IMPACT OF GEOPOLITICAL TENSIONS ON INDUSTRY SPECIFIC CDS SPREADS IN EUROPE

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ABSTRACT

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Abstract

The purpose of this study is to examine the impact of crises on European industry-level credit default swap (CDS) spreads using linear regression. The two crises analyzed are the COVID-19 pandemic and the Russian invasion and war in Ukraine. Researching geopolitical risk is important because it helps to identify and understand the potential impacts of political and territorial conflicts on financial markets, allowing for informed decision-making and risk management. By analyzing data from the two crises and using linear regression, this study aims to identify how industry-level CDS spreads are affected by these crises. This information can be valuable for policymakers and industry professionals in understanding the potential financial risks associated with different types of crises. The results of this study may also help to inform future research on the relationship between crises and financial market indicators.

Key words
Credit default swap, CDS, CDS spread, geopolitical tensions, Covid-19, pandemic, industry, Europe

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TIIVISTELMÄ (ABSTRACT IN FINNISH)

Tekijä Elisa Härkönen	
Työn nimi Geopoliittisten jännitteiden vaikutus eurooppalaisiin toimialatason CDS indeksihin	
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Tiivistelmä Tämän tutkimuksen tarkoituksena on tutkia lineaarisen regression avulla kriisien vaikutusta eurooppalaisten luottoriskinvaihtosopimusten (Credit Default Swap, CDS) marginaaleihin toimialatasolla. Analysoitavat kriisit ovat COVID-19-pandemia ja Venäjän hyökkäyssota Ukrainassa. Geopoliittisten riskien tutkiminen on tärkeää, koska se auttaa tunnistamaan ja ymmärtämään poliittisten ja alueellisten konfliktien mahdollisia vaikutuksia rahoitusmarkkinoihin, mikä mahdollistaa tietoon perustuvan päätöksenteon ja riskienhallinnan. Analysoimalla näitä kahta kriisiä koskevia tietoja lineaarista regressiota hyödyntäen tässä tutkimuksessa pyritään tunnistamaan mahdolliset suuntaukset siinä, miten nämä kriisit vaikuttavat toimialatason CDS-eriin. Nämä tiedot voivat olla arvokkaita poliittisille päättäjille ja alan ammattilaisille, kun he käsittelevät erityyppisiin kriiseihin liittyviä mahdollisia taloudellisia riskejä. Tämän tutkimuksen tulokset voivat myös auttaa hyödyntämään tulevaa tutkimusta kriisien ja rahoitusmarkkinaindikaattoreiden välisestä suhteesta.	
Asiasanat Luottoriskinvaihtosopimus, CDS, CDS erä, geopoliittiset jännitteet, Covid-19, pandemia, toimiala, Eurooppa	
Säilytyspaikka Jyväskylän Yliopiston Kirjasto	

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1 INTRODUCTION

The credit default swap (CDS) market has grown significantly in recent years, leading to a corresponding increase in empirical research on the market. Financial institutions such as banks and hedge funds have increasingly turned to CDS trading as a means of mitigating credit risk. The ongoing war in Ukraine has had far-reaching consequences, affecting not only the Ukrainian people, but also the global economy. The war has led to inflation and disrupted trade and supply chains, resulting in negative impacts on business confidence and investor uncertainty, which can affect asset prices. The global economy is also still recovering from the shock the Covid-19 pandemic caused to industries and financial instruments worldwide.

Political uncertainty, defined as a lack of clarity or predictability about government actions and decisions (Kelly et al., 2016), can have negative effects on the economy and financial markets, including increased stock price volatility, reduced investment rates, and slower employment growth. It can be difficult to disentangle the effects of political uncertainty from those of economic uncertainty, and options markets may reflect the perceived level of political risk. Options that provide protection against price, variance, and tail risks may become more expensive during times of high political uncertainty, particularly when the economy is weaker. In this thesis, the impact of geopolitical uncertainty, especially of the two abovementioned crises, on industry specific CDS indices is studied. The thesis focuses on the European CDS indices, as those are less studied compared to both the US and global CDS indices.

1.1 Motivation

The matter of crises now seems more topical than ever, as the world has been hit with a crisis after another. After surviving the global financial crisis, Europe plunged into a sovereign debt crisis that led to major economic difficulties in several European countries. Not even half a decade later, a deadly pandemic starts to spread across the globe from China, and presumably the global economy is once again being compromised due to the restrictions concerning lockdowns and quarantines. Covid-19 has had a lasting impact on the economy as millions of people were left unemployed (OECD, 2022a) leading businesses to file for bankruptcies.

While the pandemic was still going, Russia invaded Ukraine in February 2022, causing an excess increase in inflation and in detrimental oil and gas prices (OECD, 2022b) in addition to the horrific suffering and loss of lives of the people of Ukraine. As geopolitical tensions remain high, intense uncertainty has its repercussions on the economy, especially in Europe. Due to the newness of the war in Ukraine, few studies have yet been published on its impacts on the economy (see Boungou & Yatié, 2022; Ben Hassen & El Bilali, 2022; Wang et al., 2022; Zahra, 2022).

The impact of these two major and topical crises on one of the most central financial instruments, measure of credit risk, credit default swaps, is highly interesting. Political uncertainty has been linked to a change in CDS spreads by several studies (see Wisniewski & Lambe, 2015; Liu & Zhong, 2017; Wang et al., 2019; Tanyeri et al., 2022), so studying major crises causing political uncertainty and their impact on industry specific CDS indices bases on a strong foundation of literature while adding a new perspective. This thesis will contribute to the literature by researching the impact of both of these crises on industry specific CDS indices in Europe, which has not been examined from this angle to the author’s current knowledge.

Making the right policy actions depends on bank supervisors being aware of the correct factors influencing CDS spread changes, as additional monitoring could be needed in order to prevent financial institutions’ excess increase of credit risk (Annaert et al. 2013). Changes in CDS spreads can also be a sign of market malfunction needing to be addressed (Annaert et al. 2013). CDS and bond spreads have been used to analyze their capabilities in information transmission of credit risk during the European sovereign debt crisis (Arce et al., 2013), which highlights the significance of CDS spreads as a measure of credit risk, particularly during economic uncertainty.

As discussed before, the connection between crises and corporate CDS spreads is notable. The impact of the Covid-19 pandemic and CDS spreads has been studied previously in the United States and globally (see Liu et al., 2021; Apergis et al., 2022; Hasan et al., 2022; Vukovic et al., 2022.). However, the connection is yet to be studied focusing on Europe as an economic area. Europe is one of the most important markets globally, accounting for roughly 13 % of the global markets in 2021 (World Bank, 2022). The connection between the war in Ukraine and CDS spreads has also yet to be studied. These two gaps in the literature make this topic specifically interesting to study.

1.2 Research questions

The aim of this master's thesis is to investigate the industry level CDS spreads in Europe using several variables to find out which have an impact on it. The research method used in this thesis is linear regression, and three separate regressions are formed. The regressions seek to answer the research questions of this thesis by identifying the variables that correlate the most with the dependent variable. The two main research questions of this thesis are the following:

1. Which variables explain the changes in industry level CDS spreads?
2. How do the current crises of the Covid-19 pandemic and the Russian invasion of Ukraine affect industry level CDS spreads?

The variables used in this study, as well as the method and data are presented in more detail and discussion in chapter 4.

1.3 Definitions

When starting to discuss credit default swaps and CDS spreads, a key concept to understand is credit risk, as it is in the overall starting point of analyzing financial instruments to protect from it. Credit risk is considered a default risk of a borrower, making them unable to pay back their debt obligations, including both the interest payments as well as the nominal debt payments. Credit risk can cause major financial consequences for both the borrower and the lender, and therefore it is detrimental for the lender to carefully evaluate the creditworthiness of the borrower and setting appropriate interest rates based on the risk profile. By carefully managing their finances, the borrower can manage their credit risk.

Traditionally, banks carried the credit risk of its borrowers defaults by having all the debts in their balance sheets. This is however not attractive to regulators and investors, which is why banks have been shifting more towards credit derivatives such as credit default swaps to protect their loans during the late 1990s and early 2000s. (Hull, 2014).

Credit default swaps, CDSs, have been around since the 1990s (Stulz, 2010). They act as an insurance mechanism protecting the buyer from a default of the bond issuer, so they protect the money invested in a bond by transferring the risk involved to a protection seller (Hull, 2014; Bomfim, 2022). The difference between a CDS and an insurance is that to buy a conventional insurance the buyer needs to own the matter that is being insured, and for a CDS the buyer does not. Credit default swaps should increase efficiency of financial markets in principle (Stulz, 2010). In chapter 2 the mechanism of the CDS instrument is more thoroughly covered.

During the first years of CDSs, making deals was slow and required a lot of effort (Stulz, 2010). As the hedging properties of CDSs became well known allowing institutions to reduce losses during for example the global financial crisis, CDSs gained more popularity (Stulz, 2010). Another factor contributing to the rise of CDSs was the establishment of the International Swap Dealers Association (ISDA), that took responsibility for devising standardized agreements to help standardize the industry (Stulz, 2010).

A CDS spread is used to describe the cost or rate of payments paid to the issuer for protection against the company's default, and it is typically presented as basis points (Hull et al., 2004). CDS spread can also be defined as the periodic rate the buyer pays the seller on the notional amount for transferring the risk of a bond (Annaert, 2013).

