond-CDS basis for IG bonds due to the investors' requirement for cash liquidity. Exchange Traded Funds (ETF) were traded at a discounted price to Net Asset Value (NAV). During the peak of the crisis, IG ETFs were trading at a 5% discount to their underlying bonds. However, such arbitrage was not observed between high-yield ETFs and their underlying bonds. The authors concluded that the US central bank's

announcement of corporate bond purchase prompted prices to rebound and arbitrage in debt markets to disappear partially. Since banks were not major investors in corporate bonds during COVID-19, authors contemplated that bond mutual funds were leading the liquidation of sizable corporate bond positions. The authors also found that bonds of companies with significant bond issuance plans observed more selling compared to others.

Liu et al. (2021) studied the COVID-19 effects on CDS spread changes and abnormal stock returns with different levels of debt rollover requirements in the context of the US economy. Liu et al. (2021, p. 6) found that regression coefficients of Return on Assets (ROA), past returns, and stock volatility were statistically significant, indicating that companies having higher profitability, lower past stock returns, and greater stock volatility witnessed a significant increase in CDS spread during the COVID-19 crisis. The authors calculated the debt rollover measure as the ratio of a company's short-term debt (maturing within a year) to cash reserve before the crisis. The authors found that US companies witnessed lower stock market returns in March 2020 for firms having high exposure to debt rollover, and this phenomenon was observed more for real economy sector companies than the financial sector companies. Liu et al. (2021) concluded that firms with higher debt rollover risk had to witness shareholder wealth erosion and increased CDS spread levels. The authors concluded that the timing of the debt rollover was crucial, such that firms with immediate refinancing needs suffered more than those with refinancing requirements in the distant future.

Carter et al. (2022) investigated the stock return performance of travel-related firms (airlines, restaurants, and hotels) from the second half of February 2020 to the end of March 2020, a period that was the most volatile for US financial markets due to confirmation of coronavirus on US soil in February as well as relief package announcement by US senate on 25th March 2020. Carter et al. (2022) have concluded that there were abnormal returns during the sample period; abnormal returns were not the same for each firm within the industry, and market participants could distinguish the firms within the industry. Carter et al. (2022, p. 7) found that the large firms with higher cash reserves and higher market-to-book ratios were associated with less negative returns, while the leveraged firms' stocks were sold off heavily. The authors found that cash reserves were a critical factor in hotel stocks.

Apergis et al. (2022) analysed the impact of COVID-19 cases and deaths on CDS spreads at the global level. Authors had to rely on research reports based on other credit instruments like corporate bonds' default rates, except for one or two reports covering the movement of CDS spreads during COVID-19.

Apergis et al. (2022) noted how balance sheet trouble could arise for banks. On the one hand, banks faced withdrawal of deposits and funds, and at the same time, default rates increased from borrowers, so banks' asset quality came under heavy pressure. Researchers found different levels of impact across sectors, mainly banking, transportation, airline, and travel, among the hardest-hit groups. The authors found that the null hypothesis of non-causality was rejected in COVID cases and deaths, thus proving the existence of causality between COVID-19 metrics and CDS spreads. W. Zhang et al. (2022) investigated the impact of China's sovereign risk on other economies and other economies' impact on China's sovereign risk through CDS. W. Zhang et al. (2022) found that changes in China's sovereign risk had strong contagion effects on its suppliers. Meanwhile, China's sovereign risk was affected by its major importers' contagion effects, which confirmed the sovereign risk spillover through the global supply chain. The authors found that China's sovereign risk was negatively impacted by the US subprime loan default-driven GFC in 2008 and the European sovereign crisis of 2011.

Hasan et al. (2023) measured the impact of COVID-19 on companies across the globe. The authors found that at the firm level, more than stock volatility. The authors found that firms active in Corporate Social Responsibility (CSR) observed smaller changes in CDS spread. In contrast, firms with weaker corporate governance witnessed a sharp rise in CDS spread. The authors also found that countries with higher GDP, low Foreign Direct Investment (FDI), and politically stable environments were more resilient to the pandemic. Hasan et al. (2023) concluded that higher infection rates negatively affect firms with higher leverage, closer to default, weak governance, and limited stakeholder engagement. This was reflected in wider CDS spreads during the COVID-19 period.

It is natural to analyse the relationship between equity and interest rates with CDS spread, and the structural model suggests that equity returns are negatively correlated with CDS, as shown in Norden and Weber (2009) , while for interest rates, we also expect CDS to be negatively correlated with interest rates, as shown in Ericsson et al. (2009).

Considering the literature under section 2.1 and section 2.2, we propose the following hypothesis:

H1: Equity and interest rates are associated with CDS spread as per structural models such that both the variables show a negative association with CDS spread for the entire sample period and sub-periods.

2.3 Economic Policy Uncertainty (EPU) and its impact on financial markets

Baker et al. (2016) have developed an EPU index for the USA and analysed its changes since 1985. The authors constructed the EPU index based on a combination of three areas: uncertainty, economy, and the specific field for which economic uncertainty is to be measured, for example, "deficit". The authors extended policy uncertainty measurement across three dimensions: time, countries, and a specific policy category. Baker et al. (2016) found a statistically significant impact of EPU on equity volatilities, investment rates, and employment growths in specific sectors like healthcare, finance, and infrastructure construction.

Wisniewski and Lambe (2015) concluded that the first difference series of iTRAXX and CDX indices were granger caused by political uncertainty. The authors pointed out that EPU affects CDS through two channels: economic stimulation due to fiscal and monetary policy changes and systematic risk of fiscal and monetary shocks. Wisniewski and Lambe (2015) tested the impact of EPU subindices related to the government budget, CPI forecast, and budgetary revenue uncertainty on CDS index spread changes. Authors found that EPU granger caused the CDX North America Investment Grade index (CDX NA IG index).

Pan et al. (2019) conducted text analysis to measure the impact of the word "Uncertainty" on sovereign CDS. Pan et al. (2019) used the World Uncertainty Index (WUI), which is developed by Ahir et al. (2018). The WUI index is based on text analysis related to the frequency counts of "Uncertainty" in the quarterly Economist Intelligence Unit (EIU) country reports covering 189 countries. According to the authors, WUI is less subject to bias than the EPU index since WUI gives more weight to local events than the EPU index. Pan et al. (2019) found that a 1% increase in uncertainty caused a 0.86% increase in sovereign CDS. The authors tested Granger causality at a 1% significance level and proved that WUI caused the fluctuation in sovereign CDS, not vice versa.

Wang et al. (2018) investigated the impact of the EPU index on CDS of US firms and the number of liquidity providers of CDS quotes. The researchers used a relatively extended period between January 2001 and October 2016. The authors regressed CDS on independent variables like the EPU index, accounting factors like firm size, leverage, profitability, and market variables like volatility, momentum, VIX, and TED spread (difference between Eurodollar futures and treasury yield). Wang et al. (2018) found that a 10% increase in EPU brought an 8.4% increase in CDS and a 4% decrease in the number of liquidity providers. The authors also confirmed that the impact of the EPU index on CDS is more pronounced during recessionary periods.

Smales (2021) used EPU to measure the impact of uncertainty on Australian financial markets. The authors calculated monthly returns between January 1997 and March 2020. The authors used a regression model with the stock return, bond yield change, or FX return as the dependent variables while having the EPU index as an independent factor, keeping the vector of macro variables as control factors. Smales (2021) found that global and domestic uncertainty impacted equity return, bond yields, and Australian Dollar (AUD) currency; however, uncertainty impact varied depending on the state of the economy. The authors proved that the relationship between EPU and returns of equity, bond yields, and FX was more concentrated in the left tail of the return distribution. Uncertainty mattered more during the recession, before election results, and during the event-driven high uncertainty period. The authors found that the change in EPU impacted equity and bond yields at a 5% significance level while the AUD FX rate was impacted at a 1% significance level. The authors have proven that higher discount rates (higher risk premium) in financial market valuation reflect uncertainty. The authors found that EPU impacted equity returns of consumer discretionary, consumer staples, energy, information technology, and material sectors at a 5% significance level.

Uncertainty impacts all financial assets. Recent developments in the field of Large Language Models (LLM) have made it possible to measure economic policy uncertainty through text analysis. We expect positive correlation between EPU index and CDS, as shown in Wisniewski and Lambe (2015) and Wang et al. (2018). Researchers have traditionally relied on VIX index to measure the impact of uncertainty on CDS, as shown in Hammoudeh, Liu, et al. (2013). Researchers have tested the EPU index's impact on various financial assets however there exists a research gap since no prior research has focused on relative importance of EPU index and VIX index for analysis of CDS sector indices We will test whether EPU index's impact on CDS is more or less than that of VIX index.

Regarding the literature reviewed under section 2.3, we propose the following hypothesis:

H2a: An increase in EPU should lead to an increase in the CDS spread.

H2b: The effect of EPU on the CDS spread is stronger than that of the VIX.

2.4 Commodities and their impact on financial markets

Z. Zhang et al. (2022) found that emerging market sovereign CDS moved in the opposite direction of commodity prices between March 2009 and April 2022. Countries dependent on exports witnessed a significant reduction in sovereign risk when commodities had large upward moves; however, significant downward moves in commodity prices had a limited impact on the sovereign risk increase of export-driven countries. Sun et al. (2020) built a spillover network to find the interaction patterns among sovereign CDS, stocks, and commodities markets from May 2009 to December 2017. The authors used West Texas Intermediate (WTI) crude, Brent crude oil, and gold prices as commodity indicators and analysed G7 and developing countries' sovereign CDS. Major economic or financial events initiate spillover among different markets. The authors concluded that stock markets occupied the dominant position for most of the period. Lee and Ni (2002) relied on the most explored theories of oil price shock's impact on the economy: input cost and income effect. The authors confirmed that the use of oil is concentrated in two industries: petroleum refinery and industrial chemical, while the auto industry faces reduced demand due to sudden increases in oil prices. Lee and Ni (2002) investigated whether the shocks in oil prices delayed the purchase of durable goods. They found that the increased operating cost and heightened uncertainty are the medium for oil price shocks to bring the economy towards recession.

Hammoudeh, Liu, et al. (2013) investigated the impact of the VIX index and the SMOVE index (Swaption Merrill Lynch Option Volatility Estimate) on four oil-related CDS sector indices that are chemical, auto, oil & gas, and utilities. The authors applied a vector Error Correction Model (VECM), Impulse Response Function (IRF) analysis, and cointegration tests from 2004 to 2011. IRF analysis confirmed that CDS had the most potent response towards VIX and CDS sector index's own shock, while no sector showed sensitivity towards the SMOVE index. Auto sector CDS was the most error-correcting for the total sample period, while the utility sector did not show error correction. Balcilar et al. (2020) examined the impact of volatility spillover across oil-related CDS, oil markets, and stock markets from 2004 to 2020. The researchers found the link between oil and oil-related CDS through demand and supply transmission channels. Balcilar et al. (2020) also selected the same oil-related sectors, which are chemical, auto, oil& gas, and utilities, as were selected by Hammoudeh, Liu, et al. (2013). Ma et al. (2023) analysed CDS of supply chain firms in the oil industry with endogenous shocks due to oil prices and event-specific exogenous shocks. The authors used panel VAR methodology to trace the effects of shock. The authors concluded that the CDS of upstream firms experienced the most significant shock from the oil prices, while the oil price fluctuation did not impact downstream firms' CDS much.

Fan et al. (2014) decomposed gold's value into three parts: commodity value, currency value, and hedging value. The authors used the CRB index to measure gold's commodity value, while the US treasury CDS and the US dollar index were used to measure the "sovereign default risk premium," a proxy for the currency value of the gold. The authors argued that the US dollar index can also be used to measure the hedging value of gold. The authors applied the VAR model and found that one lagged CRB index, two lagged US treasury CDS, and one lagged US dollar index significantly impacted gold prices. Bouri et al. (2017) used causality tests to analyse the impact of the Commodity Research Bureau (CRB) index, equal-weighted CRB index, and CRB sub-indices on sovereign CDS of emerging and frontier countries. Energy and precious metal indices significantly influenced the variance of sovereign CDS. Shen et al. (2017) investigated how media-based emotions can predict commodity returns. The authors used Thomson Reuters MarketPsych Indices (TRMI), built on textual analysis, and tested their effectiveness in predicting the CRB index, crude oil, and gold. Researchers used the Threshold generalised Autoregressive Conditional Heteroskedasticity (TGARCH) model to test the effectiveness of TRMI index variables representing four emotions on the returns of commodities. The four TRMI variables were sentiment, optimism, fear, and joy. The authors found that commodity-specific emotions significantly influenced individual commodity returns but not the CRB index.

COVID-19 created supply chain problems through government enforced lockdowns and reduced level of economic activity, which in turn impacted commodities markets. We have found a research gap that reviewed research papers have analysed impact of CRB index or crude oil on selected sectors of the economy. We will address this research gap by running panel regression on all the CDS sector indices.

Concerning the literature reviewed under section 2.4, we propose the following hypothesis:

H3a: The commodity index is related to the CDS spread.

H3b: The commodity index and CDS relationship should be stronger during the COVID-19 period.

H3c: Commodity index explains CDS spread better than crude oil.

Chapter 3- Data

3.1 Data Collection

Financial data is collected from the Refinitiv database for daily and weekly time series of CDS indices, equity indices, commodity index, interest rates, and volatility index. The daily EPU index time series developed by Baker et al. (2016) is downloaded from www.policyuncertainty.com website. Since the original data is based on basis points for CDS and yield level for interest rates apart from price level data for indices and US oil exchange-traded fund (ETF), it has been transformed into the natural log to reduce the impact of non-stationarity, if any.

The Refinitiv database provides sectoral CDS indices based on its proprietary methodology, The Refinitiv Business Classification (TRBC). The assignment of underlying constituents to the sector is not exactly like the Global Industry Classification Standard (GICS) methodology; however, it is comparable with the GICS methodology. Each of the ten sectors has CDS sector indices based on constituents' credit ratings. The Refinitiv workspace uses Standard & Poor's (S&P) ratings between AAA and B. We have selected CDS sector indices with 5-year maturity since they are the most liquid and widely tracked by market participants. US treasury 5-year yield is chosen as an independent interest rate variable to match the maturity profile of CDS sector indices.

We have not included benchmarks and agency sector indices available in the Refinitiv database because they are unrelated to any economic sector. There are 39 sector indices among the ten sectors mentioned below. We have analysed 35 sector indices, excluding the four CDS sector indices with the stale data in daily time series. Refinitiv has the below-mentioned CDS sectors at the global level.