CDS spreads can be used to analyze credit risk and credit worthiness of an entity, and a higher spread indicates greater credit risk. This can therefore lead to a decrease in willingness to invest into that entity. CDS spreads can also be used as a measure of political uncertainty, as the CDS contracts can often be used to protect against the risk of default of a country or a region, the default risk of said area can be increased due to political instability. CDS spreads can be used as an insight into the political uncertainty level of a given area.

CDS markets have increased rapidly during the last two decades, growing their share of the global derivative market (Oehmke & Zawadowski, 2017). It is argued that short selling via the CDS market has destabilized the market, and that efficiency benefits can be reached through taking advantage of the information benefits the CDS pricing has to offer (Stulz, 2010). Credit default swaps allowed for separating risk and funding, which calls for possible problems as well as monitoring incentives (Stulz, 2010).

Another concern of the CDS markets is liquidity, as the nature of trading is non-continuous, and the trust and confidence between counterparties is heavily relied on (Pereira et al., 2018). During times of crises, liquidity might be scarce, leading to a long recovery period (Pereira et al., 2018). This is due to the trading costs of CDSs that include broker commissions, search costs and asymmetric information costs (Pereira et al., 2018).

In the empirical section of this thesis, the focus heavily relies on CDS indices for simplicity reasons. CDS indices are indices consisting of a basket of CDS spreads on companies within a selected industry that are calculated as weighted averages of the CDS spreads of selected companies. These indices measure the credit risk of said industry. However, in theoretical framework as well as in covering previous literature, credit default swaps and CDS spreads have the main role, as they are necessary to understand in order to study CDS indices and form a base for CDS indices.

1.4 Structure of the thesis

The rest of this thesis is structured as follows: the second chapter will begin by introducing the theoretical framework behind the CDS instrument, market and pricing, followed by a brief review of previous literature of the topic. Next, the data and methodology used in this thesis will be introduced followed by the results and discussion of the empirical study. Lastly, conclusions will be drawn.

2 THEORETICAL FRAMEWORK

This chapter focuses on the theoretical framework behind the CDS instrument and its pricing, also known as the CDS spread. First the CDS instrument and its mechanisms are introduced using literature, and then the CDS market and its behavior and history are described. Third, the pricing of the CDS, the CDS spread is discussed with a theory called CDS-bond basis. Lastly, another major factor behind the CDS pricing, investor sentiment is covered.

2.1 CDS instrument

Credit default swaps (CDS) are a relatively young financial instrument that allows for credit risk to be distributed as well as the credit risk to be priced more effectively (Bomfim, 2022). These qualities make CDS the most common credit derivative type. The mechanism is in buying protection from a protection seller against credit risk, to whom periodic payments (CDS spreads or premia) are paid over the maturity of the CDS or a predetermined amount of time. In a case of a default, the protection seller covers the notional amount of the contract to the protection buyer. (Bomfim, 2022). CDS market allows the buyer to benefit without holding the underlying asset of the contract, which means the buyer is not exposed to any political risk (Wisniewski & Lambe, 2015).

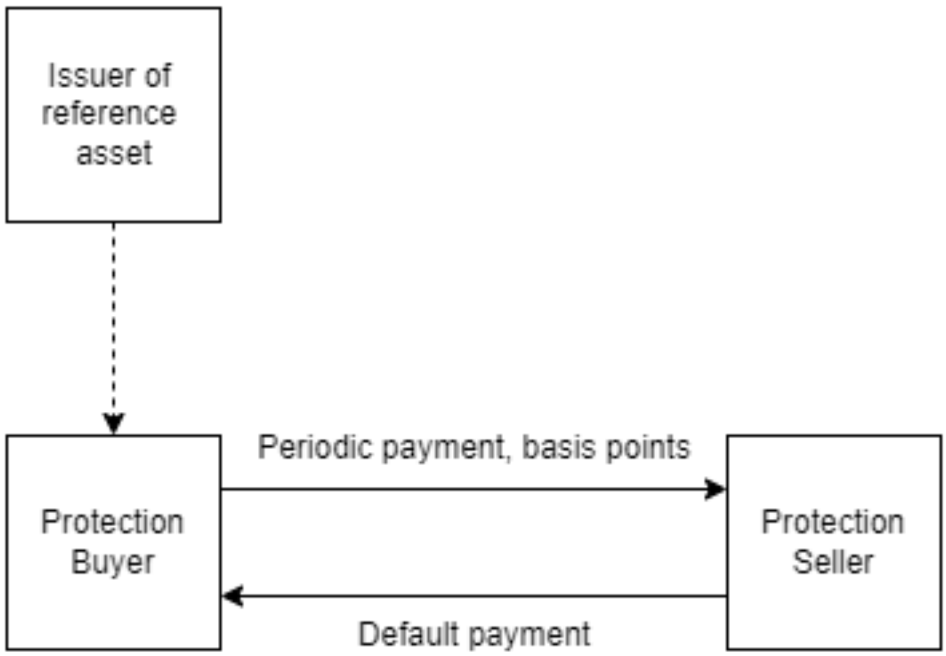

Figure 1. Cash flows in a CDS. Compiled by the author. (McDonald, 2013).

As it can be seen from figure 1, the reference asset, for example a bond deal is between the issuer and the protection buyer. At the same time the protection buyer buys the CDS from the protection seller, to whom they make periodic payments in basis points. In case the issuer defaults, the protection seller pays the protection buyer the nominal amount of the protected asset as a default payment.

CDS contracts can protect the buyer against credit risk of a single reference entity or several entities. Those options make up the types of CDS contracts: single-name and multi-name CDS. Single-name contracts are literally protecting the buyer against a single entity, a corporation for instance. Multi-name CDS contracts can be used for defaults in a portfolio or more typically be based on a single-name CDS based index, called CDS index. (Bomfim, 2022). CDS indices will be covered more thoroughly later on this thesis.

When discussing potential effects of CDS trading on the creditor-borrower relationship, credit risk, and the overall financial health of the borrower, it is suggested that CDS trading can potentially improve the borrower's access to capital and financial flexibility, but it can also lead to less vigilant monitoring and more risky decision-making by the borrower (Subrahmanyam et al., 2014). Additionally, CDS-protected creditors may be less inclined to participate in debt renegotiations, potentially increasing the risk of bankruptcy for the borrower (Subrahmanyam et al., 2014).

Subrahmanyam et al. (2014) indicate that CDS trading is associated with an increase in the likelihood of rating downgrades and bankruptcy for firms. This increase in credit risk is statistically significant and economically meaningful, with average credit ratings declining in the two years after the inception of CDS trading and the likelihood of bankruptcy more than doubling (Subrahmanyam et al., 2014). They argue that despite being designed to provide insurance against borrower default, CDS trading can actually increase the risk of borrower default (Subrahmanyam et al., 2014).

It is suggested that when credit default swaps are traded on a firm, it may become more vulnerable to bankruptcy (Subrahmanyam et al., 2014). However, it is not clear whether the benefits of the increased leverage that results from the reduction of risk outweigh the increased costs of bankruptcy (Subrahmanyam et al., 2014). Further research is needed to examine the balance between the potential benefits and the bankruptcy vulnerability caused by CDS and to understand the overall impact of CDS trading on efficiency (Subrahmanyam et al., 2014).

2.2 CDS market

CDS account only for 1.5 % of all derivative markets globally (in 2020), so the CDS market is still small compared to the derivatives market as a whole (Bomfim, 2022). Bomfim (2022) argues the market size would be drastically larger if the 2008 Global Financial Crisis (GFC) hadn't happened and increased uncertainty of regulatory policies and risk avoidance, which caused notional outstanding amounts to decrease.

The size of the CDS market has been increasing since a standardized contract was produced by the International Swaps and Derivatives Association in 1998 (Hull et al., 2004) and has expanded significantly during the last two decades (Galariotis et al., 2016). In Figure 2 the distribution of the global CDS market is presented by CDS type, end users, reference entity type and reference entity rating.

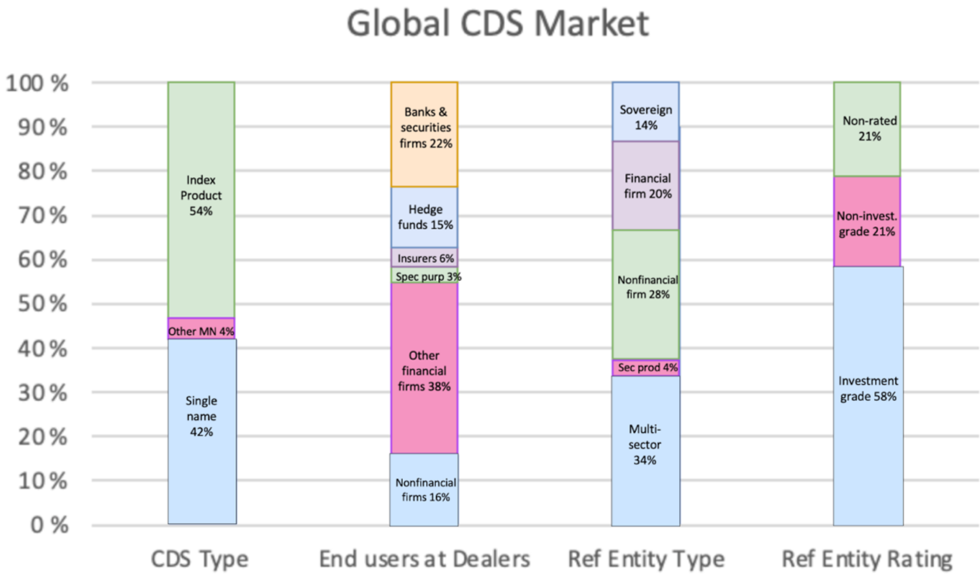

Figure 2. Global CDS Market (Bomfim, 2022).
Note: "End Users" refers to non-dealer end users.
List of abbreviations used in figure X:
Other MN: Other multi-name CDS (non-index product)
Spec purp: Special-purpose vehicle, special-purpose corporation, or special-purpose entity
Sec prod: Securitized products
Ref Entity: Reference Entity

As it can be seen from the first bar of Figure 2, more than half of the CDS market's total of $8,5 trillion (in 2020) corresponds to index products and only 4 % to other multi-name CDS, while single-name CDS make up for the rest 42 %. The second bar in Figure 2 displays the end users of CDS, the "protection buyers". Banks and securities firms together with other financial institutions make up for the largest portion, 60 %. Nonfinancial firms and hedge funds both correspond to approximately 15 % each, and insurers and special purpose corporations account for the remaining 9 %. (Bomfim, 2022).