1. Banks
2. Consumer goods
3. Energy companies
4. Manufacturing
5. Other financials
6. Electricity and Power
7. Sovereign
8. Service companies
9. Telecommunication
10. Transport

Coro et al. (2013) examined subprime events by dividing the sample period between pre-crisis and crisis. Dieckmann and Plank (2011) analysed subprime events by dividing the period between January 2007 and April 2010 into pre- and post-crisis periods. The authors considered 15th September 2008 a pre-and post-crisis breakpoint since the Lehman Brothers defaulted on that date. Annaert et al. (2013) considered 2nd April 2007 as a breakpoint and examined the US subprime events by dividing the period between pre- and post-crisis. We have applied Chiaramonte and Casu (2013)'s US subprime crisis-related event analysis approach , where the authors have divided the total sample period into pre-crisis, during the crisis, and post-crisis. This approach allows a specific focus on high volatility period as part of the “during the crisis” period.

COVID-19 was first detected in December 2019 in China, and the World Health Organisation (WHO) announced COVID-19 as a Public Health Emergency of International Concern (PHEIC) on 30th January 2020. The WHO accepted the COVID-19 outbreak as a health pandemic on 11th March 2020 while removing COVID-19 from the public health emergency list on 5th May 2023. All the G20 country lockdowns due to COVID-19 occurred between 2020 and 2021. We aim to study the impact of COVID-19 on financial markets, so we have considered 2020 and 2021 as the COVID period. We have taken care of having at least two years of sample data before and after the crisis to analyse a two-year COVID-19 period with pre- and post-crisis periods of comparable length.

We have divided the sample period from 1st January 2017 to 29th December 2023 as below.

1. Before COVID-19 period- From 1st January 2017 to 31st December 2019.
2. COVID-19 period- From 1st January 2020 to 31st December 2021.
3. After COVID-19 period- From 1st January 2022 to 29th December 2023.

3.2 Variables

CDS sector Indices:

One basis point is equal to 1/100th of a percentage point. Market participants quote and measure credit risk at a basis point level, so we used 10 CDS sector indices reported in basis points by the Refinitiv database. Refinitiv has its own calculation methodology. The CDS sector index is calculated based on a universe of single-name CDS priced by Refinitiv's end-of-the-day CDS composite pricing service. Only senior convention CDS are included in the universe. Constituents are sorted based on their rating, sector, and sub-sector buckets. Refinitiv uses S&P foreign long-term rating with seven rating buckets: AAA, AA, A, BBB, BB, B, and CCC. D& NR ratings are excluded. Single-name CDS are assigned to a specific sector based on The Refinitiv Business Classification (TRBC), a market-based classification scheme that classifies companies based on the degree of impact on markets. Refinitiv considers factors like revenue, profitability, asset utilisation, and market perception to classify a company to one primary TRBC activity. The industry, industry group, business sector, and economic sector assignments are derived from the classification hierarchy. The CDS sector indices included in this dissertation are as follows.

1. Banking sector CDS indices: AA, A, and BBB rated banking sector CDS indices with underlying constituent names like Standard Chartered Bank, ANZ bank, Commerzbank, Deutsche Bank, Citigroup, Barclays, UBS, Goldman Sachs, HSBC, Well Fargo, have been analysed. Most of these companies are part of the business sector defined as "banking and investment services."
2. Consumer sector CDS indices: The noncyclical consumer economic sector, mainly the food and beverages business sector, is used to constitute A and BBB-rated consumer CDS indices. Coca-Cola, Diago, PepsiCo, Philip Morris, Unilever, Bacardi, Danone, Heineken, and Japan Tobacco are some of the world-recognised names that are the underlying constituents of consumer CDS indices.
3. Energy sector CDS indices: AA, A, and BBB-rated energy sector CDS indices are constructed with underlying constituent names like Chevron, Exxon Mobil, BP, ConocoPhillips, Reliance, Suncor Energy, and Petrobras. These constituents belong to the Energy-Fossil fuels business sector.
4. Manufacturing sector CDS indices: A, BBB, BB, and B rated energy sector CDS indices are constructed with underlying constituent names like Siemens, ABB, AMD, BASF, Apple, LVMH, Caterpillar, Hitachi, Honeywell International, Lockheed, Rio Tinto, 3M, Boeing, GM, HP, Nippon steel, Whirlpool and Sharp. These constituents belong to economic sectors like industrial, consumer cyclical, basic materials, and technology.

5. Non-bank financial sector CDS indices: AA, A, BBB, and BB rated non-bank financial sector CDS indices have underlying single name CDS constituents like Aviva, MetLife, Prudential, Munich Re, AXA, AIG, Nomura holdings, and Boston Property. Most of these constituents belong to the insurance business sector.
6. Power sector CDS indices: Power sector CDS indices are created based on the utilities economic sector, mainly electric utilities. These indices are classified based on three rating categories: A, BBB, and BB.
7. Service sector CDS indices: Various single-name CDS firms belonging to business sectors like retailing, healthcare service, pharmaceutical and medical research, cyclical consumer services, and food retailing were used to create service sector CDS indices across five rating categories: AA, A, BBB, BB, and B.
8. Telecommunication sector CDS indices: A and BBB-rated telecommunication sector CDS indices have underlying constituents like Singtel, Chorus, AT&T, Telenor, Ericsson, Orange, Telefonica, Verizon, and Vodafone group.
9. Transportation CDS indices: A, BBB, and BB-rated transportation sector CDS indices have industry groups like freight and logistic Services and passenger transportation services. Some notable constituent names are UPS, East Japan Rail, Union Pacific, FedEx, Air France KLM, Delta Air, and United Airlines.
10. Sovereign sector CDS indices: Sovereign sector CDS indices have six rating categories: AAA, AA, A, BBB, BB, and B. Countries like Australia, Germany, Netherlands, and Sweden belong to the AAA-rated CDS index, while countries like Egypt and Iraq belong to the B rated CDS index.

S&P500:

We have selected Standard & Poor's 500 as an independent variable representing equity risk since it represents a diverse sectoral portfolio of the USA companies. S&P500 companies can also be classified based on GICS methodology, making comparing with CDS sector indices more meaningful.

STOXX50:

We have selected EURO STOXX50 as the independent variable. EURO STOXX50 is a stock index designed by STOXX, an index provider owned by major European stock exchanges. EUROSTOXX50 is a widely tracked equity indicator of the European economy since it represents fifty of the Euro Zone economy's largest and most liquid stocks.

US 5-year Treasury Yield:

We have selected the US government 5-year treasury note yield as an independent variable representing interest rate risk.

VIX:

The CBOE volatility index is used as an indicator of financial market volatility since it is calculated based on the expectation of the S&P500 's volatility.

Economic Policy Uncertainty (EPU):

Baker et al. (2016) built EPU indices of policy-related economic uncertainty based on newspaper coverage frequency. We have used the daily EPU index for the United States as an independent factor, which reflects the frequency of articles in 10 leading USA newspapers. Authors have conducted text analysis based on a trio of the terms: "economy" or "economic," "Uncertainty" or "Uncertain," and one or more of the "legislation," "regulation," "deficit," "Federal Reserve," "White House," "Congress."

TRCC Commodity Research Bureau (CRB) Index:

Since TRCCRB represents diverse commodity markets, we have used the TRCCRB excess return index as an independent variable, a widely tracked commodity index. The CRB excess return is calculated using individual commodity percentage returns. TRCCRB index is comprised of 19 individual commodities. Group 1 represents energy commodities: WTI crude oil, Heating oil, and Unleaded gas weighing 23%,5%, and 5%, respectively. Group 2 consists of energy, agriculture, and metal commodities, which are natural gas, corn, soybeans, live cattle, gold, aluminum, and copper, each having an index weight of 6%. Group 3 represents agriculture commodities: sugar, cotton, cocoa, and coffee, each having an index weight of 5%. Group 4 consists of nickel, wheat, orange juice, lean hogs, and silver, each having only 1% index weight.

United States Oil Fund (USO):

USO is a Refinitiv ticker for the United States oil fund ETF. The Fund targets to be representative of the performance of the spot price of West Texas Intermediate (WTI) light, sweet crude oil delivered to Cushing, Oklahoma, by investing in various oil futures contracts and other oil-related contracts. USO is the most liquid and one of the largest crude oil-related ETFs, so we have used USO as an independent variable to measure crude oil's impact on CDS.

3.3 Descriptive Summary

We have analysed the Mean, Median, Standard Deviation, Kurtosis, and skewness of all the dependent and independent variables for the entire sample period and before, during, and after COVID-19 with daily data.

We first analysed the whole sample period. We can observe from **Table 1** that the highest CDS spread of 1504.53 basis points(bps) was registered by the B-rated CDS index of the service industry, while the AAA-rated sovereign CDS index registered the lowest CDS spread of 8.17 bps. Maximum spread is from a low-rated index while minimum CDS spread is from a high-rated index, which is acceptable since low-rated firms have a higher probability of default, and high-rated firms have less probability of default.

The highest mean spread for the BBB-rating was from the non-bank financial sector, with a CDS spread of 98.06 bps, while the highest mean spread for A-rating was from the energy sector, with a CDS spread of 61.91 bps. For each sector except telecommunication, the difference between BBB-rating and A-rating mean spread is more than 20 bps. The service sector had a difference of 42 bps between the BBB and A-rated indices. In contrast, telecommunication had a difference of 12 bps: 79 bps for the BBB-rated index and 67 bps for the A-rated index.

BB and B rating indices have higher standard deviation levels. In contrast, all the A-rating indices have less than ten standard deviations. Low-rated firms have high volatility, so a higher standard deviation among low-rated firms is acceptable. BBB-rated CDS index of the energy sector has the highest kurtosis, while AA-rated CDS index of the service sector has the lowest kurtosis. Banking is the only sector with all the indices showing negative excess kurtosis.

Table 1- Summary of variables, the entire sample period

Variable	Rating	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Obs.
Banking CDS Indices	AA	48.48	11.07	24.28	83.73	0.05	2.39	1,818
	A	57.02	14.86	33.02	107.71	0.63	2.75	1,818
	BBB	87.64	18.64	54.22	158.40	0.40	2.71	1,818
Consumer CDS Indices	A	42.60	4.20	25.16	59.11	0.50	4.56	1,818
	BBB	63.12	12.13	39.08	101.72	0.62	2.92	1,818
Energy CDS Indices	AA	42.93	13.31	25.69	106.46	1.65	6.08	1,818
	A	61.91	16.28	38.72	147.75	1.29	5.20	1,818
	BBB	94.67	25.80	56.58	310.89	3.70	22.83	1,818
Manufacturing CDS Indices	A	47.08	6.86	34.24	77.27	1.06	4.12	1,818
	BBB	84.56	18.10	57.88	175.86	1.48	5.21	1,818
	BB	212.86	59.50	92.73	420.86	0.88	3.17	1,818
	B	431.38	154.85	241.22	1,026.22	1.36	3.96	1,818
Non-Bank Financials CDS Indices	AA	49.08	9.30	31.12	92.21	1.36	5.42	1,818
	A	61.77	8.73	40.11	91.54	0.88	3.68	1,818
	BBB	98.06	10.47	67.87	148.13	0.46	2.59	1,818

	BB	195.19	65.34	95.47	464.53	0.77	3.19	1,818
	A	48.53	11.63	23.67	85.97	0.99	3.58	1,818
Power CDS Indices	BBB	71.11	13.77	48.55	117.90	0.84	3.60	1,818
	BB	219.96	87.09	89.39	502.18	0.38	2.28	1,818
	AA	28.58	5.65	15.02	41.92	0.04	2.03	1,818
	A	37.17	5.82	26.88	61.01	0.73	3.16	1,818
Service CDS Indices	BBB	79.20	12.66	57.26	155.13	1.24	6.79	1,818
	BB	232.46	51.26	149.85	544.72	1.47	6.12	1,818
	B	552.91	187.21	308.46	1,504.53	1.09	3.33	1,818
	AAA	14.82	4.43	8.17	25.45	0.90	2.56	1,818
	AA	32.18	7.15	15.61	49.55	-0.38	2.74	1,818
	A	60.34	11.39	33.80	102.39	0.64	3.13	1,818
Sovereign CDS Indices	BBB	96.73	21.04	61.94	176.40	0.86	3.49	1,818
	BB	212.75	35.10	101.37	312.75	0.19	3.28	1,818
	B	465.93	85.35	301.12	793.73	0.95	3.88	1,818
	A	30.77	5.47	18.42	49.90	-0.22	3.09	1,818
Transportation CDS Indices	BBB	81.38	14.66	50.27	167.07	0.49	3.58	1,818
	BB	231.45	89.02	123.72	973.25	2.62	14.61	1,818
	A	66.80	16.11	27.94	130.59	-0.17	2.37	1,818
Telecommunication CDS Indices	BBB	79.22	11.19	56.80	129.97	0.48	3.16	1,818
Commodity Index	TRCCRB	210.15	48.35	106.29	329.59	0.50	2.22	1,818
EPU Index	EPU	138.16	98.66	10.92	807.66	2.36	10.22	1,818
Euro Stoxx 50	STOXX50	3,663.22	400.20	2,385.82	4,549.44	0.20	2.47	1,818
Oil ETF	USO	73.77	24.94	17.04	128.64	-0.30	2.31	1,818
S&P500	S&P500	3,426.73	756.19	2,237.40	4,796.56	0.16	1.55	1,818
US Govt Bond Yield	US5YT	2.15	1.22	0.20	4.96	0.23	2.17	1,818
Volatility Index	VIX	19.19	8.08	9.14	82.69	2.31	13.34	1,818

We can observe from **Table 2** that the highest CDS spread of 597.61 bps is from the B-rated CDS index of the service industry, while the lowest CDS spread of 10.08 bps is from the AAA-rated sovereign CDS index. The B-rated CDS index of the service industry has the highest standard deviation, while the lowest standard deviation is of the A-rated consumer CDS index. Most CDS indices are Platykurtic, indicating lighter tails and fatter peaks.

We analysed the mean CDS spread difference between A and BBB rating CDS indices for each sector. Before COVID-19, The transportation sector had a difference of 45 bps between the BBB and A-rated CDS index, the highest difference among all the ten sectors. The telecommunication sector had an anomaly since the BBB-rated CDS index mean spread was 76.23 bps, which was two basis points lower than the A-rated CDS index (78.63 bps).

Table 2- Summary of variables, Before COVID-19

Variable	Rating	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Obs.
Banking CDS Indices	AA	49.53	7.33	35.88	70.35	0.56	2.49	779
	A	54.18	8.85	36.96	74.58	0.50	2.60	779
	BBB	89.92	15.92	59.90	125.85	0.25	2.08	779
Consumer CDS Indices	A	42.34	2.94	29.08	47.04	-1.02	4.52	779
	BBB	65.07	12.98	45.36	101.72	0.51	2.62	779
Energy CDS Indices	AA	39.86	10.70	25.69	65.21	0.71	2.20	779

	A	54.28	10.37	38.72	85.03	1.04	3.50	779
	BBB	93.22	17.52	56.58	138.45	0.71	2.47	779
Manufacturing CDS Indices	A	46.03	3.91	34.49	58.00	0.32	3.50	779
	BBB	79.07	8.88	57.88	105.42	0.15	2.82	779
	BB	174.09	25.36	92.73	253.19	0.34	3.61	779
	B	358.90	71.36	241.22	547.36	0.60	2.14	779
Non-Bank Financials CDS Indices	AA	46.47	4.61	36.66	61.16	0.33	2.55	779
	A	58.98	5.64	40.11	73.45	0.08	3.00	779
	BBB	93.59	6.65	67.87	107.74	-0.09	3.14	779
Power CDS Indices	BB	145.79	26.99	95.47	223.65	0.48	2.55	779
	A	46.11	4.99	31.52	57.89	0.20	3.16	779
	BBB	77.06	13.71	53.88	117.90	0.95	3.65	779
Service CDS Indices	BB	139.20	33.55	89.39	223.99	0.53	2.12	779
	AA	29.61	3.86	21.59	39.14	0.13	2.89	779
	A	37.82	5.20	29.53	56.82	1.02	4.10	779
	BBB	80.62	7.83	57.99	102.29	0.38	2.92	779
Sovereign CDS Indices	BB	202.39	19.85	149.85	259.57	0.19	3.06	779
	B	456.74	48.75	343.00	597.61	0.03	3.00	779
	AAA	15.42	4.49	10.08	25.45	1.02	2.50	779
	AA	35.73	5.15	21.01	49.55	0.33	2.49	779
Transportation CDS Indices	A	60.27	8.43	42.90	83.46	0.68	3.00	779
	BBB	96.52	14.59	69.24	134.14	0.53	2.69	779
	BB	213.07	18.71	165.86	260.84	0.08	2.64	779
	B	437.74	47.28	301.12	590.91	-0.37	3.23	779
Telecommunication CDS Indices	A	27.29	4.97	18.42	37.10	-0.27	1.92	779
	BBB	71.85	8.60	50.27	89.93	-0.34	2.23	779
	BB	175.02	23.64	125.68	242.79	0.23	3.55	779
Commodity Index	TRCCRB	185.69	8.62	166.50	206.38	0.15	2.22	779
Oil ETF	USO	95.33	12.22	69.68	128.64	0.34	2.51	779
EPU Index	EPU	94.11	44.59	10.92	305.98	1.39	5.76	779
Euro Stoxx 50	STOXX50	3436.64	158.79	2937.36	3782.27	-0.59	3.29	779
S&P500	S&P500	2702.38	228.37	2238.83	3240.02	-0.03	2.25	779
US Govt Bond Yield	US5YT	2.20	0.47	1.31	3.09	0.18	1.71	779
Volatility Index	VIX	14.41	4.21	9.14	37.32	1.61	6.82	779

Table 3 shows that the EPU index and VIX have the highest levels of 807.66 and 82.69 for the entire sample period, which were observed during COVID-19. Utility sectors are more resistant to credit stress than other sectors due to stable cash flows and lower exposure to economic cycles, apart from utility companies providing essential services. Power is a utility sector. A-rated and BBB-rated CDS indices of the power sector did not observe an increase in credit risk during COVID-19 than before COVID-19. The power sector's BB-rated CDS index mean level is 238.75 bps during COVID-19, a 72% increase from before the COVID-19 period level of 139.20 bps. Such a sharp increase for low-rated power sector firms indicate borrowing stress for low-rated firms overall.

All except four CDS sector indices are leptokurtic, indicating heavier tails and sharper peaks. The four platykurtic CDS indices are for the power and sovereign sectors. All the CDS indices except the BBB-rated consumer CDS index and the A-rated Power CDS index are positively skewed. US oil ETF hit the

lowest level of 17.04 during the COVID-19 period. US Federal Reserve cut the interest rates in anticipation of economic recession, due to which the US 5-year treasury yield dropped as low as 0.20% during COVID-19. S&P500 touched the lowest level of 2237.50 while EUROSTOXX50 hit the lowest level of 2385.82 during COVID-19.

Table 3- Summary of variables, During COVID-19

Variable	Rating	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Obs.
Banking CDS indices	AA	40.23	12.68	24.28	83.73	1.38	4.19	520
	A	45.82	11.17	33.02	91.72	1.79	5.96	520
	BBB	76.57	21.84	54.22	158.40	1.64	5.03	520
Consumer CDS indices	A	40.75	2.77	25.16	53.94	1.55	9.68	520
	BBB	56.98	8.38	39.08	90.50	-0.03	3.49	520
Energy CDS indices	AA	45.09	16.56	26.57	106.46	1.99	6.15	520
	A	61.68	18.26	42.52	147.75	1.95	7.46	520
	BBB	101.42	40.92	67.52	310.89	2.71	10.56	520
Manufacturing CDS indices	A	42.90	6.82	34.24	77.27	2.61	9.87	520
	BBB	77.86	19.36	60.96	175.86	2.42	8.50	520
	BB	199.97	43.60	121.10	367.56	1.02	4.48	520
	B	373.25	97.97	282.65	815.84	2.32	7.74	520
Non-Bank Financials CDS indices	AA	44.81	8.72	31.12	92.21	1.89	7.53	520
	A	58.86	8.58	45.72	91.54	1.37	4.84	520
	BBB	95.46	9.83	80.77	148.13	0.95	4.45	520
	BB	205.71	66.02	102.08	464.53	1.29	5.05	520
Power CDS indices	A	38.59	4.76	23.67	49.79	-0.06	1.87	520
	BBB	58.12	5.57	48.55	80.91	0.92	3.68	520
	BB	238.75	42.44	161.00	379.30	0.51	2.67	520
Service CDS indices	AA	22.43	2.94	15.02	41.10	1.76	10.84	520
	A	33.01	4.97	27.17	61.01	2.67	11.06	520
	BBB	72.55	17.17	57.26	155.13	2.46	9.14	520
	BB	227.79	56.27	163.05	544.72	2.45	10.70	520
	B	489.46	175.12	308.46	1,147.93	1.50	4.75	520
Sovereign CDS indices	AAA	11.97	3.08	8.17	25.07	2.04	6.08	520
	AA	26.13	8.17	15.61	46.55	0.68	2.33	520
	A	53.84	11.64	33.80	102.39	1.42	4.67	520
	BBB	85.07	22.29	61.94	176.40	1.85	5.75	520
	BB	194.42	46.37	101.37	312.75	0.83	2.85	520
	B	418.25	60.01	339.93	580.41	1.08	3.43	520
Transportation CDS indices	A	33.14	4.21	25.25	49.90	0.09	3.56	520
	BBB	81.26	15.24	59.44	167.07	1.35	6.63	520
Telecommunication CDS indices	BB	266.96	127.52	123.72	973.25	2.22	8.86	520
	A	48.73	12.35	27.94	130.59	2.93	16.30	520
Commodity Index	BBB	72.92	11.26	56.80	129.97	2.13	8.44	520
	TRCCRB	178.81	35.64	106.29	241.18	0.05	1.82	520
EPU Index	EPU	210.72	136.43	22.25	807.66	1.34	4.51	520
Euro Stoxx 50	STOXX50	3,649.51	464.06	2,385.82	4,401.49	-0.41	2.21	520
Oil ETF	USO	44.06	17.90	17.04	105.44	1.47	5.16	520
S&P500	S&P500	3,748.44	607.78	2,237.40	4,793.06	-0.13	2.00	520
US Govt Bond Yield	US5YT	0.70	0.38	0.20	1.68	0.68	2.52	520
Volatility Index	VIX	24.32	10.22	12.10	82.69	2.45	11.02	520

Non-investment grade CDS indices are the ones with BB or B ratings. **Table 4** shows that all the mean levels of non-investment grade CDS sector indices except the BB-rated Sovereign CDS index observed more than a 25% increase compared to mean levels before the COVID-19 period. These increased mean levels after COVID-19 than before COVID-19 indicate that credit markets have a post-COVID-19 effect for low-rated firms. Transportation and telecommunication sector CDS indices are still leptokurtic, while all the sovereign CDS sector indices are platykurtic after the COVID-19 period of 2020-2021.

The US 5-year treasury yield was 1.37% at the start of 2022, close to the lowest yield level observed during the year. US Federal Reserve increased the Fed funds rate from near zero at the start of 2022 to 4.25% by the end of 2022 due to inflation fears and the possibility of a quick rebound in the US economy, due to which the US 5-year treasury yield peaked at 4.96% after COVID-19. When we analysed the weekly time series, we found a downward trend for S&P500 and Eurostoxx50 in 2022; however, both equity indices had an upward trend in 2023 on a weekly basis.

Table 4- Summary of variables, After COVID-19

Variable	Rating	Mean	Std. dev.	Min	Max	Skewness	Kurtosis	Obs.
Banking CDS indices	AA	55.16	8.55	33.84	70.34	-0.58	2.89	519
	A	72.51	12.40	43.37	107.71	0.00	3.25	519
	BBB	95.31	13.04	64.58	131.68	0.30	2.86	519
Consumer CDS indices	A	44.84	5.71	29.92	59.11	-0.20	3.05	519
	BBB	66.34	11.77	50.67	92.26	0.57	1.87	519
Energy CDS indices	AA	45.38	12.23	31.00	76.91	1.11	2.58	519
	A	73.60	14.48	46.13	115.34	0.50	2.97	519
	BBB	90.09	11.21	69.40	126.03	0.62	3.20	519
Manufacturing CDS indices	A	52.85	6.56	39.86	70.37	0.50	2.77	519
	BBB	99.53	18.44	65.39	147.22	0.72	2.71	519
	BB	283.96	45.35	177.76	420.86	0.38	3.44	519
	B	598.44	166.10	319.70	1,026.22	0.18	1.78	519
Non-Bank Financials CDS indices	AA	57.28	9.98	37.04	88.65	0.88	3.58	519
	A	68.88	8.67	51.01	91.11	0.47	2.53	519
	BBB	107.36	9.91	82.28	124.17	-0.78	2.54	519
Power CDS indices	BB	258.81	40.95	160.87	359.42	-0.03	2.98	519
	A	62.11	11.03	35.53	85.97	-0.04	2.40	519
	BBB	75.18	10.58	53.46	103.45	0.40	2.85	519
Service CDS indices	BB	322.35	49.40	214.88	502.18	0.61	4.49	519
	AA	33.20	4.45	20.05	41.92	-0.90	3.72	519
	A	40.37	5.01	26.88	53.46	-0.08	2.94	519
Sovereign CDS indices	BBB	83.74	10.30	62.70	110.73	0.29	2.62	519
	BB	282.28	39.79	167.26	386.99	0.54	2.82	519
	B	760.81	165.48	386.49	1,504.53	-0.14	3.12	519
	AAA	16.77	4.07	10.01	24.99	0.32	2.09	519
Sovereign CDS indices	AA	32.91	4.02	23.46	42.57	-0.22	2.91	519
	A	66.95	11.25	43.21	97.30	0.42	2.98	519
	BBB	108.72	21.32	69.59	170.38	0.66	2.95	519
	BB	230.62	31.36	173.75	310.04	0.35	2.72	519
	B	556.00	83.53	378.59	793.73	0.37	2.79	519

Transportation CDS indices	A	33.60	4.30	25.02	46.00	0.58	3.27	519
	BBB	95.81	8.05	65.79	114.12	-0.57	3.40	519
	BB	280.58	46.79	181.69	421.69	0.42	3.33	519
Telecommunication CDS indices	A	67.16	10.07	40.16	100.03	-0.20	3.13	519
	BBB	90.03	7.56	70.66	107.75	-0.26	3.10	519
Commodity Index	TRCCRB	278.25	16.82	233.00	329.59	0.57	3.58	519
EPU Index	EPU	131.57	65.29	14.69	632.37	1.91	11.16	519
Euro Stoxx 50	STOXX50	4,017.04	324.55	3,279.04	4,549.44	-0.44	1.98	519
Oil ETF	USO	71.20	6.73	54.83	91.99	0.37	2.94	519
S&P500	S&P500	4,191.64	279.64	3,577.03	4,796.56	0.03	2.14	519
US Govt Bond Yield	US5YT	3.54	0.84	1.37	4.96	-0.82	3.01	519
Volatility Index	VIX	21.21	5.74	12.07	36.45	0.36	2.25	519

Chapter 4- Research Methods

4.1 Multicollinearity Test

The general rule of thumb about multicollinearity is to modify the model when the Variance Inflation Factor (VIF) level is above 10; however, O'Brien (2007) points out that a Variance Inflation Factor above 10 is also acceptable in certain situations. VIF between 5 and 10 shows a moderate level of multicollinearity, which requires further investigation, while VIF less than 5 is acceptable, showing no significant multicollinearity. Therefore, we use the VIF test for multicollinearity in our four regression models mentioned in the following sub-section.

4.2 Regression Analysis

Panel data is a widely used data structure in empirical finance, so we have used the panel regression with fixed effects to analyse credit default swaps before, during, and after the COVID-19 crisis.

The fixed effects model allows for the model to be fixed in cross-section dimensions to analyze changes in the relationship among CDS sectors over time. Wolf and Best (2013) confirm that fixed effects models provide a workaround for omitted variable bias. Most reviewed research papers have applied the fixed effects models while analysing firm-level CDS data; we apply a similar framework to CDS sectors. We apply the fixed effects model to investigate whether intercepts vary across groups or time periods. Benoit (2011) points out that logarithmic transformation effectively transforms a highly skewed variable into an approximately normal variable. Benoit (2011) confirms that when the independent and dependent variables are log-transformed, then the coefficient of the independent variable can be referred to as elasticity. Log transformation reduces the impact of the outlier variable, which makes the regression results more robust to outliers. The below-mentioned log-log regression models are analysed for daily and weekly frequency at a 1%, 5%, and 10% statistical significance level in Stata 18. Following Coro et al. (2013), we will derive t-statistics with panel-robust standard errors (with clustering at CDS index level) to control for autocorrelation and heteroskedasticity. We look at simultaneous relations and we do not pretend there are not causalities.

Model 1:

Our primary focus has been to confirm EPU's impact on the credit risk of the bond issuers. CDS sector indices have underlying firm-level CDS contracts. These CDS contracts have a specific bond assigned to them as an underlying reference entity. Since our scope is to analyse CDS sector indices, we will use the specified **Model 1** below to test hypothesis **H2a**, that an increase in EPU will lead to an increase in the CDS sector index's spread. We will also use **Model 1** to analyse equity and interest rate's relationship with CDS and conclude hypothesis **H1**. COVID-19 was a once-in-a-century health pandemic, and it has created an extreme level of uncertainty at the peak of the COVID crisis. This high

level of uncertainty gradually subsided, so that we will test the hypothesis for the entire period and three sub-periods related to the COVID-19 event (before, during, and after COVID-19).

Panel regression with fixed effects:

Model 1 has five independent variables that are EPU, TRCCRB, SPX, STOXX50, and US5YT.

$$\text{Ln}(\text{CDS}_{i,t}) = \beta_0 + \beta_1 \text{Ln}(\text{EPU}_t) + \beta_2 \text{Ln}(\text{CRB}_t) + \beta_3 \text{Ln}(\text{SPX}_t) + \beta_4 \text{Ln}(\text{STOXX}_t) + \beta_5 \text{Ln}(\text{US5Y}_t) + u_i + \epsilon_{it} \quad (1)$$

Where, β_0 is the intercept term. β_1, \dots, β_5 are coefficients of the independent variables, u_i is CDS sector fixed effects and $\epsilon_{t,i}$ is the error term. Please refer to **Table 5** for more information regarding variables.