Reference entity types are also displayed in bar 3 of Figure 2: sovereign entities make up for only 14 % of entities that buyers seek protection against. Multi-sector entities are the largest entity type, corresponding to approximately a third of all reference entities. Financial firms account for a fifth of the entities while nonfinancial firms account for slightly more than that, 28 %. Bar 4 represents the financial rating of the reference entity. More than half of the entities are in the Investment Grade -class and a fifth of entities are in Non-Investment Grade, while the rest of the entities are non-rated. (Bomfim, 2022).

There is found a cluster of approximately fourteen major dealers in the CDS market, and where most of the investors are net buyers (Peltonen et al., 2014). CDS spreads indicate market participants' perceptions of creditors' financial health and can serve as a warning about potential financial instability (Annaert et al., 2013).

The CDS markets have a role as an alternative trading venue combining standardization and liquidity where investors are taking more of a speculative trading stance compared to the bond market (Oehmke & Zawadowski, 2017). The underlying bond has higher trading frictions than the CDS markets, which makes it intriguing to invest in the CDS markets (Oehmke & Zawadowski, 2017).

The feature of the CDS market serving a standardization role is shown in higher CDS net notional amounts of companies that have bonds divided into several issues rather than one when controlling for the amount of outstanding bonds and trading motives (Oehmke & Zawadowski, 2017). This is resulted from a conclusion of hedging and speculation both being factors to CDS positioning, although these factors are not enough reasoning as to why would investors invest in CDS markets rather than directly trading the underlying bond (Oehmke & Zawadowski, 2017).

Credit derivatives are more significant than one might assume. During the time period between 2000 and 2004 when corporate defaults were at historically high levels, CDS instruments positively affected the robustness of financial institutions (Acharya & Johnson, 2007). At the same time, CDS markets have been repeatedly debated in policies during the last decade: its role, impact on debtor-creditor relationship and consequences on financing choices, credit risk and firms' cost of capital have been debated (Oehmke & Zawadowski, 2017).

As can be seen from figure X, more than half of the CDS products are indices. They consist of averages of single name contracts, and often represent a basket of a number of corporations CDSs (Stulz, 2010). In Europe there are for example iTraxx Europe, that includes 125 corporate credit default swaps. Buying an index product, the buyer gets protection against all corporations included in the basket without having to purchase all of them separately (Stulz, 2010).

2.3 CDS pricing

The pricing of CDS is not as straightforward as it is for some other OTC derivatives, where factors affecting the prices are dependent on interest and exchange rates and indices for instance (Hull, 2014). CDS spreads on the other hand depend on the default probability of an individual entity such as a company or a country, over a set period of time (Hull, 2014). This leads to a problem referred to as information asymmetry, as some partakers on the market have access to more and better information than others (Hull, 2014). Because of this information asymmetry problem protection purchasing decisions are often left to professional risk managers (Hull, 2014).

The difference between a CDS spread of a bond and a credit spread paid on the same bond is called a CDS-bond basis. The CDS-bond basis is defined as following by Hull (2014) and Bai and Collin-Dufresne (2018):

$$\text{CDS-bond basis} = \text{CDS spread} - \text{Bond yield spread} \tag{1}$$

If the basis is negative, meaning the CDS spread paid to the protection seller is less than the bond yield spread, the annual yield from the bond issuer, there is an opportunity for an arbitrage. This means that there is a chance for riskless profits. (Hull, 2014; Bai & Collin-Dufresne, 2018). Using this mechanism of “insuring” the bond investment with a CDS contract, not only can the investor avoid potential losses, but also create profit without carrying the risk related to it as the risk is shifted to the protection seller. By this assumption, where an investor makes a CDS contract on a bond, and therefore ends up owning a synthetic default-free bond, it is suggested that CDS spread should equal the bond default premium (McDonald, 2013).

However, this is not a typical arbitrage opportunity, as the investor needs to consider the probability of the CDS contract issuer default as well. There also exists an issue of capital raising quickly enough to benefit from the arbitrage, as well as how difficult it might be to short sell bonds. These violations offer a chance to test some theories of limits to arbitrage. (Bai & Collin-Dufresne, 2018). If the bond yield spread is significantly below the CDS spread, the investor can benefit by borrowing at less than the risk-free rate by shorting the corporate bond and writing a CDS on the bond (Hull, 2018).

In theory this basis should not offer an arbitrage opportunity, as the difference between the CDS and bond spreads should be close to zero when technical issues and market friction is ignored (Kim et al., 2016). A non-zero basis might result from a mispricing of either the CDS or the bond (Kim et al., 2016) or the CDS market absorbing information related to prices more efficiently than the bond market (Acharya & Johnson, 2007). Other factors might be risks related to the arbitrage or other market friction (Kim et al., 2016).

The CDS-bond basis can be utilized in predicting bond returns in the future as arbitrageurs buy bonds that have a low residual basis, which means the unexplained part of the CDS-bond basis (Kim et al., 2016). Using CDS in predicting future bond returns can be used to fix the bond mispricing problem by narrowing the gap between market value and the fundamental value of corporate bonds (Kim et al., 2016).

A negative CDS-bond basis is predicted in a study by Oehmke and Zawadowski (2015), who created a model utilizing nonredundant CDSs and that builds on the assumption of bonds having higher transaction costs compared to CDSs. They argue that introducing a CDS brings a trade-off between decreasing the demand for bonds and improving the allocation of bonds (Oehmke & Zawadowski, 2015). This improvement is achieved by enabling long-term investors to leverage their positions as basis traders; they can take on more of the bond supply (Oehmke & Zawadowski, 2015).

The model produces several predictions regarding the fluctuations in the CDS-bond basis in terms of both time and cross-sectional differences (Oehmke & Zawadowski, 2015).. Their predictions suggest that the basis is more likely to be negative for bonds with higher trading costs, when there is a greater disparity in opinions about the bond's default probability, and when basis traders are limited in the amount of leverage they can use (Oehmke & Zawadowski, 2015).

In conclusion, the model offers a framework for analyzing the effects of regulatory interventions on CDS markets (Oehmke & Zawadowski, 2015). For instance, a ban on naked CDS positions, such as the one implemented by the European Union through regulation 236/2012, may actually cause yields to rise for the affected issuers (Oehmke & Zawadowski, 2015). This is because if investors with a bearish outlook are unable to take naked CDS positions, some of them will instead short the bond (Oehmke & Zawadowski, 2015). This puts downward pressure on bond prices, as differences in trading costs mean that naked CDS positions are not equivalent to shorting the bond, as a different group of investors will be on the other side of the trade (Oehmke & Zawadowski, 2015). Similarly, interventions that completely ban CDS markets or both CDSs and short selling of bonds do not necessarily lead to higher bond prices (Oehmke & Zawadowski, 2015).

The CDS market increases its importance, making its role more vital, but the information relevance of CDS spreads is not agreed on (Pereira et al., 2018). The use of CDS spreads in evaluating firms' financial performance has been increasing as CDS implied default probability measures of Moody's and Bloomberg's are used more frequently (Pereira et al., 2018). The drivers behind the changes in CDS spreads are crucial for investors, policy makers and analysts to know in order to make the best choices possible (Pereira et al., 2018).

Pereira et al. (2018) found that a positive correlation exists between the CDS spread and return volatility, which implies that the higher is the volatility, the higher is the credit risk. CDS spreads can be used to better analyze a firm's credit risk during economic turbulence (Pereira et al., 2018). However there seems to exist an increasing effect of non-default drivers of CDS spreads, which needs to be considered when making decisions and policies, as CDS spreads should not be used as the only measure of credit risk rather than use other measures combined with CDS spreads (Pereira et al., 2018).

Factors of CDS spreads are not fixed, rather than changing over time, which highlights the importance of timely awareness by policymakers in choosing the correct estimation model depending on the economic environment and its stability, making market-based variables more essential during and after the financial crisis (Pereira et al., 2018). CDS spread determinants vary across time, and especially during crisis periods other factors than credit risk drivers are more common (Annaert, 2013). Other factors contributing to variation in CDS spreads include overall perception of bank stability as well as liquidity (Annaert, 2013).