Table 5- Variable Definition

Type of Variable	Name of the variable	Variable	Measurement
Dependent Variable	CDS sector Index	$\text{Ln}(\text{CDS}_{i,t})$	Natural log of the CDS sector Index “i” at time t (in basis points)
Independent Variable	Economic Policy Uncertainty Index (EPU)	$\text{Ln}(\text{EPU}_t)$	Natural log of the Economic Policy Uncertainty Index (EPU)
Independent Variable	FTSE Core Commodity CRB Index (TRCCRB)	$\text{Ln}(\text{CRB}_t)$	Natural log of the FTSE Core Commodity CRB Index
Independent Variable	US Crude Oil ETF(USO)	$\text{Ln}(\text{USO}_t)$	Natural log of US Crude Oil ETF
Independent Variable	CBOE Market Volatility Index (VIX)	$\text{Ln}(\text{VIX}_t)$	Natural log of the CBOE Market Volatility Index
Independent Variable	S&P500 Index (SP500)	$\text{Ln}(\text{SPX}_t)$	Natural log of the S&P500 Index
Independent Variable	Euro STOXX Index (STOXX50)	$\text{Ln}(\text{STOXX}_t)$	Natural log of the Euro STOXX50 Index
Independent Variable	US 5 Year Treasury Bond Yield (US5YT)	$\text{Ln}(\text{US5Y}_t)$	Natural log of the five-year USD Govt Bond Yield

Model 2:

We aim to study the impact of financial and non-financial aspects of volatility on the CDS, along with equity, interest rates, and commodity prices as the drivers of CDS. Therefore, we build on **Model 1** by incorporating VIX to measure financial volatility in **Model 2**. **Model 2** contains a diverse group of variables, and we will use it to compare **Model 1** and **Model 3**, so we consider **Model 2** as the baseline model. Pan et al. (2019) have used a similar approach by using a specific model as a baseline and comparing it with other models while analysing the impact of EPU on sovereign CDS. **Model 2** will test hypotheses **H3a** and **H3b** related to the CRB index’s relationship with CDS. We will also use **Model 2** to test hypothesis **H2b**, whether the effect of EPU on CDS is stronger than that of VIX.

Here, the panel regression specification with fixed effects is the same as in **Model 1** except for the group of independent variables.

$$\text{Ln}(\text{CDS}_{i,t}) = \beta_0 + \beta_1 \text{Ln}(\text{EPU}_t) + \beta_2 \text{Ln}(\text{CRB}_t) + \beta_3 \text{Ln}(\text{VIX}_t) + \beta_4 \text{Ln}(\text{SPX}_t) + \beta_5 \text{Ln}(\text{STOXX}_t) + \beta_6 \text{Ln}(\text{US5Y}_t) + u_i + \epsilon_{it} \quad (2)$$

Please refer to **Table 5** for more information regarding variables.

Model 3:

Energy commodities have 39% weightage in the CRB index (please refer to the TRCCRB index). Among the reviewed literature in **Chapter 2**, (Hammoudeh, Liu, et al. (2013); Ma et al. (2023); Balçilar et al. (2020)) have proven the impact of oil on oil-related sector level CDS. Lee and Ni (2002) analysed crude oil's impact on the overall economy and found that crude oil price shocks can trigger a recession. COVID-19 created supply chain disruptions, and there was high uncertainty regarding the supply and demand for crude oil during the peak COVID-19 period of March 2020. We will use **Model 3** to analyse crude oil's impact on the overall economy and at sector levels and then compare it with **Model 2** which measures the CRB index's impact on CDS. This analysis will help us in examining hypothesis **H3c**. Here, the panel regression specification with fixed effects for **Model 3** is the same as in **Model 1** except for the group of independent variables.

Model 3 has five independent variables that are USO, EPU, SPX, US5YT, STOXX50 and VIX.

$$\text{Ln}(\text{CDS}_{i,t}) = \beta_0 + \beta_1 \text{Ln}(\text{EPU}_t) + \beta_2 \text{Ln}(\text{USO}_t) + \beta_3 \text{Ln}(\text{VIX}_t) + \beta_4 \text{Ln}(\text{SPX}_t) + \beta_5 \text{Ln}(\text{STOXX}_t) + \beta_6 \text{Ln}(\text{US5Y}_t) + u_i + \epsilon_{it} \quad (3)$$

Please refer to **Table 5** for more information regarding variables.

Model 4:

Financial researchers have traditionally relied on VIX to measure the impact of uncertainty on CDS. We will compare **Model 4** with **Model 1** to substantiate Hypothesis **H2b** that the effect of EPU on CDS is stronger than that of VIX.

Here, the panel regression specification with fixed effects for **Model 4** is the same as in **Model 1** except for the group of independent variables.

Model 4 has five independent variables: TRCCRB, VIX, SPX, STOXX50, and US5YT.

$$\text{Ln}(\text{CDS}_{i,t}) = \beta_0 + \beta_1 \text{Ln}(\text{CRB}_t) + \beta_2 \text{Ln}(\text{VIX}_t) + \beta_3 \text{Ln}(\text{SPX}_t) + \beta_4 \text{Ln}(\text{STOXX}_t) + \beta_5 \text{Ln}(\text{US5Y}_t) + u_i + \epsilon_{it} \quad (4)$$

For more information on the variables, please refer to **Table 5**.

Chapter 5- Empirical Analysis and Results

5.1 Multicollinearity Test Results

Table 6- VIF results of each model for the entire sample period is less than 10.

Our primary goal is to study the impact of EPU on CDS, so we checked VIF for **Model 1** first, which is 5.49. We add VIX to the **Model 2** since we want to cover financial market uncertainty apart from economic uncertainty. Our model 2 VIF is 6.68. We want to analyse the impact of VIX after excluding EPU, so we created **Model 4**. **Model 4** VIF result is 7.60 which is below 10. Our lowest VIF result of 5.47 is achieved when we replaced CRB index by crude oil in **Model 3**.

Table 6- VIF results for the entire sample period

Daily Full Period (2017-2023)					
Model 2 (Base regression)			Model 3 (Changes from base regression as inclusion of USO and exclusion of CRB)		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
SPX	10.73	0.09	SPX	8.59	0.12
CRB	9.49	0.11	STOXX	8.43	0.12
STOXX	8.45	0.12	USO	5.84	0.17
US5YT	6.03	0.17	US5YT	4.36	0.23
VIX	3.74	0.27	VIX	3.79	0.26
EPU	1.66	0.60	EPU	1.82	0.55
Mean	VIF	6.68	Mean	VIF	5.47
Model 4 (Changes from base regression as excluding EPU)			Model 1 (Changes from base regression as excluding VIX)		
Variable	VIF	1/VIF	Variable	VIF	1/VIF
SPX	10.71	0.09	CRB	9.21	0.11
CRB	9.49	0.11	SPX	7.04	0.14
STOXX	8.44	0.12	US5YT	5.96	0.17
US5YT	5.85	0.17	STOXX	3.68	0.27
VIX	3.52	0.28	EPU	1.56	0.64
Mean	VIF	7.60	Mean	VIF	5.49

5.2 Regression Analysis

5.2.1 Global level panel regression – Including all sectors of the economy

5.2.1.1 - Determinants of CDS

Our empirical analysis investigates the relationship between explanatory variables and CDS sector indices. Stata results of the four models defined in **Chapter 4- Research Method** at the global level (including all sectors) are available on request. First, we present regression results, including all sectors, to analyse the impact of the independent variable for the whole sample and sub-periods. Predicted signs of equity indices and US 5-year treasury yield are as per structural models.

Table 7- Model 1- Global level daily panel regression

Variable	Predicted Sign	Full	Before	During	After
Ln(US5Y)	----	0.07** (2.97)	-0.07** (-2.07)	0.11*** (8.65)	0.16*** (5.39)
Ln(STOXX)	----	-1.16*** (-11.33)	-1.19*** (-7.56)	-1.76*** (-11.78)	-0.61*** (-6.18)
Ln(CRB)		0.48*** (5.99)	-0.05 (-0.5)	-0.02 (-0.21)	-0.07 (-1.41)
Ln(EPU)	+++	0.11*** (10.46)	0.01*** (4.28)	0.07*** (10.54)	0.01*** (4.05)
Ln(SPX)	----	0.09 (0.98)	-0.6*** (-3.92)	0.51*** (4.22)	-0.97*** (-6.24)
Adjusted R-squared		0.2900	0.2964	0.5045	0.5053
No of obs.		63,630	27,265	18,200	18,165
No of Grps		35	35	35	35

Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. T- statistics are shown in brackets. Dependent variable: LnCDS
The panel estimation is carried out by using CDS index-level fixed-effects and panel-robust standard error (clustering at the CDS index level) to control for autocorrelation and heteroskedasticity.

The Eurostoxx50 has a negative relationship with CDS sector indices at a 1% significance level for the entire period and as sub-periods. S&P500 has a positive coefficient at a 1% significance level during COVID-19, while the SPX coefficient is negative before and after COVID-19. The Eurostoxx50 coefficient is statistically more robust than that of the S&P500 for all the periods except after COVID-19. **Model 1** results align with a theoretical understanding of equity's impact on CDS. We can accept hypothesis **H1 on p18** that equity indices are negatively associated with CDS except for SPX's relationship with CDS sector indices for the whole sample period, where the SPX coefficient is marginally positive and insignificant. The negative relationship between equity returns and CDS has been confirmed by researchers in the past (Breitenfellner et al., (2012);Hassan et al. (2013);Hibbert and Pavlova (2017)).

Model 1 results do not align with theoretical expectations for the US 5-year treasury yield's impact on CDS, except before COVID-19. An extraordinarily low interest rate policy adopted by the US Federal Reserve in anticipation of COVID-19 driven recession may be the reason for an unexpected impact of interest rates on sector CDS indices during and after COVID-19. Even though positive interest rate coefficients are smaller in magnitude, they are significant at a 1% level for all periods except before COVID-19, so we can reject **hypothesis H1 on p18**, which is that interest rates have a negative relationship with CDS except before COVID-19 period. The negative relationship between interest rates and CDS is validated by (Coro et al. (2013);Ericsson et al. (2009)). Hassan et al. (2013) justified the negative relationship between interest rates and CDS, as it indicates an improvement in economic activity.

Positive coefficients of EPU at a 1% significance level validate the acceptance of **hypothesis H2a on p20** that an increase in EPU will lead to an increase in CDS spread for the whole period and sub-periods.

CRB commodity index has statistically insignificant results before, during, and after COVID-19. While the coefficient of the CRB index is 0.48 and significant at a 1% level for the entire sample period, the same is negative for all the sub-periods. Although we find a negative relationship between the CRB index and CDS during the sub-periods, the CRB coefficient is marginal and not significant, so we require further findings to accept or reject **hypothesis H3a and H3b on p22** that commodity index is related to CDS spread, and this relationship should be stronger during COVID-19 period.

5.2.1.2 - EPU and VIX

Table 8- Model 2 - Baseline model- Global level daily panel regression

Variable	Predicted				
	Sign	Full	Before	During	After
Ln(US5Y)	----	0.08*** (3.51)	-0.08** (-2.26)	0.11*** (8.41)	0.08*** (3.38)
Ln(STOXX)	----	-0.56*** (-4.86)	-1.51*** (-9.1)	-0.98*** (-7.92)	-0.79*** (-7.66)
Ln(CRB)		0.41*** (5.35)	-0.03 (-0.3)	-0.22** (-2.72)	0.02 (0.35)
Ln(VIX)	+++	0.16*** (8.81)	-0.07*** (-4.87)	0.18*** (11.31)	-0.18*** (-5.16)
Ln(EPU)	+++	0.09*** (10.09)	0.01*** (4.08)	0.06*** (9.61)	0.01*** (5.31)
Ln(SPX)	----	-0.17* (-1.81)	-0.5*** (-3.51)	0.4*** (3.44)	-1.34*** (-6.76)
Adjusted R-squared		0.3077	0.3036	0.5225	0.5163
No of obs.		63630	27265	18200	18165
No of Grps		35	35	35	35

Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. T- statistics are shown in brackets. Dependent variable: LnCDS
The panel estimation is carried out by using CDS index-level fixed-effects and panel-robust standard error (clustering at the CDS index level) to control for autocorrelation and heteroskedasticity.

For the entire sample period, **Model 2** results are as expected for EPU and VIX's relationship with CDS sector indices. However, the magnitude of the EPU's coefficient is lesser than the VIX coefficient for the entire period. The negative coefficient of the VIX before COVID-19 requires further analysis. VIX had a negative coefficient after COVID-19, which may be driven by a rally in the S&P500 post-COVID-19; however, the relationship between VIX and CDS sector indices before and after COVID-19 is unexpected. Market participants widely accept the positive relationship between financial volatility and CDS, and the same has also been validated by financial researchers, including (Ericsson et al. (2009); Coro et al. (2013), Hassan et al. (2013), Han and Zhou (2015)).

VIX and EPU had positive coefficients of 0.16 and 0.09, respectively, for the entire sample period, and a similar direction and magnitude of VIX and EPU coefficients was observed during COVID-19. VIX coefficient was three times that of EPU during COVID-19. Even though VIX coefficients were negative before and after COVID-19, coefficients cannot be ignored since those results are statistically significant at a 1% level. After COVID-19, a 1% increase in EPU resulted in a 0.01% increase in CDS spread, while a 1% increase in VIX led to a 0.18% decrease in CDS spread.

During the COVID-19 crisis, VIX dominated the increase in CDS with a larger magnitude. However, before and after COVID-19, VIX coefficient signs were negative. This case may be because of a decrease in risk aversion before and after the crisis but an increase in risk aversion during COVID-19. EPU coefficient is consistently positive for all the sub-periods and the entire sample period, leading the CDS spread in an increasing direction. When we include both VIX and EPU as independent variables, the adjusted R squared slightly increases in every sub-period and the whole sample period for **Model 2** compared to the adjusted R squared of **Model 1**. These **Model 2** (baseline regression) observations are the basis to reject **hypothesis H2b on p20**, which is that the effect of EPU on the CDS spread is stronger than that of the VIX.

We also ran regression by removing EPU from the base model- **Model 2** and separately compared the impact of EPU and VIX on CDS. Please refer to **Table 21-** Model 4- global level daily panel regression in Chapter 7- Appendix.