Acknowledging the CDS spread changes and its drivers correctly is detrimental to supervisors and and makers of monetary policies as actions taken might differ depending on the driver of the change in CDS spreads (Annaert, 2013). CDS spread changes should not only be viewed for financial institutions, but also for other indicators such as equity prices and expected default frequencies for an accurate prediction (Annaert, 2013).

According to the Merton model and its expansions, the main determinants of credit spreads include leverage, asset volatility, market conditions (such as interest rates), stock volatility, leverage, total asset size, profitability, cash ratios, and investor risk aversion (Guesmi et al., 2018). These factors are all firm-level variables that can impact the creditworthiness and perceived risk of a company (Guesmi et al., 2018).

A model by Oehmke and Zawadowski (2015) predicts a negative CDS-bond basis as the CDS spreads are cheaper than the bonds' trading costs. A trade-off between CDSs and bonds happens when a new CDS is introduced: demand for bonds decreases while the demand allocates more towards long-term bond holders (Oehmke & Zawadowski, 2015). The theory is based on the observation that bond trading is more expensive than trading CDS (Oehmke & Zawadowski, 2015). This framework explains several matters in the CDS and bond markets, such as the vague effect on bond prices after introducing a CDS, trading volumes and impact of pricing, as well as the CDS-bond basis (Oehmke & Zawadowski, 2015).

CDS spreads can be used as reflections of credit institutions' financial health and the market perceptions of them as well as noticing warning signs related to financial stability by prudential authorities (Annaert, 2013). The role of CDS market liquidity should play a bigger role in analyzing CDS spreads, as it has affected bank CDS spread changes in the Euro area (Annaert, 2013).

In normal market conditions (mid-quantiles), the long-term factor (level) of the yield rate is the most significant determinant in the pricing of CDS spreads, regardless of the industrial sector (Aman, 2019). This inverse relationship is strongest in normal market conditions (Aman, 2019). The sensitivity of CDS spreads to yield rate factors varies by industrial sector and is better illustrated by the quantile regression (QR) approach than by ordinary least squares (OLS) estimates (Aman, 2019). In booming market conditions, the long-term yield curve factor (slope) and the market index are the most important factors in explaining the variability in CDS spreads (Aman, 2019). In bearish or normal market conditions (lower or mid-quantiles), there are limited diversification benefits from changes in the yield curve factors (specifically slope and curvature) in relation to CDS spreads for most industrial sectors (Aman, 2019).

2.4 Investor sentiment

A behavioral viewpoint is often overlooked in the literature, and the focus is on macroeconomic or financial information. However, recent years have shown that there is an important role of behavioral determinants when studying factors impacting the CDS spreads. Including behavioral determinants might help capture investor sentiment. Galariotis et al. (2016) show that based on recent studies, stock and bond returns are impacted by investor sentiment as well as behavioral biases. This correlation is found to be stronger during crisis periods (Galariotis et al., 2016).

A variable for investor sentiment called Economic Sentiment Indicator (ESI) by the European Commission is used alongside with ZEW Economic Sentiment Indicator that combines analyst views about the next six months of economic climate in Europe (Galariotis et al., 2016). During the global financial crisis, investor sentiment is found to be an important determinant of CDS spreads (Galariotis et al., 2016).

When studying the determinants of CDS spreads in the CESEE (Central Europe and South East Europe) region, global investor sentiment is found to play an important role (Heinz & Sun, 2014). A study by Du (2017) examines the relationship between credit default swap (CDS) returns and corporate restatements. It finds that more positive CDS returns are associated with restatements involving fraud and affecting more accounts (Du, 2017). The study investigates the impact of market-wide investor sentiment on the CDS market's response to restatements (Du, 2017). It highlights that investors in the CDS market react more adversely to negative restatements when sentiment is low (Du, 2017). The study also compares the CDS and stock market reactions to restatements and finds that the stock market overreacts to negative news during periods of low sentiment and overreacts to positive news during periods of high sentiment (Du, 2017).

A study by Papakyriakou et al. (2019) investigates the effect of investor sentiment on international stock market reactions to large financial firm bankruptcy announcements in the United States. The study finds that stock markets in countries with higher declines in investor sentiment after the announcement experience greater negative reactions to the bankruptcy announcement (Papakyriakou et al., 2019). The study also finds that in cases of positive surprise (i.e. positive change in investor sentiment), the negative effect of the bankruptcy announcement is temporarily masked by other local good news (Papakyriakou et al., 2019). These findings suggest that investor sentiment can explain the reaction of international stock markets to unexpected exogenous shocks (Papakyriakou et al., 2019).

Wu et al. (2016) investigate the relationship between investor sentiment and stock returns. They find that stock returns display a nonlinear path and that the three risk premiums are time-varying, depending on different proxies of investor sentiment in different regimes (Wu et al., 2016). The study also finds that in normal sentiment of investment, value stocks earn more returns than growth stocks, and that the value premium increases as the TED spread is over a certain threshold (Wu et al., 2016). Additionally, the study finds that the three proxies of investor sentiment have different impacts on the three risk premiums (Wu et al., 2016). These findings suggest that using the indicator of investor sentiment to evaluate their impacts on risk premiums or stock returns requires careful consideration of the individual proxies of investor sentiment (Wu et al., 2016).

3 LITERATURE REVIEW

The impact of crises and political uncertainty on CDS spreads has been studied quite a lot, with different emphases of variables and geographical areas. Both of the two crises selected for this thesis can be seen as more or less political. The Covid-19 pandemic is a health crisis that countries and political leaders had to take action against from early 2020. The actions taken to combat the pandemic differed between countries and therefore caused a wide variety of outcomes in pandemic cases and deaths. The Russian invasion of Ukraine is obviously a political matter and political leaders around the world have had to take or not to take action related to sanctions towards Russia.

In this chapter the impact of overall political uncertainty on CDS spreads is covered first with several references from the literature. The next chapter focuses on the two crises of this thesis. These crises affect the economy as a whole and with increasing inflation in Europe, other financial and hedging instruments are also affected. The impact of the pandemic has been researched in a global context, as well as for the USA, and some of these studies are discussed in this chapter. The war in Ukraine has not been studied a lot, as it is such a new issue, but its impacts on the economy are covered in this chapter as well. The last chapter focuses on the connection between the CDS and the stock markets.

3.1 Political uncertainty and CDS Spreads

Political uncertainty refers to a lack of clarity or predictability about the actions and decisions that will be made by governments and political leaders (Pástor & Veronesi, 2013). It has become a prominent feature in the economic landscape in recent years, particularly in the United States and Europe (Pástor & Veronesi, 2013). Political uncertainty might have negative impacts on financial markets, including by increasing stock price volatility and correlation, especially when economic conditions are weaker (Pástor & Veronesi, 2013). Despite the apparent relevance of political uncertainty for global financial markets, there is a lack of theoretical guidance on the impact of political news on asset prices (Pástor & Veronesi, 2013).

The first study that investigates how political uncertainty affects firm credit risk and credit default swaps in an international setting is by Liu and Zhong (2017). It shows that political uncertainty is linked to firm level CDS spreads when measured across 30 countries using a national election dummy to determine whether it is or is not an election year (Liu & Zhong, 2017). A firm's credit risk is shown to increase during national election years utilizing a difference-in-differences approach and while taking into account variables such as corruption level, religion in politics and stability of the government (Liu & Zhong, 2017).

Liu and Zhong (2017) were also able to examine the channels connecting policy risk with a firm's credit risk, and they suggest two channels; debt rollover and equity volatility channels (Liu & Zhong, 2017). By acknowledging the transmission mechanisms, changes in firm level CDS spread can better and more accurately be taken into account (Liu & Zhong, 2017).

Wang et al. (2019) had similar results of the positive correlation between economic policy uncertainty and CDS spreads. To study this correlation they used a measure of economic policy uncertainty (EPU) created by Baker et al. (2016), which is based on a news index in which the effect of EPU on CDS spreads is quantified (Wang et al., 2019). Using this method they were able to show an economically significant negative correlation between EPU and the number of liquidity providers in the CDS market, where a 10 % increase in EPU leads to a 4 % decrease in the number of CDS market makers, which is a considerable deviation (Wang et al., 2019). Out of all components used, the highest explanatory capability on CDS spreads was on the news component, which reinforces the importance of news on economic policies in determining prices in the CDS markets (Wang et al., 2019).

Findings of Wang et al. (2019) about the connection between economic and political uncertainty and CDS spreads are in line with findings of Wisniewski and Lambe (2015) and Liu and Zhong (2017). Unfavorable implications occur during times of policy uncertainty on economy and financial markets by increasing unemployment and stock price volatility as well as decreasing investments (Wang et al., 2019). Decreasing liquidity provision and increasing credit risk of firms are both consequences of uncertainty in the political environment, and can potentially start a downward spiral in the economy (Wang et al., 2019). The cost of credit insurance for investors expands during times of high EPU while also making it more difficult due to a plunge in the number of sellers (Wang et al., 2019).

Policy uncertainty has been linked to higher stock price volatility, reduced investment, and lower employment in sectors that are sensitive to policy changes, such as defense, health care, finance, and infrastructure construction by Baker et al. (2016). At the macroeconomic level, policy uncertainty has been found to precede declines in investment, output, and employment in the United States and other major economies (Baker et al., 2016). An index of policy uncertainty in the United States shows that it rose significantly in the 1930s and has trended upwards since the 1960s (Baker et al., 2016).

Effects of political uncertainty on the stock and CDS market have also been studied in the form of an event study, where asset prices were studied before and after the Arab Spring, which included several anti-government protests and armed rebellions in the Arabic countries in 2011, where civilians began to rise against economic stagnation and corruption (Tanyeri et al., 2022). The Arab Spring was a fruitful event as a research topic due to the political outcomes of the protests, which then led to economic impacts (Tanyeri et al., 2022). They were able to show that both local and regional protests of the Arab Spring did considerably affect the stock and the CDS markets (Tanyeri et al., 2022).

Investors were able to price and anticipate the effect of current political unrest on stock market indices and CDS spreads by considering political protests in neighboring countries to affect and spread to the home country (Tanyeri et al., 2022). During a time of increased political uncertainty investors naturally demand for higher returns as they carry increased risks, which leads to an increase in firms' financing together with risk premia (Tanyeri et al., 2022).

Wisniewski and Lambe (2015) studied how changes in economic policy uncertainty affect credit protection cost fluctuation using Granger-causality and vector autoregressive (VAR) framework. They show a relationship between policy uncertainty and CDS spreads (Wisniewski & Lambe, 2015). They argue the superiority of credit default swaps as financial instruments is due to their excellent diversification features, as it co-varies with economic policy uncertainty (Wisniewski & Lambe, 2015).

A lack of awareness about the connection between political environment changes and CDS spreads is highlighted, although the CDS market size exceeds the value of goods and services in the US in 2013 (Wisniewski & Lambe, 2015). Therefore the authors suggest that in order to forecast future changes in CDS spreads, traders and financial institutions should keep a closer eye on the political environment and its changes (Wisniewski & Lambe, 2015).

A study by Kelly et al. (2016) finds that political uncertainty carries a risk premium, which means that it is perceived as a source of risk by financial markets. This risk premium is typically larger when the economy is weaker, as policy changes and election upsets are more likely to occur in these conditions (Kelly et al., 2016). Political uncertainty can also have real effects, such as raising the cost of financing. The research has found that political uncertainty can have spillover effects across countries, especially in times of economic weakness. Political events, such as elections and summits, can also impact financial markets and the pricing of financial assets. However, these events only capture a subset of the political uncertainty faced by investors, and more research is needed to understand the full impact of political risk on financial markets. (Kelly et al., 2016).

Political uncertainty, or a lack of clarity or predictability about the actions and decisions of governments and political leaders, has negative impacts on financial markets, including increased stock price volatility and correlation, especially during times of weaker economic conditions. Several studies have investigated the relationship between political uncertainty and credit default swaps .

Liu and Zhong (2017) found that political uncertainty is linked to firm-level CDS spreads and that a firm's credit risk increases during national election years. Wang et al. (2019) found a negative correlation between economic policy uncertainty and the number of liquidity providers in the CDS market. Baker et al. (2016) found that policy uncertainty has negative effects at both the sectoral and macroeconomic level, leading to reduced investment, output, and employment. Overall, political uncertainty has negative impacts on financial markets and can lead to decreased liquidity and increased credit risk for firms.

3.2 The impact of crises on CDS spreads

Several crises have shocked the global economy during the last decades. The dot com bubble, the global financial crisis and the European sovereign debt crisis were all endogenous to the economy, while both the Covid-19 pandemic and the Russian invasion of Ukraine are exogenous to the economy.

CDS spreads have been widely studied related to previous crises, arguably most about the global financial crisis as well as the European sovereign debt crisis. Galariotis et al. (2016) studied the CDS spread determinants and their spillover effects for Eurozone countries during the European debt crisis. Their findings indicate that the factors influencing CDS variance are not consistent or stable across different periods and countries. Additionally, investor sentiment played a significant role in determining CDS spreads during the subprime crisis, along with other factors (Galariotis et al., 2016). Furthermore, spillover effects from larger peripheral economies such as Spain and Italy had a greater impact on core countries, while spillover effects from Portugal, Greece, and Ireland were relatively insignificant (Galariotis et al., 2016).

In this chapter previous literature related to crises and the CDS spreads is presented, focusing on the two crises that this thesis has been narrowed to: the Covid-19 pandemic and the war in Ukraine. Both of these crises are currently happening, and the aftermath of them is yet to be seen. However, these two very different types of crises and their impact mechanisms have already been studied in the literature. First in this chapter findings of overall impacts of crises to the economy are presented, followed by chapters for both two crises mentioned.

Different safety measures implemented by the governments during the Covid-19 pandemic have caused damaging outcomes to the economy (Apergis et al., 2022). For instance, profitability and productivity have decreased due to the pandemic, and the unpredictability of these effects has led to an increase in the stock market volatility (Apergis et al., 2022).

Naturally, during highly volatile and uncertain times it is necessary for firms to rethink their investment and research ad development (R&D) strategies, leading to even more unfavorable profitability outcomes (Apergis et al., 2022).

The effects of Covid-19 have been remarkable, with significant adverse effects on companies due to the worldwide disruption of economic activity (Liu et al., 2021). Not only has the economy been affected by the major wave of unprecedented unemployment, but decreasing the cash flows created a sudden liquidity shock increasing the risk of a default (Liu et al., 2021). This is likely to create a "bankruptcy boom" if the crisis does not fade (Liu et al., 2021).

Overall, previous literature on the impact of crises on the economy and on CDS spreads has been discussed, with a focus on the Covid-19 pandemic and the war in Ukraine. The literature indicates that the factors influencing CDS variance are not consistent or stable across different periods and countries, and that investor sentiment plays a significant role in determining CDS spreads during times of crisis. Additionally, the chapter discusses the effects of the Covid-19 pandemic on the economy, including reduced profitability and productivity, increased stock market volatility, and a potential "bankruptcy boom."

3.2.1 The Covid-19 pandemic

Apergis et al. (2022) studied the impact of the Covid-19 pandemic on corporate-level CDS spreads in the United States. By using both global and local variables in a panel dataset consisting of daily observations of US firms in order to study how CDS spreads were affected by the pandemic transmitting its effects (Apergis et al., 2022).

They were able to prove a statistically and economically significant positive correlation with the volume of the pandemic and corporate-level CDS spreads in the US (Apergis et al., 2022). Transmission channels were also confirmed to transmit the disadvantageous outcomes of the pandemic into the CDS markets, in other words, measures used for the pandemic significantly increase the probability of a default of a company (Apergis et al., 2022).

Apergis et al. (2022) proved a significant correlation between the Covid-19 pandemic and corporate-level CDS spreads in the US with the pandemic causing the CDS prices to increase in different industries. Evidence was also found on the increased financial uncertainty in firms after a rating agency had downgraded the rating (Apergis et al., 2022).

The effect of Covid-19 on CDS spreads and stock returns in the US was studied by using the pandemic as an event in an experiment study by Liu et al. (2021). Covid-19 is seen as a shock that leads to insufficient cash flows and increased risk of defaults due to the lack of liquidity (Liu et al., 2021). The findings of this study are harmonious with the findings of Apergis et al. (2022), as both of these studies report that the Covid-19 pandemic has remarkably affected the CDS spreads by driving up the price and impacting the shareholder price adversely (Liu et al., 2021). Both studies also agree that the unfavorable impacts of the shock are affecting financially unstable and highly volatile firms the most (Apergis et al., 2022, Liu et al. 2021).

Liu et al. (2021) found that the further away in the distance are the firm's refinancing needs, the more likely it is to survive the shock with no severe damage. This is said to reinforce the importance of debt rollover risk of a firm in determining the resistance to the shock (Liu et al., 2021).

The study also concluded that the impact the pandemic has on corporate-level CDS spreads with different debt rollover risk is heterogeneous (Liu et al., 2021). CDS spreads were increased by 349-880 basis points over various CDS contract maturities caused by the Covid-19 shock (Liu et al., 2021). High firm volatility and strict financial constraints are main variables influencing the increase of shock on the firm's CDS spread (Liu et al., 2021).

Stock returns and CDS spreads were instantly influenced by the shock as a consequence of the liquidity shortage especially for the firms that carried a high debt rollover risk level (Liu et al., 2021). Also, as discussed previously, the firms with the highest volatilities and most financial constraints were the most damaged by the shock of the Covid-19 pandemic (Liu et al., 2021).

Hasan et al. (2022) studied the effect of Covid-19 pandemic on corporate CDS spreads on a global level, and the results of the study align with previously discussed studies of the US markets by Liu et al. (2021) and Apergis et al. (2022), showing that the shock caused by the pandemic caused an increase in CDS spreads. Said increase was greater if a firm had more leverage and was already closer to a default (Hasan et al., 2022).

Other variables strengthening the effect were poor corporate governance and limited shareholder engagement (Hasan et al., 2022). The study was able to point out that a firm's credit risk can deteriorate when a country's government has limited capacity for fiscal policies, especially in a situation where a default is possible in the near future (Hasan et al., 2022).

The study included Covid-19 infection rate data and CDS spread data from 27 countries and 655 firms worldwide (Hasan et al., 2022). Unlike in the previously discussed studies, Hasan et al. (2022) also showed that the CDS spread sensitivity towards the infection rates of the pandemic was affected by measures taken by the country of the firm, such as stability of the political environment, GDP and the devotion towards managing the crisis, which includes for instance Covid-19 lockdowns and other health policies.