Coefficients of EPU for **Model 1** were positive and statistically significant at a 1% significance interval for the entire period and sub-periods. The VIX coefficient was 0.21 for the whole sample period in **Model 4**, while the EPU coefficient was 0.11 for the entire sample period in **Model 1**. The VIX coefficient was 0.2 during the COVID-19 period of **Model 4**, while the EPU coefficient was 0.07 during the COVID-19 period of **Model 1**. Even though the VIX coefficients were not in line with the theoretical understanding before and after COVID-19 for **Model 4**, they were statistically significant. They had a stronger magnitude than the EPU coefficients before and after COVID-19 for **Model 1**. This comparison between **Model 1** and **Model 4** further supports our conclusion to reject hypothesis **H2b on p20**, which is that the effect of EPU on the CDS spread is stronger than the VIX.

5.2.1.3 - US oil ETF and CRB index

CRB index is composed of diverse commodities, so it may average out the impact of oil while oil is most essential commodity of the economy. Therefore, we have investigated the impact of crude oil separately.

Table 9 reports daily regression results where we replace the commodity index with the oil ETF in **Model 3**. The adjusted R squared of **Model 3** is 7% point more than that of **Model 2** (please refer to **Table 8**) for the entire sample period. There is no significant difference in adjusted R squared between **Model 2** and **Model 3** for any sub-sample periods. The coefficient of the USO for **Model 3** is negative and significant at a 1% level for the entire sample period. In comparison, the coefficient of the CRB index is positive at a 1% significance level for the whole sample period. Before COVID-19, the coefficient of the USO for **Model 3** was positive and significant at a 1% level, while the CRB index

coefficient was statistically insignificant under **Model 2**. During COVID-19, TRCCRB under **Model 2** and USO under **Model 3** had a negative relationship with CDS sector indices at a 5% significance level. TRCCRB under **Model 2** and USO under **Model 3** do not have statistically significant coefficient results after COVID-19. Since we do not have any empirical support to compare the regression coefficient signs with predicted signs at the whole economy level and our regression results have inconsistent signs for the entire period and sub-periods for both the models, we cannot accept or reject the **hypothesis H3c on page 22**, which is that commodity index explains CDS spread better than crude oil.

Table 9- Model 3 - Global level daily panel regression

Variable	Predicted Sign	Full	Before	During	After
Ln(US5Y)	----	0.31*** (13.98)	-0.15*** (-4.7)	0.17*** (11.59)	0.08*** (3.72)
Ln(STOXX)	----	-0.66*** (-5.44)	-1.61*** (-8.86)	-0.68*** (-5.86)	-0.8*** (-7.99)
Ln(VIX)	+++	0.11*** (6.53)	-0.08*** (-4.93)	0.17*** (9.87)	-0.17*** (-5.13)
Ln(EPU)	+++	0.04*** (10.29)	0** (2.92)	0.05*** (9.51)	0.01*** (5.3)
Ln(SPX)	----	-0.12 (-1.54)	-0.61*** (-4.32)	-0.09 (-1.02)	-1.33*** (-6.98)
Ln(USO)		-0.4*** (-8.84)	0.16*** (3.5)	-0.18*** (-5.98)	0 (0.09)
Adjusted R-squared		0.3806	0.3090	0.5340	0.5162
No of obs.		63,630	27,265	18,200	18,165
No of Grps		35	35	35	35

T- statistics are shown in brackets. Dependent variable: LnCDS

5.2.2 Sector-wise panel regression

5.2.2.1 - Determinants of CDS for baseline model (Model 2)

Stata output of the baseline model's (**Model 2**) sector-level results is available on request.

The S&P500 is considered a leading indicator for other financial markets and is a widely tracked equity index of the USA. Mixed results for statistical significance of the SPX coefficient are the unexpected outcome (Please refer to **Table 10**). The S&P500 coefficient is not a negative number with statistical significance for any of the sectors during COVID-19. This situation may be due to a rally in the S&P500 after March 2020, which was not followed by expected spread tightening (fall in CDS bps) in the CDS market. Banking, power, and sovereign CDS are the only three sectors where the SPX coefficient was negative for daily and weekly frequency before and after COVID-19 at a 10% significance level. For daily frequency, the energy sector had a considerable coefficient magnitude of 1.22 during COVID-19, which means a 1% positive change in S&P500 increased energy sector CDS by 1.22% in contrast to a large negative SPX coefficient before and after COVID-19.

Table 10- Model 2 - Sector-wise regression results for SPX- S&P500 equity index

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	-0.24	-0.64*	0.14	-1.72**	-0.21	-0.66*	0.12	-1.78**
	T- stat	(-2.6)	(-3.09)	(0.32)	(-5.3)	(-2.34)	(-3.01)	(0.37)	(-4.88)
Consumer	Coeff	0.17	0.41	-0.05	0	0.14	0.4	-0.2	-0.02
	T- stat	(0.36)	(0.6)	(-0.13)	(0)	(0.29)	(0.58)	(-0.6)	(-0.02)
Energy	Coeff	-0.79	-1.51	1.22**	-1.13	-0.76	-1.5	1.27**	-1.22
	T- stat	(-1.81)	(-2.56)	(9.26)	(-1.31)	(-1.76)	(-2.65)	(5.43)	(-1.45)
Manufacturing	Coeff	0.19	0.06	0.59*	-2.25	0.21	0.03	0.51	-2.27
	T- stat	(2.19)	(0.21)	(2.55)	(-2.1)	(2.3)	(0.09)	(2.3)	(-2.06)
Non-bank Fin	Coeff	0.11	-0.37	0.73*	-1.09**	0.12	-0.4	0.65	-1.1**
	T- stat	(1.07)	(-1.02)	(2.53)	(-3.97)	(1.27)	(-1.08)	(2.02)	(-3.54)
Power	Coeff	-0.74**	-1.23**	-0.01	-1.82**	-0.73**	-1.22**	-0.1	-1.86**
	T- stat	(-7.08)	(-6.46)	(-0.06)	(-6.32)	(-6.8)	(-6.06)	(-0.44)	(-6.59)
Service	Coeff	-0.04	-0.31	0.2	-1.56**	-0.02	-0.33	0.13	-1.53**
	T- stat	(-0.19)	(-1.32)	(0.48)	(-3.64)	(-0.09)	(-1.46)	(0.28)	(-3.54)
Sovereign	Coeff	-0.4	-0.86*	0.35	-1.3*	-0.37	-0.87*	0.37	-1.37*
	T- stat	(-1.37)	(-2.26)	(1.74)	(-2.06)	(-1.34)	(-2.24)	(1.93)	(-2.13)
Telecommunication	Coeff	-0.42	-0.64**	-0.38	-1.01	-0.41	-0.65**	-0.43	-1.09
	T- stat	(-2.44)	(-25.66)	(-0.53)	(-2.14)	(-2.7)	(-43.88)	(-0.7)	(-2.2)
Transportation	Coeff	0.45*	0.31	0.83	-0.69**	0.47**	0.29	0.85	-0.64**
	T- stat	(3.81)	(0.52)	(1.72)	(-10.56)	(5)	(0.49)	(1.64)	(-7.21)

Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. T- statistics are shown in brackets. Dependent variable: LnCDS

Table 11 shows the EuroStoxx50 coefficient for each sector. For the entire sample period and subperiods, EuroStoxx50 coefficient signs are as expected for all the sectors except for the energy and power sector's positive coefficients for the entire period. Although the coefficients of EuroStoxx50 are negative for consumer and telecommunication, those coefficients are not statistically significant even at a 10% level.

Table 11- Model 2 - Sector-wise regression results for EuroStoxx50 equity index

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	-0.91*	-2.47**	-0.85	-0.9*	-0.86*	-2.34*	-1.02*	-0.85**
	T- stat	(-3.38)	(-4.35)	(-2.57)	(-3.89)	(-3.16)	(-3.77)	(-3.48)	(-4.23)
Consumer	Coeff	-1.02	-1.4	-0.27	-1.18	-0.98	-1.3	-0.34	-1.09
	T- stat	(-1.1)	(-0.88)	(-1.24)	(-2.13)	(-1.03)	(-0.84)	(-1.21)	(-1.64)
Energy	Coeff	0.15	-1.48	-2.11***	-0.45	0.2	-1.39	-2.43***	-0.4
	T- stat	(0.22)	(-1.39)	(-26.26)	(-0.74)	(0.29)	(-1.41)	(-37.19)	(-0.77)
Manufacturing	Coeff	-0.91**	-1.84***	-1.35**	-0.92	-0.88**	-1.72***	-1.52***	-0.88
	T- stat	(-4.99)	(-9.63)	(-4.11)	(-2.03)	(-5.12)	(-8.81)	(-7.77)	(-1.98)
Non-bank Fin	Coeff	-0.73**	-1.58***	-1.15**	-0.97**	-0.69**	-1.44***	-1.25**	-0.91**
	T- stat	(-4.1)	(-12.99)	(-6.82)	(-3.62)	(-4.08)	(-14.34)	(-5.91)	(-3.27)
Power	Coeff	0.29	-0.32	-0.02	-0.75**	0.32	-0.24	-0.24	-0.66**
	T- stat	(0.55)	(-0.46)	(-0.05)	(-10.31)	(0.56)	(-0.3)	(-0.88)	(-7.4)
Service	Coeff	-0.6**	-1.09**	-1.1*	-0.72**	-0.55**	-0.98**	-1.1*	-0.67**
	T- stat	(-4.16)	(-4.71)	(-2.27)	(-4.3)	(-3.88)	(-4.6)	(-2.43)	(-3.59)
Sovereign	Coeff	-0.61*	-1.55***	-0.84***	-0.78**	-0.56*	-1.5***	-0.98***	-0.75**
	T- stat	(-2.31)	(-6.29)	(-5.84)	(-2.93)	(-2.26)	(-6.08)	(-6.16)	(-2.92)
Telecommunication	Coeff	-0.33	-1.18	-0.43	-0.5	-0.31	-1.14	-0.48	-0.45
	T- stat	(-2.07)	(-4.03)	(-1.42)	(-1.52)	(-1.52)	(-3.65)	(-1.94)	(-1.37)
Transportation	Coeff	-0.79*	-2.16*	-1.18*	-0.71	-0.75*	-2.01*	-1.43**	-0.65
	T- stat	(-3.24)	(-3.29)	(-4.07)	(-1.18)	(-2.93)	(-3.24)	(-5.58)	(-1.13)

T- statistics are shown in brackets. Dependent variable: LnCDS

Table 12 shows that the US 5-year treasury yield coefficient does not align with the expected negative sign for most CDS sector indices. The interest rate coefficient of the energy sector before COVID-19 is the only one with a negative sign at a 5% significance level. Banking, manufacturing, service, and sovereign CDS sector indices had positive coefficients at a 10% statistical significance for the total sample period and sub-periods.

Table 12- Model 2 - Sector-wise regression results for the US5YT- the US 5 Year treasury yield

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	0.18**	0	0.15**	0.09	0.19**	0.03	0.16**	0.08
	T- stat	(9.2)	(0.02)	(8.98)	(1.25)	(9.51)	(1.08)	(10.18)	(1.14)
Consumer	Coeff	0.07	0.01	0.13	-0.02	0.06	0.03	0.11	-0.02
	T- stat	(0.86)	(0.1)	(1.29)	(-0.26)	(0.84)	(0.27)	(1.11)	(-0.55)
Energy	Coeff	-0.1	-0.35**	0.18*	-0.12	-0.09	-0.33**	0.19	-0.16

Manufacturing	T- stat	(-1.22)	(-5.27)	(3.19)	(-1.38)	(-1.08)	(-5.21)	(2.8)	(-1.45)
	Coeff	0.14**	-0.07	0.16*	0.01	0.15**	-0.06	0.15*	0.01
Non-bank Fin	T- stat	(3.31)	(-0.65)	(2.57)	(0.19)	(3.54)	(-0.53)	(2.89)	(0.11)
	Coeff	0.05	-0.04	0.04	0.12**	0.06	-0.02	0.03	0.12**
Power	T- stat	(1.17)	(-0.72)	(1.27)	(6.4)	(1.3)	(-0.3)	(1.36)	(5.35)
	Coeff	-0.11	-0.31	0.02	-0.01	-0.1	-0.29	0.01	-0.01
Service	T- stat	(-1.16)	(-1.18)	(1.61)	(-0.1)	(-1.1)	(-1.17)	(2.05)	(-0.08)
	Coeff	0.15**	0.04	0.1**	0.14**	0.16**	0.05	0.09**	0.14**
Sovereign	T- stat	(5.33)	(0.62)	(4.52)	(2.82)	(5.3)	(0.74)	(3.09)	(3.04)
	Coeff	0.1*	-0.04	0.13***	0.16**	0.11*	-0.03	0.14***	0.16**
Telecommunication	T- stat	(2.26)	(-1.14)	(6.93)	(4.05)	(2.49)	(-1.03)	(6.27)	(3.62)
	Coeff	0.18	0.12	0.14	0.19*	0.18	0.12	0.14	0.19*
Transportation	T- stat	(1.73)	(1.38)	(4.66)	(9.7)	(1.76)	(1.5)	(2.99)	(8.36)
	Coeff	0.05	-0.17	0.09	0.07	0.06	-0.15	0.09*	0.07
	T- stat	(0.83)	(-1.47)	(2.06)	(1.02)	(0.91)	(-1.19)	(3.07)	(1.13)

T- statistics are shown in brackets. Dependent variable: LnCDS

The banking, non-bank financials, manufacturing, service, and sovereign CDS sectors indices had positive and statistically significant EPU coefficients for the whole sample period. Weekly regression results are in line with daily regression results. Banking and manufacturing had significant EPU coefficients at a 10% significance level for the entire sample period and all the sub-periods. Power sector CDS indices had positive coefficients for the entire period and sub-periods, but those were not supported by a 10% statistical significance level. The negative coefficients of the consumer sector are marginal in magnitude for the whole period and sub-periods, and they were also statistically insignificant. For the whole sample and sub-periods, EPU coefficients are positive for all the sectors except the consumer sector. **Table 13** confirms hypothesis **H2a on p20** that EPU is positively associated with CDS.