The variables affecting the variation of CDS spread and infection rate sensitivity were studied, and those can be found from country-, industry-, and firm-level determinants (Hasan et al., 2022). Firms operating in countries with strict fiscal policies and -constraints were affected the most if they carried a higher risk of a default in addition (Hasan et al., 2022). Furthermore the correlation between taking part in corporate social responsibility (CSR) and credit risk was found to be negative, which encourages firms to focus on the relationship between the firm and its stakeholders (Hasan et al., 2022).

Corporate-level CDS spreads are found to increase as the Covid-19 infection rates increase, which leads to a conclusion where CDS spreads were priced during a shock that led to greater uncertainty and credit risk (Hasan et al., 2022). During the Covid-19 pandemic, information exchange is found between CDS and stock markets, where CDS spreads were joined with firm's size, leverage and CSR matters, whereas stock markets react more to changes in firm's volatility and profitability (Hasan et al., 2022).

Forecasting performance of various methods for CDS spreads has been researched by Vukovic et al. (2022). They compared methods such as Support Vector Machines, Long Short-Term Memory, Group Method of Data Handling and Markov switching autoregression in order to see how the Covid-19 pandemic affected the forecasting performance of said methods and if market efficiency was influenced (Vukovic et al., 2022).

They showed that there appears to be a plunge in market efficiency during the pandemic due to the shock the pandemic caused and its transmission mechanism (Vukovic et al., 2022). Firm's nonlinear credit risk seems to be a main factor in forecasting performance during an uncertain time period, such as the Covid-19 pandemic, however, no major prediction differences were distinguished between the times before and after the pandemic (Vukovic et al., 2022).

Pereira et al. (2018) studied the determinants of credit default swap spreads and their behavior related to the Covid-19 pandemic. Market-based variables have grown in relevance in recent literature, therefore highlighting the significance of forward-looking risk measures when studying pre-crisis, crisis and post-crisis period spreads (Pereira et al., 2018). The predictive power of market-based variables increases their importance, as backward-looking accounting variables are said to decrease their importance (Pereira et al., 2018).

In conclusion, Apergis et al. (2022) studied the impact of the Covid-19 pandemic on corporate-level CDS spreads in the United States. They found a significant positive correlation between the volume of the pandemic and corporate-level CDS spreads in the US. Liu et al. (2021) also studied the effect of Covid-19 on CDS spreads and stock returns in the US and found that the further away in the distance are the firm's refinancing needs, the more likely it is to survive the shock with no severe damage. Hasan et al. (2022) studied the effect of Covid-19 pandemic on corporate CDS spreads on a global level and found that the increase in CDS spreads was greater if a firm had more leverage and was already closer to a default.

3.2.2 The Russian invasion of Ukraine

The war in Ukraine has already in 2022 caused massive damages and suffering to the Ukrainian civilians, and the Western countries have strongly condemned Russia and have imposed sanctions against it. The purpose of the sanctions is to get Russia to terminate its deadly attacks in Ukraine. Zahra (2022) predicts that the sanctions set against Russia by international institutions might have an effect on the birth-, growth- and survival rates of new business ventures.

The war does not only have an economical, but also a socioeconomic impact, as the global food security is under a threat when two major food producing countries are at a war (Ben Hassen & El Bilali, 2022). It is found that as the food prices were already increasing before the armed attack due to supply chain issues caused by poor crops and increased demand and the Covid-19 pandemic, the war has had a strong negative consequence on global food security (Ben Hassen & El Bilali, 2022). The war in Ukraine has caused labor and fertilizer shortages, which stopped exports and has led to an increasing uncertainty, and the increasing inflation does not help (Ben Hassen & El Bilali, 2022).

The invasion has led researchers around the globe to study the impacts of the war causing uncertainty in the economy, and one of the first ones were Boungou and Yatié (2022), who studied the impact of the war on the reaction the global financial market has. They used daily stock market data in nearly 100 countries over a two month period during which Russia invaded Ukraine, and found a significant and negative correlation between the armed invasion and world stock returns (Boungou & Yatié, 2022). This effect was strong despite Russia and Ukraine having had high tensions for several years between the attack on February 24th in 2022 (Boungou & Yatié, 2022).

Weaker performance of stock market indices was also recorded during the time when the armed invasion began in bordering countries of both Russia and Ukraine (Boungou & Yatié, 2022). United Nations member countries demanding for Russia to end the war were also affected with bigger decreases in stock returns than those countries who decided to remain more neutral (Boungou & Yatié, 2022).

Wang et al (2022) studied how the war impacted the commodity returns and volatilities using granger causality and quantile regression models. Related to the increased geopolitical risk the war has caused, they also examined transmission and spillover of volatility and returns (Wang et al., 2022). They found that volatility spillover increases rapidly, from 35 % to 85 %, and that commodities serve a different purpose during the war in volatility spillover and return systems (Wang et al., 2022). The increase in geopolitical risk granger causes spillover indices and is related to higher levels of returns and volatility spillover (Wang et al., 2022).

The findings of this study are important to several stakeholders, as predictability, asset allocation and risk management are detrimental to portfolio managers and traders, and as analysis and results of potential additional spillovers are important to both managers of the commodity firms and policy makers (Wang et al., 2022).

The war in Ukraine has caused damages and suffering to civilians and has been condemned by Western countries, which have imposed sanctions against Russia. The war has also had a negative impact on global food security, leading to labor and fertilizer shortages, reduced exports, and increasing uncertainty. Researchers have studied the impact of the war on the global financial market and found a significant negative correlation between the armed invasion and world stock returns. Wang et al. (2022) also found that the war has caused an increase in geopolitical risk, leading to higher levels of returns and volatility spillover in the commodity market. These findings are important for stakeholders involved in portfolio management, asset allocation, and risk management.

3.3 CDS and the stock market

The relationship between credit default swap, bond and stock markets has been analyzed by Norden and Weber (2009). Examining intertemporal co-movement using a vector autoregressive model they found that stock returns are followed by the CDS and bond spread changes. A granger causality is also found between CDS spread changes and bond spread changes (Norden & Weber, 2009). CDS markets have been found to behave more sensitively towards stock market movements than bond market movements (Norden & Weber, 2009). The CDS market is found to contribute to price discovery more compared to the bond market (Norden & Weber, 2009).

There are differences between firms that have low credit rating compared to those with a good rating: changes in CDS spreads have a higher sensitivity to stock returns in low-grade firms, whereas firms with higher ratings do not have such dependency (Norden & Weber, 2009). As a consequence of bond markets' liquidity effects, bond spread changes are found to react more to stock returns the bigger the bond issue size (Norden & Weber, 2009).

When studying the relationship between bid-ask spreads of liquidity providers and changes in insider-trading risk the results showed that on average, the bid-ask spreads of corporate entities with multiple banking relationships seem to be smaller (Acharya & Johnson, 2007). No correlation was found between the level of CDS fees and the percentage bid-ask spread, which is an immediate measure of illiquidity (Acharya & Johnson, 2007).

A study by Jacoby et al. (2009) examines the spillover of liquidity shocks across the credit default swap, corporate bond, and equity markets. The results indicate that there is a dominant first principal component in each market and that liquidity shocks show spillover between the equity and CDS markets, but not between the equity and bond markets (Jacoby et al., 2009). There also exists a time lag in the spillover of liquidity shocks from the CDS market to both the bond and equity markets, and no evidence of liquidity spillover from the bond market to the CDS market (Jacoby et al., 2009).

The comovements of CDS, stock and bond illiquidity has been studied by Wang et al. (2020). The study investigates the extent to which illiquidity in the stock, bond, and credit default swap markets moves together, or comoves, during different time periods. Using both marketwide and firm-level measures of illiquidity, the study finds that comovements of illiquidity across markets increased significantly during the global financial crisis and remained higher in the period of postcrisis and regulatory period compared to the pre-crisis period (Wang et al., 2020).

The distribution of firm-level comovements between markets was also found to be notably different before and after the crisis, with a larger proportion of firms showing positive correlations between illiquidity measures in the postcrisis period (Wang et al., 2020). These findings suggest that the financial crisis and subsequent regulations may have had an impact on the comovements of illiquidity across markets (Wang et al., 2020).

Forte and Peña (2009) compared the use of stock returns and stock market spreads for credit risk discovery analysis and argue that stock market spreads have two main advantages. First, they incorporate information on other variables, such as the risk-free rate, in addition to stock prices, and capture the nonlinear relationship between these variables and credit risk premia (Forte & Peña, 2009). Second, they allow for the examination of long-run equilibrium relationships between bond, CDS, and stock market spreads.

Based on a sample of North American and European companies, the study finds that stocks tend to lead CDS and bonds more often than the opposite, while also confirming the leading role of the CDS market in relation to the bond market (Forte & Peña, 2009). In an older study, Zhu (2006) argues that the derivatives market plays a crucial role in improving the efficiency of the process of determining the price of corporate credit risk. From the perspective of tracking developments in this market, the results suggest that CDS spreads are more likely to provide a reliable indication of the cost of default risk than bond spreads (Zhu, 2006) .

There have been several studies that have examined the relationship between credit default swaps (CDS), bonds, and stocks. Norden and Weber (2009) found that changes in CDS spreads tend to follow stock returns and that there is a granger causality between CDS spread changes and bond spread changes. They also found that the CDS market is more sensitive to stock market movements than bond market movements, and that it plays a larger role in price discovery than the bond market.