Table 13- Model 2 - Sector-wise regression results for EPU-Economic Policy Uncertainty Index

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	0.12***	0.01**	0.09***	0.02**	0.14***	0.04***	0.11***	0.03*
	T- stat	(14.97)	(4.4)	(33.16)	(6.54)	(19.83)	(16.45)	(42.89)	(3.68)
Consumer	Coeff	-0.02	-0.01	0.03	0	-0.02	0	0.02	-0.02
	T- stat	(-0.63)	(-0.42)	(2.71)	(0.31)	(-0.75)	(-0.22)	(3.04)	(-4.21)
Energy	Coeff	0.12**	0	0.08	0.01	0.12**	0.02	0.09	0.01
	T- stat	(8.89)	(1.05)	(2.63)	(2.3)	(8.03)	(1.28)	(2.39)	(1.97)
Manufacturing	Coeff	0.1**	0.01**	0.07***	0.01*	0.11**	0.01**	0.09**	0.02**
	T- stat	(5.21)	(3.16)	(9.87)	(2.68)	(6.01)	(4.58)	(7.4)	(3.24)
Non-bank Fin	Coeff	0.09**	0	0.06	0.01*	0.1**	0.01*	0.08	0.01**
	T- stat	(3.27)	(1.23)	(1.73)	(2.44)	(3.54)	(2.62)	(1.54)	(3.45)
Power	Coeff	0.09	0.01	0.03	0	0.11	0.03	0.05	0.01
	T- stat	(2.35)	(2.46)	(1.67)	(0.75)	(2.14)	(2.01)	(1.17)	(1.1)
Service	Coeff	0.09**	0.01**	0.05**	0	0.09**	0.02**	0.05	0.02**
	T- stat	(3.39)	(3.39)	(3.08)	(0.78)	(3.39)	(3.16)	(2.06)	(2.88)

Sovereign	Coeff	0.1***	0	0.06**	0.02**	0.12***	0.01	0.08**	0.02***
	T- stat	(9.12)	(-1.34)	(4.57)	(2.81)	(11.1)	(1.79)	(4.44)	(5.18)
Telecommunication	Coeff	0.06	0	0.05**	0	0.06	0	0.07*	0.01
	T- stat	(4.1)	(-0.25)	(21.55)	(-0.02)	(3.51)	(-0.19)	(7.05)	(0.89)
Transportation	Coeff	0.09	0.02**	0.07	0.01	0.09	0.04**	0.06	0.02*
	T- stat	(1.57)	(5.78)	(2.41)	(2.1)	(1.71)	(9.61)	(1.62)	(3.74)

T- statistics are shown in brackets. Dependent variable: LnCDS

Table 14 shows that banking, energy, manufacturing, service, sovereign, and transportation sector CDS indices had positive coefficient signs for the entire sample period based on a daily and weekly frequency. However, the negative coefficients of VIX for non-bank finance and the sovereign CD sector before and after COVID-19 have contrasting results at a 5% significance level. The coefficient of VIX for the banking sector was -0.17 before COVID-19 at a 5% significance level, while the same was -0.32 after COVID-19 at a 10% significance level. Coefficients of VIX for the sovereign sector were -0.18 and -0.20 before and after COVID-19, respectively, at a 1% significance level.

Table 14- Model 2 - Sector-wise regression results for VIX- S&P500's volatility index

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	0.14**	-0.17**	0.19**	-0.32*	0.12**	-0.17*	0.14**	-0.35*
	T- stat	(5.55)	(-4.42)	(5.34)	(-3.6)	(4.74)	(-3.61)	(4.33)	(-3.81)
Consumer	Coeff	0.07	0.04	0.18	0.06*	0.08	0.05	0.17	0.1*
	T- stat	(1.58)	(1.02)	(1.82)	(6.11)	(1.88)	(1.69)	(1.92)	(6.2)
Energy	Coeff	0.28**	-0.07	0.3**	-0.04	0.27**	-0.07	0.23**	-0.07
	T- stat	(6.28)	(-1.59)	(6.02)	(-0.14)	(6.29)	(-2.32)	(5.18)	(-0.29)
Manufacturing	Coeff	0.24**	-0.01	0.18**	-0.25*	0.23**	0.01	0.13**	-0.26*
	T- stat	(3.76)	(-0.2)	(4.88)	(-2.74)	(3.71)	(0.31)	(5.54)	(-2.77)
Non-bank Fin	Coeff	0.14	-0.07**	0.14	-0.2**	0.14*	-0.06**	0.1*	-0.19**
	T- stat	(2.27)	(-6.05)	(1.91)	(-5.42)	(2.35)	(-5.47)	(2.31)	(-4.42)
Power	Coeff	0.18	-0.07	0.18	-0.19*	0.16	-0.07	0.12	-0.18**
	T- stat	(1.41)	(-0.9)	(2.73)	(-3.45)	(1.3)	(-0.78)	(2.37)	(-4.17)
Service	Coeff	0.17**	-0.01	0.18***	-0.25*	0.17**	0.01	0.16***	-0.25*
	T- stat	(5.38)	(-0.61)	(6.39)	(-2.4)	(5.71)	(0.47)	(5.9)	(-2.27)
Sovereign	Coeff	0.08**	-0.18***	0.1**	-0.2**	0.07**	-0.18***	0.06**	-0.22**
	T- stat	(3.36)	(-8.76)	(4.42)	(-3.89)	(3.65)	(-8.55)	(4.14)	(-3.74)
Telecommunication	Coeff	0.11	-0.09	0.18**	-0.11	0.1	-0.09	0.14	-0.12
	T- stat	(2.02)	(-2)	(18.51)	(-0.63)	(1.61)	(-1.61)	(4.83)	(-0.7)
Transportation	Coeff	0.2***	-0.04	0.24**	-0.08	0.2***	-0.03	0.21**	-0.06
	T- stat	(17.65)	(-0.86)	(5.18)	(-0.5)	(90.92)	(-0.56)	(9.27)	(-0.43)

T- statistics are shown in brackets. Dependent variable: LnCDS

Coefficients of VIX were positive for all ten sectors for the entire sample period and during COVID-19, and these positive VIX coefficients were stronger in magnitude compared to coefficients of EPU (please refer to **Table 13**) for the entire sample period and during COVID-19. After COVID-19, banking, manufacturing, power, and service sectors had a statistically significant negative VIX coefficient at a 10% significance level. These negative coefficients have considerable magnitudes compared to small

magnitudes of EPU after COVID-19 (please refer to **Table 13**). For example, the manufacturing and service sectors' -0.25 coefficient can be interpreted as a 0.25% decrease in CDS spread when the VIX increases by 1%. These observations provide the basis to reject **hypothesis H2b on page 20**, which is that the effect of EPU on the CDS spread is stronger than that of the VIX.

TRCCRB is a diverse commodity index, with underlying commodities from precious metals, agricultural produce, and energy products. **Table 15** shows that TRCCRB coefficient signs are mixed, and results are also not statistically significant for most CDS sector indices except for the energy sector CDS indices.

For daily and weekly data, the energy sector has a positive CRB index coefficient for the entire sample period at a 10% significance level; however, for daily data, the energy sector has a negative CRB index coefficient during and after COVID-19 at a 5% significance level. For daily and weekly data, the power sector has a positive CRB index coefficient for the whole sample period at a 5% significance level; however, it does not have significant results for the sub-periods at a daily and weekly frequency. The CRB index significantly impacted the transportation sector CDS before COVID-19. For daily and weekly frequency, a 1% change in CRB index caused around 0.95% increase in transportation sector CDS spread at a 5% significance level; however, transportation sector CDS did not show any remarkable relationship during and after COVID-19. We do not find any noticeable observation for the remaining seven sectors. Hence, due to contradictory and statistically insignificant results, we cannot accept **hypotheses H3a and H3b on Page 22**, which is that the commodity index is related to CDS spread and that its relationship is stronger during the COVID-19 period for all sectors. We will investigate the commodity index's relationship with energy sector CDS since Ma et al. (2023) found a relationship between oil prices and the CDS of the energy sector firms.

Table 15- Model 2 - Sector-wise regression results for TRCCRB- Commodity Research Bureau index

Sector	Value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	0.34	-0.09	-0.42	0.07	0.31	-0.17	-0.27	0.13
	T- stat	(2.51)	(-0.69)	(-2.18)	(0.47)	(2.23)	(-1.23)	(-1.38)	(0.96)
Consumer	Coeff	0.22	-0.26	0.23*	0.29	0.23	-0.29	0.39**	0.31
	T- stat	(1.71)	(-1.16)	(8.31)	(0.88)	(1.88)	(-1.41)	(11.67)	(1.04)
Energy	Coeff	0.67*	-0.22	-0.5**	-0.24***	0.64*	-0.28	-0.39*	-0.26**
	T- stat	(3.02)	(-0.62)	(-4.32)	(-30.71)	(2.87)	(-0.81)	(-2.97)	(-5.05)
Manufacturing	Coeff	0.32	-0.68*	-0.2	0.13	0.3	-0.75*	-0.01	0.16
	T- stat	(2.22)	(-2.67)	(-2.09)	(1.16)	(2.03)	(-2.94)	(-0.08)	(1.31)
Non-bank Fin	Coeff	0.38	0.08	-0.24	-0.14	0.36	0.01	-0.1	-0.13
	T- stat	(1.57)	(1.13)	(-1.5)	(-0.8)	(1.48)	(0.1)	(-0.57)	(-0.64)
Power	Coeff	1.3**	0.49	0.16	0.39	1.29**	0.46	0.39	0.43
	T- stat	(6.95)	(2)	(0.66)	(1.65)	(7.1)	(2.03)	(1.2)	(1.66)
Service	Coeff	0.21*	-0.13	0.01	0.04	0.18	-0.16	0.08	0.06
	T- stat	(1.57)	(-1.13)	(0.01)	(0.16)	(1.48)	(-1.23)	(0.96)	(0.43)

	T- stat	(2.19)	(-0.6)	(0.03)	(0.93)	(1.77)	(-0.68)	(0.23)	(0.89)
Sovereign	Coeff	0.4	-0.14	-0.6**	-0.02	0.38	-0.19	-0.53**	-0.01
	T- stat	(1.79)	(-0.58)	(-4.15)	(-0.21)	(1.67)	(-0.74)	(-2.86)	(-0.06)
Telecommunication	Coeff	0.12	-0.04	0.07	-0.32	0.11	-0.08	0.15	-0.23
	T- stat	(0.63)	(-0.36)	(0.3)	(-1.07)	(0.55)	(-0.66)	(1.02)	(-0.91)
Transportation	Coeff	0.17	0.99**	-0.25	-0.02	0.14	0.94**	-0.15	-0.04
	T- stat	(0.66)	(6.65)	(-0.47)	(-0.12)	(0.51)	(6.65)	(-0.25)	(-0.3)

T- statistics are shown in brackets. Dependent variable: LnCDS

Above sector wise panel regression results help us understand the credit risk perception of the investors. Higher uncertainty impacts more to the sectors exposed to policy changes. Banking, Non-bank Fin, and Sovereign CDS indices are more exposed to the policy changes so EPU index can be a leading indicator for predicting the movement in these indices. CRB index is a diversified commodity index, but it still lacks in explaining movement of CDS sector indices compared to crude oil prices. It validates the constant attention of investors towards oil market since it helps in understanding economic activity level.

5.2.2.2 - EPU and VIX

Sector-level regression results for **Model 1**, **Model 2**, and **Model 4** will be provided on request. Critical observations derived from the comparison between the two models are as follows.

Daily and weekly Adjusted R squared of the complete sample period increases by almost 5% for the banking, energy, and sovereign sectors with VIX and EPU together (**Model 2**-baseline model) compared to VIX alone (**Model 4**) as explanatory variables. All three models mentioned below have a very minimum difference in adjusted R squared during COVID-19 for daily and weekly frequency. For the remaining seven sectors, daily and weekly adjusted R squared among the three models has less than a 5%-point difference for the entire period and subperiods.

Table 16- Adjusted R squared-comparison for EPU and VIX

Sector	Model Type	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Model 2	0.56	0.62	0.74	0.70	0.56	0.60	0.74	0.71
Banking	Model 1	0.54	0.58	0.73	0.66	0.55	0.58	0.73	0.66
Banking	Model 4	0.50	0.61	0.73	0.70	0.50	0.59	0.72	0.70
Energy	Model 2	0.34	0.67	0.80	0.25	0.34	0.66	0.80	0.25
Energy	Model 1	0.30	0.67	0.77	0.25	0.30	0.66	0.78	0.25
Energy	Model 4	0.29	0.67	0.79	0.25	0.29	0.66	0.79	0.25
Sovereign	Model 2	0.41	0.49	0.70	0.52	0.42	0.49	0.70	0.52
Sovereign	Model 1	0.41	0.45	0.69	0.51	0.42	0.45	0.69	0.51
Sovereign	Model 4	0.36	0.49	0.69	0.52	0.37	0.49	0.68	0.52

5.2.2.3 - US oil ETF and CRB index

Sector-level regression results for **Model 3** will be provided on request. Below is a summary of the critical observations related to the comparison between **Model 2**-baseline model and **Model 3**.

Table 17 shows that daily and weekly Adjusted R squared of the total sample period increases by 12% for the energy sector when USO is considered an independent variable instead of TRCCRB. Non-bank finance, sovereign, and banking sector daily adjusted R squared increased by 14%, 13%, and 11%, respectively, and weekly regression results confirm the trend. There is no significant difference (more or less than 5%) in adjusted R squared for sub-periods between **Model 2** and **Model 3**, the exception being adjusted R squared before the COVID-19 period of the transportation sector. The energy sector shows a very high adjusted R squared of around 80% during COVID-19 for both the models for daily and weekly frequency.

Table 17- Adjusted R squared-comparison for TRCCRB and USO

Sector	Model Type	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Model 2	0.56	0.62	0.74	0.70	0.56	0.60	0.74	0.71
Banking	Model 3	0.67	0.63	0.75	0.70	0.67	0.62	0.75	0.71
Consumer	Model 2	0.38	0.27	0.36	0.66	0.38	0.27	0.34	0.66
Consumer	Model 3	0.40	0.27	0.35	0.66	0.40	0.27	0.32	0.66
Energy	Model 2	0.34	0.67	0.80	0.25	0.34	0.66	0.80	0.25
Energy	Model 3	0.46	0.67	0.81	0.25	0.46	0.66	0.80	0.25
Manufacturing	Model 2	0.54	0.43	0.69	0.74	0.55	0.43	0.69	0.74
Manufacturing	Model 3	0.61	0.41	0.71	0.74	0.62	0.41	0.71	0.74
Nonbank Finance	Model 2	0.39	0.42	0.61	0.64	0.39	0.41	0.62	0.64
Nonbank Finance	Model 3	0.53	0.44	0.64	0.63	0.53	0.42	0.64	0.63
Power	Model 2	0.33	0.51	0.13	0.82	0.34	0.51	0.13	0.81
Power	Model 3	0.28	0.51	0.13	0.81	0.29	0.51	0.12	0.80
Service	Model 2	0.42	0.33	0.57	0.65	0.43	0.32	0.57	0.66
Service	Model 3	0.51	0.33	0.57	0.65	0.52	0.33	0.57	0.66
Sovereign	Model 2	0.41	0.49	0.70	0.52	0.42	0.49	0.70	0.52
Sovereign	Model 3	0.54	0.50	0.70	0.52	0.54	0.49	0.70	0.52
Telecommunication	Model 2	0.54	0.68	0.63	0.68	0.55	0.67	0.63	0.69
Telecommunication	Model 3	0.60	0.69	0.64	0.68	0.60	0.68	0.63	0.69
Transportation	Model 2	0.46	0.25	0.39	0.42	0.47	0.25	0.39	0.41
Transportation	Model 3	0.52	0.31	0.41	0.42	0.52	0.31	0.40	0.41

Table 18 confirms that an increase in US Oil ETF reduces energy sector CDS, which aligns with expectations since higher crude oil prices increase asset value and profits for energy companies. TRCCRB has mixed coefficient signs for the energy sector, and the results are less significant than those of USO.

Table 18- Energy sector comparison for TRCCRB and USO

Sector	Variable	Model	value	Daily				Weekly			
				Full	Before	During	After	Full	Before	During	After
Energy	TRCCRB	Model 2	Coeff	0.67*	-0.22	-0.5**	-0.24***	0.64	-0.28	-0.39*	-0.26**
Energy	TRCCRB	Model 2	t	(3.02)	(-0.62)	(-4.32)	(-30.71)	(2.87)	(-0.81)	(-2.97)	(-5.05)
Energy	USO	Model 3	Coeff	-0.57***	-0.17	-0.27*	-0.22**	-0.55***	-0.19	-0.21	-0.21**
Energy	USO	Model 3	t	(-12.56)	(-0.77)	(-3.24)	(-8.44)	(-11.65)	(-0.81)	(-2.75)	(-4.72)

T- statistics are shown in brackets. Dependent variable: LnCDS

Table 19 shows that Banking, Energy, manufacturing, and sovereign sector CDS indices had a negative relationship with US oil ETF at a 5% significance level for the entire sample period. These sectors also had a negative relationship during COVID-19. Banking, energy, and sovereign sector CDS indices also had higher adjusted R squared when we considered oil instead of the CRB index for the impact of commodities on CDS.

Table 19- Model 3 -Sector-wise regression results for USO- US oil ETF

Sector	value	Daily				Weekly			
		Full	Before	During	After	Full	Before	During	After
Banking	Coeff	-0.49**	0.32**	-0.21**	-0.05	-0.47**	0.3**	-0.15**	-0.02
	T- stat	(-6.58)	(6.55)	(-7.44)	(-0.98)	(-6.36)	(6.74)	(-6.7)	(-0.46)
Consumer	Coeff	0.14	0.1	-0.02	0.22	0.16	0.09	0	0.23
	T- stat	(0.82)	(2.47)	(-0.48)	(1.34)	(0.9)	(1.68)	(0.06)	(1.66)
Energy	Coeff	-0.57**	-0.17	-0.27*	-0.22**	-0.55**	-0.19	-0.21	-0.21**
	T- stat	(-12.56)	(-0.77)	(-3.24)	(-8.44)	(-11.65)	(-0.81)	(-2.75)	(-4.72)
Manufacturing	Coeff	-0.4**	-0.03	-0.21**	0.01	-0.38**	-0.04	-0.17*	0.03
	T- stat	(-3.58)	(-0.28)	(-3.11)	(0.26)	(-3.35)	(-0.42)	(-2.4)	(0.85)
Non-bank Fin	Coeff	-0.48*	0.2**	-0.25	-0.04	-0.47*	0.16**	-0.21	-0.03
	T- stat	(-2.76)	(6.14)	(-1.88)	(-0.5)	(-2.73)	(5.74)	(-1.82)	(-0.37)
Power	Coeff	-0.43*	0.2**	-0.05	0.15	-0.4*	0.19**	0.01	0.16
	T- stat	(-3.49)	(13.62)	(-0.94)	(1.29)	(-3.53)	(10.13)	(0.11)	(1.35)
Service	Coeff	-0.39**	0.08	-0.1	0.04	-0.37**	0.07	-0.09	0.04
	T- stat	(-3.09)	(0.7)	(-1.21)	(1.26)	(-2.96)	(0.63)	(-0.99)	(1.42)
Sovereign	Coeff	-0.48***	0.16*	-0.23***	0.06	-0.47***	0.15	-0.2***	0.08
	T- stat	(-7.38)	(2.14)	(-6.16)	(0.95)	(-7.35)	(1.94)	(-5.26)	(1.1)
Telecommunication	Coeff	-0.29	0.12	-0.08	-0.17	-0.28*	0.12	-0.04	-0.11
	T- stat	(-5.98)	(0.85)	(-1.77)	(-1.14)	(-7.48)	(0.88)	(-1.27)	(-0.86)
Transportation	Coeff	-0.33	0.66**	-0.28	-0.04	-0.31	0.64**	-0.22	-0.05
	T- stat	(-1.14)	(5.96)	(-1.19)	(-0.53)	(-1.08)	(5.41)	(-1.1)	(-0.74)

T- statistics are shown in brackets. Dependent variable: LnCDS

The above three tables (**Table 17, Table 18, and Table 19**) help us conclude that banking, energy, and sovereign are the most impacted sectors for the whole sample and during COVID-19 due to oil prices than the CRB index. We do not find any indication that the commodity index explains CDS spread better than crude oil, so we reject **hypothesis H3c** Error! Bookmark not defined..

5.2.3 Robustness tests

5.2.3.1 - Rating wise panel regression

Table 20 shows an increasing trend of Adjusted R squared from AA to B ratings. The coefficients of EPU and VIX are significant for each rating category except for the coefficient of VIX for the B rating. Coefficient signs are as expected for VIX and EPU for all the ratings. The coefficient of SPX for the B rating is the only anomaly from expected signs of equity indices. Regression results of the SPX coefficient for ratings A & BBB are not as significant as EuroSTOXX50 coefficients of ratings A & BBB.

Table 20- Rating wise regression results for **Model 2** – the entire sample period

Variable	value	AA		A		BBB		BB		B	
		Daily	Weekly	Daily	Weekly	Daily	Weekly	Daily	Weekly	Daily	Weekly
Ln(US5Y)	Coeff	0.09	0.1	0.09**	0.1**	0.08**	0.08**	-0.02	-0.01	0.23**	0.24**
	T- stat	(1.04)	(1.1)	(3.02)	(3.29)	(3.18)	(3.36)	(-0.29)	(-0.13)	(9.23)	(9.33)
Ln(STOXX)	Coeff	-0.21	-0.16	-0.59***	-0.55***	-0.82***	-0.77***	-0.46	-0.42	-0.8**	-0.76**
	T- stat	(-0.45)	(-0.35)	(-6.11)	(-6.14)	(-4.09)	(-3.85)	(-1.24)	(-1.1)	(-12.35)	(-13.75)
Ln(CRB)	Coeff	0.38	0.36	0.39**	0.37**	0.3**	0.28**	0.72**	0.71**	0.01	-0.04
	T- stat	(1.76)	(1.63)	(3.18)	(3.03)	(2.58)	(2.36)	(3.07)	(3.02)	(0.16)	(-0.78)
Ln(VIX)	Coeff	0.15**	0.15**	0.14***	0.13***	0.11***	0.11***	0.26***	0.24***	0.22	0.21
	T- stat	(2.73)	(2.76)	(8.31)	(7.46)	(4.53)	(4.34)	(5.38)	(5.17)	(1.81)	(1.83)
Ln(EPU)	Coeff	0.1**	0.1**	0.06***	0.07***	0.07***	0.08***	0.14***	0.16***	0.13**	0.14**
	T- stat	(5.68)	(5.64)	(4.12)	(4.18)	(4.88)	(4.75)	(7.63)	(7.98)	(4.58)	(5.23)
Ln(SPX)	Coeff	-0.53	-0.52	-0.18	-0.17	-0.1	-0.09	-0.01	0.02	0.42**	0.46**
	T- stat	(-1.8)	(-1.8)	(-1.48)	(-1.5)	(-0.59)	(-0.55)	(-0.09)	(0.11)	(6.8)	(10.16)
R squared Within		0.33	0.33	0.39	0.39	0.39	0.40	0.44	0.45	0.46	0.47
R squared- Overall		0.17	0.17	0.16	0.16	0.26	0.26	0.42	0.42	0.40	0.41
No of obs		9090	1820	18180	3640	18180	3640	10908	2184	5454	1092
No of Groups		5	5	10	10	10	10	6	6	3	3

Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. T- statistics are shown in brackets. Dependent variable: LnCDS

5.2.3.2 - Univariate analysis

Consistency in univariate regression results with respect to multivariate regressions reinforces the validity of the findings. We have run univariate regressions for daily frequency only. A total of 308 unique univariate fixed effect panel regressions were run. We ran 40 fixed effect panel regressions to test the relationship between S&P500 and CDS since we tested the relationship for an entire sample period and three sub-periods. Seven independent variables were used among four models defined under **Chapter 4**, and 280 univariate regressions were run for sectoral univariate analysis. We also tested the one-to-one relationship between each of the seven independent variables and CDS by running 28 unique fixed effect panel regressions for all the sectors together.

Table 22-Independent variable Ln(EPU)'s sector-wise univariate results show positive EPU coefficients for all the sectors for the entire period and sub-periods except the negative EPU coefficient of the consumer and telecommunication sector for the entire sample period. These negative coefficients are statistically insignificant, so we can accept the **hypothesis H2a on page 20** that an increase in EPU will lead to an increase in the CDS spread. Energy and manufacturing have statistically significant coefficients for the entire period and sub-periods at a 5% significance level. Further analysis showed that during the COVID-19 period, all the sectors except consumer, power, and transportation had statistically significant EPU coefficients at a 5% significance level. While running the univariate regression for all the sectors together, the magnitude of the EPU coefficient is strongest during COVID-19, which is 0.2, which means a 1% increase in EPU will cause a 0.2% increase in CDS spread.

Table 24-Independent variable Ln(CRB)- Commodity index's sector-wise univariate results show negative coefficients for all the sectors except the consumer sector during COVID-19. Banking, manufacturing, non-bank finance, services, and sovereign sectors have a negative CRB coefficient at a 5% significance level during COVID-19; however, these sectors also have positive CRB coefficients after COVID-19 at a 10% significance level. For baseline **Model 2**, only energy and sovereign sector had negative CRB index coefficients at a 5% significance level during COVID-19 (please refer to **Table 15**), so these contradictions between univariate and multivariate regressions do not allow us to accept **hypothesis H3a and H3b on page 22**, which is that the commodity index is related to CDS spread and that its relationship is stronger during the COVID-19 period for all sectors.

Sovereign sector CDS had a negative coefficient for SPX and Eurostoxx50 at a 5% significance level for the sub-periods. Its negative relationship with equity indices is also confirmed at a 10% significance level for the entire sample period. (Please refer to **Table 26** and **Table 27**). We also find a negative relationship between equity indices and CDS indices at the macro level, including at the global level for the whole period and sub-periods.

Table 28- Independent variable Ln(US5YT)- US five-year treasury yield's sector-wise univariate results confirm positive interest rate coefficient for the sectors except energy and transportation for the entire sample period. Most of CDS sectors have positive coefficients for the entire sample period and after COVID-19, which aligns with **Table 12- Model 2** - Sector-wise regression results for the US5YT- the US 5 Year treasury yield. Hence, we reject hypothesis **H1 on p18**, which is that interest rates have a negative relationship with CDS. During COVID-19, all the sectors except consumer have a negative association of interest rate and CDS, which is in contrast to **Model 2** results showing a positive

relationship between interest rate and CDS (please refer to **Table 12- Model 2** - sector-wise regression results for the US5YT- the US 5 Year treasury yield), an anomaly which requires separate investigation.

Chapter 6- Conclusion

This dissertation investigates the movement of CDS sector indices before, during, and after COVID-19 between January 2017 and December 2023. We test the EPU index's effect on CDS indices and analyse the predictive power of two different uncertainty measurements that are VIX and EPU. We have also analysed commodity index and crude oil's influence on CDS sector indices. We have also evaluated the impact of CDS structural drivers like equity prices, interest rates, and volatility on CDS sector indices. Our dissertation contributes to the literature since we are the first to analyse the CRB index's impact on all the CDS sector indices before and after COVID-19. We used fixed effects panel regressions since we had very well-structured data of 35 CDS indices across seven years with daily and weekly frequency. We ran panel regression at the global level, including all sectors and sector levels (for ten sectors).

We expected to find a negative relationship between equity and CDS. Even though researchers have proposed contradictory views about interest rates' impact on CDS, we anticipated a negative relationship between interest rates and CDS since our reviewed literature papers had shown a negative relationship between interest rates and CDS. We also relied on the assumption that higher interest rates result from economic growth, and high growth decreases companies' probability of default. We anticipated a positive association between the uncertainty measurements (VIX and EPU index) and CDS.

We found a negative relationship between the S&P500 equity index and CDS sector indices for the whole period, before COVID-19 and after COVID-19. A positive relationship between the S&P500 and CDS indices during the COVID-19 is a significant exception. EUROSTOXX50 negatively impacted CDS indices for the entire sample period and three sub-periods. The European equity had a more robust impact on CDS than the S&P500 since EUROSTOXX50 coefficients were negative across all the sectors with statistical significance, and the magnitude of the coefficient was also considerable. Panel regressions confirmed an unexpected positive association between the US 5-year treasury yield and CDS for the entire sample period and after COVID-19. The above results help us accept our **first hypothesis** that equity is negatively associated with CDS; however, we must reject our **hypothesis** concerning interest rates' negative impact on CDS.

Our main contribution is the analysis of EPU index's impact on all the CDS sector indices before, during, and after the COVID-19 period as well as relative importance of EPU index and VIX index for analysis

of CDS sector indices. For the whole sample and sub-periods, EPU coefficients were positive for all the sectors except the consumer sector, which confirms our **second hypothesis** that EPU is positively associated with CDS. The banking, non-bank financials, manufacturing, service, and sovereign CDS sector indices had positive and statistically significant EPU coefficients for the whole sample period.

VIX was positively associated with CDS for all ten sectors for **Model 2** for the entire sample period and during COVID-19. Even though VIX coefficients were not in line with the reviewed literature before and after COVID-19 for **Model 4**, those coefficients were statistically significant, and those coefficients had a more substantial magnitude than EPU coefficients before and after COVID-19 for **Model 1**. This unique result indicates that VIX is a dominant uncertainty measurement index between VIX and EPU. Considerable magnitudes of VIX coefficients during COVID-19 solidify VIX's position as a barometer of volatility indicator in the crisis period.

The CRB index had no statistically significant association with CDS sector indices except the energy, power, and transportation sectors. The absence of predicted signs for the commodity index and crude oil's relationship with CDS at the global level, followed by a lack of sector-specific meaningful results for the CRB index, does not allow us to accept our **third hypothesis** that a diversified commodity index is a better predictor of CDS than crude oil at large.

We have concluded our investigation of whether the commodity index explains CDS spread better than crude oil with two points. Firstly, the daily and weekly adjusted R squared of the total sample period increases by 12% for the energy sector when USO is considered an independent variable instead of the CRB commodity index. Non-bank finance, sovereign, and banking sector daily adjusted R squared increased by 14%, 13%, and 11%, respectively, and weekly regression results confirm the trend (please refer to **Table 17**). Second, banking, energy, manufacturing, and sovereign sector CDS indices had a negative relationship with the US oil ETF at a 5% significance level for the entire sample period and a negative US oil ETF coefficient during COVID-19 (please refer to **Table 19**). The above two points help us conclude that banking, energy, and sovereign are the most impacted sectors for the whole sample and during COVID-19 due to oil prices than the CRB index. We do not find any indication that the commodity index explains CDS spread better than crude oil.