In contrast, Jacoby et al. (2009) found that liquidity shocks show spillover between the equity and CDS markets, but not between the equity and bond markets, and there is a time lag in the spillover of liquidity shocks from the CDS market to both the bond and equity markets. Wang et al. (2020) found that comovements of illiquidity across markets increased significantly during the global financial crisis and remained higher in the postcrisis period, and that there were notable differences in firm-level comovements between markets before and after the crisis. Forte and Peña (2009) found that stocks tend to lead CDS and bonds more often than the opposite, while also confirming the leading role of the CDS market in relation to the bond market. Zhu (2006) argued that the derivatives market plays a crucial role in improving the efficiency of the process of determining the price of corporate credit risk, and that CDS spreads are more likely to provide a reliable indication of the cost of default risk than bond spreads.

4 DATA AND METHODOLOGY

The purpose of this chapter is to provide an overview of the data and methodology used in this study, which aims to examine the impact of crises on European industry-level credit default swap (CDS) spreads using linear regression.

The results of the linear regression analysis will be used to identify the variables that have the greatest impact on industry specific CDS spreads and to see whether the two crises chosen for this thesis have an impact on the CDS spreads as well. The findings of this study will be of interest to policymakers, financial market participants, and researchers who are interested in understanding the factors that drive CDS spreads in the European market.

4.1 Data

Linear regression is a statistical method used to model the relationship between a dependent variable and one or more independent variables. In this study, industry-level CDS spreads are the dependent variable, while the independent variables include various economic and financial variables that may impact CDS spreads. These variables will be explained in more detail later in this chapter.

The analysis will be conducted using statistical software Stata. The model will be estimated using ordinary least squares (OLS) regression, which is a widely used method for estimating linear regression models. The OLS method seeks to minimize the sum of squared residuals, which represent the difference between the observed values and the values predicted by the model. The data for this study were collected from Refinitiv Eikon and consist of monthly observations from 2007 to 2022.

The industries chosen for this thesis are banks, auto, leisure, chemicals, telecom, oil and gas, manufacturing, transportation and electricity as power. These industries were selected for this study due to their significance in contemporary society. The banking sector plays a crucial role in the financial system, offering vital financial services such as lending, depositing, and payment processing. The automotive industry is a major contributor to economic growth and provides employment for a significant portion of the workforce. The leisure industry, comprising sectors such as travel and hospitality, enhances the quality of life for individuals and drives economic growth. The chemicals industry produces a wide array of products used in various fields, including consumer goods, construction, and agriculture. The telecommunications industry is essential for the infrastructure and services that facilitate communication and information exchange. The oil and gas industry is vital for providing the energy that powers modern society and is a major contributor to the global economy. The manufacturing industry produces a diverse range of goods and is a key driver of economic growth and employment. The transportation industry enables the movement of people and goods and is a crucial component of the global economy. The power industry, responsible for generating and distributing electricity, is essential for modern life.

Caldara and Iacoviello (2022) define geopolitical risk as the risk of loss or damage resulting from geopolitical events or conditions that can impact macroeconomic variables such as loss of human life, destruction of capital stock, higher military spending, or increased precautionary behavior. These events or conditions are perceived by the press, the public, global investors, and policymakers, and can have an adverse impact on economic outcomes such as investment and employment (Caldara & Iacoviello, 2022). Geopolitical risk can also have a stronger impact on firms in more exposed industries (Caldara & Iacoviello, 2022). They also suggest that higher geopolitical risk is associated with an increased probability of an economic disaster and lower investment and employment (Caldara & Iacoviello, 2022).

Geopolitical risk is a critical factor that should be taken into consideration by businesses and investors due to its potential impact on various stakeholders. The stability of a country or region can be adversely affected by geopolitical risk, which can have consequences for the value of investments, the availability of resources, and the ease of doing business. In addition, geopolitical risk has the potential to damage the reputation and credibility of a company, and can create uncertainty and risk for employees and other stakeholders. By measuring geopolitical risk, businesses and investors can effectively assess and manage the potential risks and impacts of geopolitical events and conditions, enabling them to make informed decisions about investments, operations, and other activities. This, in turn, allows them to protect their assets, reputation, and other interests, and to navigate the complex and rapidly changing global landscape more effectively.

4.2 Descriptive statistics

Table 1 presents a summary of key statistics for the data used in the econometric models, including the mean, median, standard deviation, number of observations, minimum, and maximum of all dependent variables, meaning the CDS indices of all nine industries. Additionally, unit root test results are included in the table. Table 2 presents the abovementioned statistics for explanatory variables.

TABLE 1: Descriptive statistics for dependent variables

CDS Index	N	Mean	Median	SD	Min	Max	ADF	PP
Banks	176	0.005	-0.007	0.156	-0.429	0.481	-4.322***	-13.547***
Auto	176	0.006	-0.015	0.174	-0.439	0.936	-5.846***	-11.931***
Chem	176	0.004	-0.009	0.159	-0.321	0.797	-4.656***	-12.589***
Travel	176	0.004	-0.001	0.201	-1.141	0.629	-6.160***	-13.962***
Industr	176	0.002	-0.010	0.248	-1.685	1.555	-5.373***	-19.323***
Transp	176	0.004	-0.148	0.134	-0.490	0.514	-4.392***	-11.891***
Tele	176	0.001	-0.008	0.145	-0.542	0.546	-4.491***	-14.136***
Oilgas	176	0.006	-0.014	0.200	-0.658	1.041	-5.341***	-12.203***
Electr	176	0.008	0.002	0.175	-0.900	0.650	-5.354***	-14.423***

Notes: This table is compiled by the author and is made with Stata software. Abbreviations used in the table are the following: Logarithmic differences of industry CDS indices for following industries: Banks, auto, chemical (Chem), travel and leisure (Travel), industrial (Industr), transportation (Transp), telecommunications (Tele), oil and gas (Oilgas), and electricity as a power (Electr). Number of observations (N), standard deviation (SD). Augmented Dickey-Fuller test for unit root (ADF), (H_0: unit root), Phillips-Perron test for unit root (PP), (H_0: unit root).

In table 1 the number of observations for all nine industries is 176. The mean of logarithmic differences of CDS indices across industries varies between 0.001 and 0.008. The median for most indices is negative, varying from -0.148 for the transportation industry to 0.002 for electricity as a power industry. The standard deviations values vary between 0.134 and 0.248. All dependent variables are stationary according to the two unit root tests, ADF and PP, that show that the variables do not contain unit root.

TABLE 2: Descriptive statistics for explanatory variables

Variable	N	Mean	Median	SD	Min	Max	ADF	PP
Banks	176	-0.006	0.004	0.081	-0.350	0.303	-5.204***	-11.244***
Auto	176	0.002	-0.000	0.083	-0.325	0.251	-4.635***	-13.784***
Chem	176	0.004	0.009	0.053	-0.197	0.126	-5.462***	-11.786***
Travel	176	0.001	0.008	0.065	-0.253	0.168	-4.535***	-13.522***
Industr	176	0.003	0.011	0.057	-0.231	0.018	-5.481***	-12.079***
Transp	176	0.001	0.004	0.059	-0.263	0.128	-5.236***	-12.295***
Tele	176	-0.003	-0.002	0.043	-0.142	0.113	-4.220***	-13.863***
Oilgas	176	-0.001	0.002	0.060	-0.150	0.309	-4.249***	-14.054***
Electr	176	-0.001	-0.000	0.053	-0.169	0.142	-4.095***	-13.980***
Vstoxx	176	0.002	-0.031	0.215	-0.516	0.901	-4.808***	-20.342***
Gold	176	0.002	-0.000	0.066	-0.293	0.165	-3.455***	-14.622***
Oil	176	-0.002	0.013	0.156	-1.241	0.650	-4.865***	-10.709***
ECB	176	0.010	0.007	0.038	-0.122	0.291	-4.213***	-12.163***
Covid	177	133.82	0	1388.64	0	17795.0	-3.777***	-9.916***
GPR	177	94.568	88.554	28.552	60.602	325.44	-1.530*	-6.060***
March	177	0.006	0	0.075	0	1	-	-
April	177	0.006	0	0.075	0	1	-	-
Long	177	1.022	1.021	0.576	0.4	2.25	-1.341*	-3.378*
Short	177	0.172	0.093	0.326	-0.704	1.155	-2.249**	-2.973
Eur 3M	177	0.466	0.039	1.323	-0.573	5.277	-3.675***	-2.374

Notes: This table is compiled by the author and is made with Stata software. Abbreviations used in the table are the following: Logarithmic differences of industry stock indices for following industries: Banks, auto, chemical (Chem), travel and leisure (Travel), industrial (Industr), transportation (Transp), telecommunications (Tele), oil and gas (Oilgas), and electricity as a power (Electr). Logarithmic differences for European volatility stock index (Vstoxx), gold (Gold), and oil (Brent). Assets of European Central Bank (ECB), new cases of covid-19 (Covid), geopolitical risk index (GPR), dummy variables for March and April of 2020. Logarithmic differences for long European interest rates (Long), short European interest rates (Short). Euribor three-month rate (Eur 3M). Augmented Dickey-Fuller test for unit root (ADF), (H_0: unit root), Phillips-Perron test for unit root (PP), (H_0: unit root).