We have three suggestions related to further research. First, based on our conclusion of EPU's consistently positive relationship with CDS indices, finance researchers need to dive deep into various

textual analysis-based models to find meaningful relationship patterns between variants of uncertainty indices and traded financial instruments like CDS, commodity indices, and equity indices. Second, future studies can use energy ETFs with diversified portfolios of crude oil prices to better understand the implications of the impact on energy sector CDS due to energy prices. Third, Researchers can use event study approach to analyse CDS sector indices. Researchers can also use Generalised Method of Moments (GMM) dynamic panel regression method since it helps in controlling endogeneity issues through lag of dependent variables as one of the independent factors.

A positive relationship between the S&P500 and CDS indices during COVID-19 has raised the question of finding the drivers behind the unexpected association between equity and CDS indices. One reason might be the rally in information technology sector stocks, which may not have CDS indices since information technology companies traditionally do not issue debts. As a result, the information technology sector does not have an active CDS market. A firm-level lead-lag relationship between equity price and single-name CDS can help us confirm our view. Otherwise, it may reveal other reasons for a positive association between the S&P500 and CDS during COVID-19.

Chapter 7- Appendix

Table 21- Model 4- Global level daily panel regression

Variable	Predicted Sign	Full	Before	During	After
Ln(US5Y)	----	0.05** (0.02)	-0.08** (0.02)	0.1*** (0.00)	0.07*** (0.00)
Ln(STOXX)	----	-0.6*** (0.00)	-1.53*** (0.00)	-1.1*** (0.00)	-0.78*** (0.00)
Ln(CRB)		0.41*** (0.00)	-0.02 (0.83)	-0.32*** (0.00)	0.02 (0.72)
Ln(VIX)	+++	0.21*** (0.00)	-0.07*** (0.00)	0.2*** (0.00)	-0.17*** (0.00)
Ln(SPX)	----	-0.14 (0.14)	-0.5*** (0.00)	0.49*** (0.00)	-1.36*** (0.00)
Adjusted R-squared		0.2738	0.3033	0.5133	0.5157
No of obs.		63,630	27,265	18,200	18,165
No of Grps		35	35	35	35

T- statistics are shown in brackets. Dependent variable: LnCDS

Table 22- Independent variable Ln(EPU) sector-wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	0.07***	0.04***	0.2***	0.03***
	T-stat	(4.36)	(11.44)	(9.43)	(7.52)
Banking	Coeff	0.04*	0.05**	0.28**	0.03
	T-stat	(3.72)	(6.9)	(11.99)	(2.59)
Consumer	Coeff	-0.01	0.01	0.01	0.04**
	T-stat	(-0.52)	(0.62)	(0.31)	(13.41)
Energy	Coeff	0.16***	0.07**	0.34***	0.06**
	T-stat	(20.65)	(7.35)	(33.78)	(11.17)
Manufacturing	Coeff	0.1**	0.05**	0.21***	0.06**
	T-stat	(3.79)	(4.4)	(8.62)	(3.55)
Non-bank Fin	Coeff	0.11	0.03**	0.21**	0.02*
	T-stat	(2.28)	(6.63)	(4.01)	(2.5)
Power	Coeff	0.05	0.04**	0.04	0.05***
	T-stat	(0.5)	(4.64)	(0.65)	(35.59)
Service	Coeff	0.05	0.03***	0.2**	0.02
	T-stat	(1.06)	(11.07)	(2.82)	(1.64)
Sovereign	Coeff	0.03**	0.03**	0.25***	0.03
	T-stat	(3.65)	(4.54)	(10.06)	(1.92)
Telecommunication	Coeff	-0.04	0.02	0.15***	0.01
	T-stat	(-0.49)	(1.99)	(792.98)	(0.72)
Transportation	Coeff	0.16	0.04**	0.21	0.03
	T-stat	(2.69)	(6.89)	(1.49)	(2.06)

Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. T- statistics are shown in bracket. Dependent variable: LnCDS

The panel estimation is carried out by using CDS index-level fixed-effects and panel-robust standard error (clustering at the CDS index level) to control for autocorrelation and heteroskedasticity.

Table 23- Independent variable Ln(VIX) sector-wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	0.18***	0.04	0.42***	0.21***
	T-stat	(5.86)	(1.4)	(11.44)	(7.75)
Banking	Coeff	0.12**	0.07	0.55***	0.15
	T-stat	(4.16)	(1.92)	(18.2)	(1.96)
Consumer	Coeff	0.11	0.23	0.1	0.39
	T-stat	(3.29)	(1.01)	(2.95)	(3.78)
Energy	Coeff	0.29**	-0.1	0.7***	0.3***
	T-stat	(6.04)	(-0.77)	(22.26)	(20.15)
Manufacturing	Coeff	0.31**	0.2**	0.43***	0.35***
	T-stat	(4.62)	(3.77)	(10.61)	(8.75)
Non-bank Fin	Coeff	0.25*	0.08*	0.41**	0.15
	T-stat	(2.72)	(2.75)	(4.51)	(2.22)
Power	Coeff	0.17	-0.2	0.13	0.33***
	T-stat	(0.81)	(-2.26)	(1.33)	(16.66)
Service	Coeff	0.16	0.11*	0.42**	0.12
	T-stat	(1.92)	(2.27)	(3.9)	(2.06)
Sovereign	Coeff	0.06	-0.07	0.47***	0.14
	T-stat	(1.72)	(-1.08)	(10.02)	(1.76)
Telecommunication	Coeff	-0.04	0.03	0.35**	0.06
	T-stat	(-0.24)	(3.39)	(21.43)	(1.25)
Transportation	Coeff	0.39**	0.18	0.44	0.18
	T-stat	(4.77)	(1.21)	(1.89)	(1.42)

T- statistics are shown in bracket. Dependent variable: LnCDS

Table 24- Independent variable Ln(CRB)- Commodity index's sector-wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	0.23***	-0.32**	-0.64***	0.66***
	T-stat	(5.47)	(-2.52)	(-8.71)	(8.52)
Banking	Coeff	0.22	-0.16	-0.94**	0.65**
	T-stat	(1.61)	(-1.28)	(-7.82)	(5.36)
Consumer	Coeff	0.15	-0.38	0.01	1.29
	T-stat	(2.29)	(-4.39)	(0.03)	(2.14)
Energy	Coeff	-0.1	-1.24**	-1.04***	0.29
	T-stat	(-0.66)	(-6.57)	(-19.22)	(1.12)
Manufacturing	Coeff	0.41**	-1.06	-0.63***	0.96**
	T-stat	(3.8)	(-2.05)	(-8.32)	(5.33)
Non-bank Fin	Coeff	0.25*	-0.12	-0.63**	0.54*
	T-stat	(2.76)	(-0.48)	(-5.53)	(2.84)
Power	Coeff	0.6	-0.36	-0.09	1.09**
	T-stat	(2.59)	(-0.66)	(-0.35)	(6.35)
Service	Coeff	0.28**	-0.09	-0.63**	0.58***
	T-stat	(3.04)	(-0.34)	(-2.79)	(5.93)
Sovereign	Coeff	0.11	-0.24	-0.85***	0.59**
	T-stat	(1.71)	(-0.78)	(-7.52)	(3.25)
Telecommunication	Coeff	0.13	0.33	-0.53*	0.16
	T-stat	(1.26)	(2.12)	(-9.15)	(0.73)

Transportation	Coeff	0.23**	0.27	-0.6	0.57
	T-stat	(10.55)	(0.5)	(-1.24)	(1.45)

T- statistics are shown in bracket. Dependent variable: LnCDS

Table 25- Independent variable Ln(USO)- US oil ETF's sector-wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	-0.02	-0.26***	-0.25***	0.37***
	T-stat	(-0.47)	(-3.5)	(-7.09)	(8.48)
Banking	Coeff	0.11**	-0.24**	-0.31**	0.35**
	T-stat	(5.31)	(-5.95)	(-10.06)	(4.96)
Consumer	Coeff	0.1	0.17	0.06	0.72
	T-stat	(1.46)	(0.58)	(0.77)	(2.25)
Energy	Coeff	-0.21**	-1.05*	-0.45***	0.03
	T-stat	(-9.91)	(-4)	(-36.23)	(0.16)
Manufacturing	Coeff	-0.05	-0.18**	-0.24**	0.48**
	T-stat	(-0.95)	(-3.33)	(-3.87)	(3.38)
Non-bank Fin	Coeff	-0.12	-0.15	-0.33**	0.35**
	T-stat	(-1.31)	(-1.56)	(-3.09)	(3.58)
Power	Coeff	-0.04	-0.67*	-0.05	0.55**
	T-stat	(-0.17)	(-2.91)	(-0.47)	(5.94)
Service	Coeff	0.04	-0.09	-0.22	0.37***
	T-stat	(0.47)	(-0.8)	(-1.87)	(8.14)
Sovereign	Coeff	0.07**	-0.42*	-0.3***	0.41***
	T-stat	(2.52)	(-2.15)	(-10.53)	(5.14)
Telecommunication	Coeff	0.21	-0.13**	-0.1	0.14
	T-stat	(1.05)	(-58.88)	(-1.39)	(1.34)
Transportation	Coeff	-0.23	0.27	-0.31	0.3
	T-stat	(-2.23)	(1.26)	(-1.36)	(1.33)

T- statistics are shown in bracket. Dependent variable: LnCDS

Table 26- Independent variable Ln(SPX)- S&P500's sector-wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	0.02	-0.76***	-0.77***	-1.63***
	T-stat	(0.31)	(-5.45)	(-9.52)	(-12.72)
Banking	Coeff	-0.22	-1.08**	-1.16**	-1.76***
	T-stat	(-2)	(-8.41)	(-7.2)	(-33.53)
Consumer	Coeff	-0.03	0.27	-0.09	-1.24**
	T-stat	(-1.4)	(0.57)	(-0.47)	(-12.14)
Energy	Coeff	-0.11	-1.78**	-1.21***	-1.28
	T-stat	(-0.79)	(-4.22)	(-15.32)	(-1.63)
Manufacturing	Coeff	0.24	-0.18	-0.78**	-2.42**
	T-stat	(1.78)	(-0.6)	(-7.62)	(-5.03)
Non-bank Fin	Coeff	0.2	-0.63	-0.68**	-1.47**
	T-stat	(1.38)	(-1.72)	(-7.57)	(-5.39)
Power	Coeff	0.34	-1.36**	-0.12	-2.05**
	T-stat	(0.72)	(-5.83)	(-0.46)	(-11.13)
Service	Coeff	0.02	-0.45	-0.79**	-1.64***

	T-stat	(0.16)	(-1.9)	(-3.46)	(-9.61)
Sovereign	Coeff	-0.26*	-1.19**	-1.02***	-1.61**
	T-stat	(-2.33)	(-3.13)	(-7.11)	(-3.59)
Telecommunication	Coeff	-0.36	-0.84*	-0.75	-1.25
	T-stat	(-0.95)	(-10.43)	(-4.62)	(-5.15)
Transportation	Coeff	0.41**	-0.04	-0.68	-1.16*
	T-stat	(12.33)	(-0.08)	(-1.31)	(-4.05)

T- statistics are shown in bracket. Dependent variable: LnCDS

Table 27- Independent variable Ln(STOXX)- EUROSTOXX50's sector- wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	-0.27***	-1.31***	-1.09***	-1.03***
	T-stat	(-3.06)	(-8.79)	(-9.71)	(-11.78)
Banking	Coeff	-0.6	-2.15**	-1.54**	-0.98**
	T-stat	(-2.54)	(-6.57)	(-9.66)	(-5.9)
Consumer	Coeff	-0.29	-1.38	-0.1	-1.48
	T-stat	(-2.83)	(-0.98)	(-0.41)	(-3.71)
Energy	Coeff	-0.7*	-1.2	-1.78***	-0.98
	T-stat	(-2.99)	(-1.76)	(-20.74)	(-2.69)
Manufacturing	Coeff	-0.1	-1.71**	-1.1***	-1.56***
	T-stat	(-0.61)	(-7.03)	(-8.96)	(-9.5)
Non-bank Fin	Coeff	-0.11	-1.41**	-1.05**	-0.91**
	T-stat	(-0.83)	(-5.64)	(-5.6)	(-3.81)
Power	Coeff	0.53	0.02	-0.2	-1.44***
	T-stat	(0.87)	(0.02)	(-0.57)	(-18.41)
Service	Coeff	-0.22	-1.28**	-1.09**	-0.85***
	T-stat	(-1.48)	(-5.38)	(-3.16)	(-6.77)
Sovereign	Coeff	-0.58**	-1.19***	-1.36***	-0.88**
	T-stat	(-3.42)	(-6.37)	(-8.35)	(-3.08)
Telecommunication	Coeff	-0.53	-1.35	-0.92*	-0.53**
	T-stat	(-1.32)	(-4.46)	(-9.51)	(-50.1)
Transportation	Coeff	0.01	-1.48*	-1.06	-0.85
	T-stat	(0.04)	(-2.92)	(-1.46)	(-2.01)

T- statistics are shown in bracket. Dependent variable: LnCDS

Table 28- Independent variable Ln(US5YT)- US five-year treasury yield's sector- wise univariate results

Sector Type	Value	Daily			
		Full	Before	During	After
All sectors	Coeff	0.07***	0.02	-0.16***	0.17***
	T-stat	(5.44)	(0.55)	(-7.06)	(5.68)
Banking	Coeff	0.13**	0.14**	-0.22**	0.26
	T-stat	(4.69)	(6.62)	(-9.93)	(2.56)
Consumer	Coeff	0.06	0.13	0.05	-0.1
	T-stat	(2)	(0.59)	(0.69)	(-0.86)
Energy	Coeff	-0.05	-0.29*	-0.29***	-0.08
	T-stat	(-1.9)	(-3.07)	(-19.96)	(-0.42)
Manufacturing	Coeff	0.09**	0	-0.15**	0.18**

	T-stat	(7.31)	(-0.01)	(-4.55)	(4.27)
Non-bank Fin	Coeff	0.03	0.08	-0.21**	0.21***
	T-stat	(2.02)	(1.32)	(-3.64)	(9.24)
Power	Coeff	0.1	-0.26	-0.02	0.12
	T-stat	(1.41)	(-0.95)	(-0.29)	(1.75)
Service	Coeff	0.1**	0.11	-0.15	0.28**
	T-stat	(3.4)	(1.47)	(-2.01)	(3.96)
Sovereign	Coeff	0.09***	0	-0.21***	0.27***
	T-stat	(9.37)	(0.03)	(-8.46)	(8.1)
Telecommunication	Coeff	0.14	0.18	-0.08	0.26
	T-stat	(2.08)	(2.23)	(-2.74)	(2.66)
Transportation	Coeff	-0.02	0.16	-0.19	0.09
	T-stat	(-0.8)	(1.29)	(-1.2)	(0.91)

T- statistics are shown in bracket. Dependent variable: LnCDS

Chapter 8- References

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