As can be seen from table 2, the number of observations remains mostly constant throughout the variables, varying between 176 and 177, as some variables are presented in logarithmic difference. All other variables are presented as the logarithmic differences of the original values, except for all three pandemic variables (Covid, March, April), the geopolitical risk (GPR), and the interest variables (Euribor 3M, Long and Short). The mean values are presented next in the table, followed by median and standard deviation values. Next, the minimum and maximum values are presented for all explanatory variables.

Most industry stock returns have similar values for mean and median: close to zero. The standard deviation for industry stock returns varies between 0.043 and 0.083. March and April are dummy variables, that equal 1 in that month of 2020, and 0 otherwise. They are used for the two worst beginning months of the pandemic, as the spreading rate began to increase rapidly. The long interest rate varies between 0.4 and 2.25 % per annum during the sample period, whereas the short interest rate varies between -0.704 and 1.155 %.

At the end of the descriptive statistics table, the results of tests for unit root and stationarity are presented, which are important requirements for time series analysis. The Augmented Dickey-Fuller test (ADF) is used, the null hypothesis being that the series contain a unit root and the alternative hypothesis being that the series is stationary and does not contain a unit root. The goal is to show that the data is stationary and does not have a unit root. The ADF test results show that all of the variables don't have unit root at the 10 % significance level, while most don't have unit root even at 1 % level. Additionally, a Phillips Perron test is conducted, which shows that most variables are stationary at 1 % significance level, excluding only the three last interest rate variables.

Graphs are also provided for all dependent variables used in the models, as well as some explanatory variables. A key explanatory variable, geopolitical risk is presented below in Figure 3. It captures the global geopolitical risk, the threats following the risk and the acts following the threats in separate curves. The Geopolitical Risk (GPR) index is created by Dario Caldara and Matteo Iacoviello and is based on a measure of newspaper article mentions of adverse geopolitical events and tensions since 1900. The first spike in this graph was most likely caused by the 9/11 terrorist attack in the United States.

As can be predicted, geopolitical risks also spiked in 2014-2015 due to several reasons, for example the rise of ISIS and the ongoing conflict in Syria, as well as the ongoing conflict in Ukraine due to Russia invading Crimea. Europe also had a massive refugee crisis during those years. Another spike can be noticed in the graph during 2021 and 2022, which can be expected to be due to the Russian invasion of Ukraine, that has led to an increase in relationships between other countries as well, as sanctions are set against Russia and nations have chosen sides by helping Ukraine and decreasing trade with Russia.

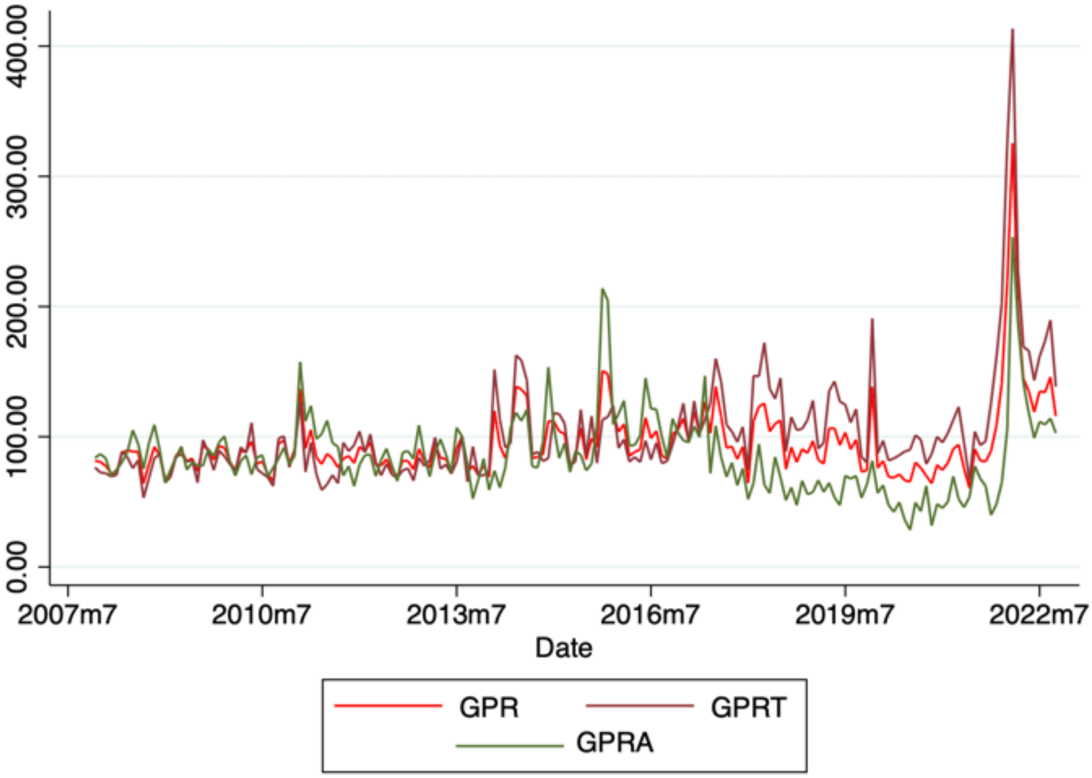

Figure 3. Geopolitical risk 2007-2022. Abbreviations used in the figure are the following: Recent geopolitical risk index: 1985:2019=100 (GPR), Recent geopolitical risk threats index: 1985:2019=100 (GPRT), Recent geopolitical risk acts index 1985:2019=100 (GPRA).

The dependent variable of this thesis is the industry specific CDS indices in Europe. The following figures 4, 5, and 6 represent said industry CDS indices and are represented in the figures with other industries based on the scale of the price of the index. Figure 4 represents four industries: banking, auto, telecommunications and manufacturing. Auto and manufacturing indices spiked drastically more due to the global financial crisis in 2007-2009 compared to banking and telecommunications indices. The European sovereign debt crisis in that began in the 2010s had its impact on all said industries and it was made worse by slow economic growth and the aftermath of the global financial crisis.

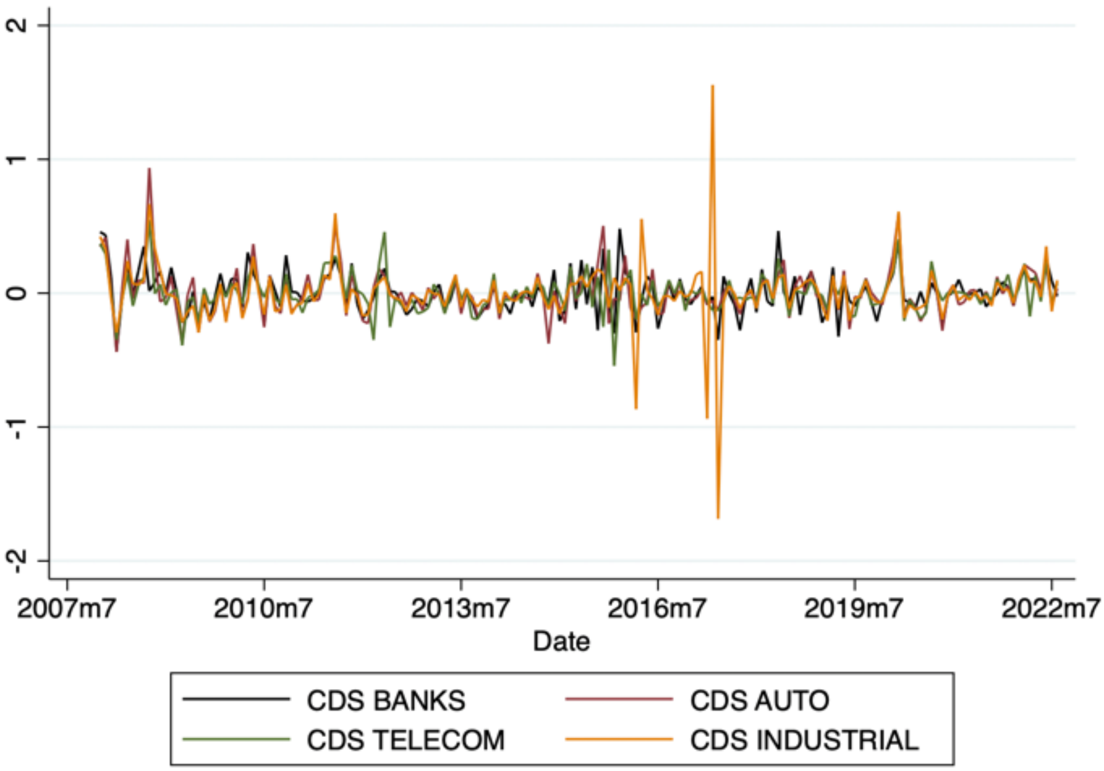

Figure 4: Percentage change of European credit default swap indices by industry between 2007-2022. Abbreviations used in the figure are the following: Bank industry (CDS BANKS), Auto industry (CDS AUTO), Telecommunications industry (CDS TELECOM), Industrial industry (CDS INDUSTRIAL).

In figure 5 are presented two industries: travel and leisure, as well as transportation. Travel and leisure industries are known for their high variance and tendency to fluctuate independently of one another. These industries are often considered non-essential or luxury items in a consumer's budget, leading to increased fluctuations during times of economic instability as they are often the first areas to face budget cuts.

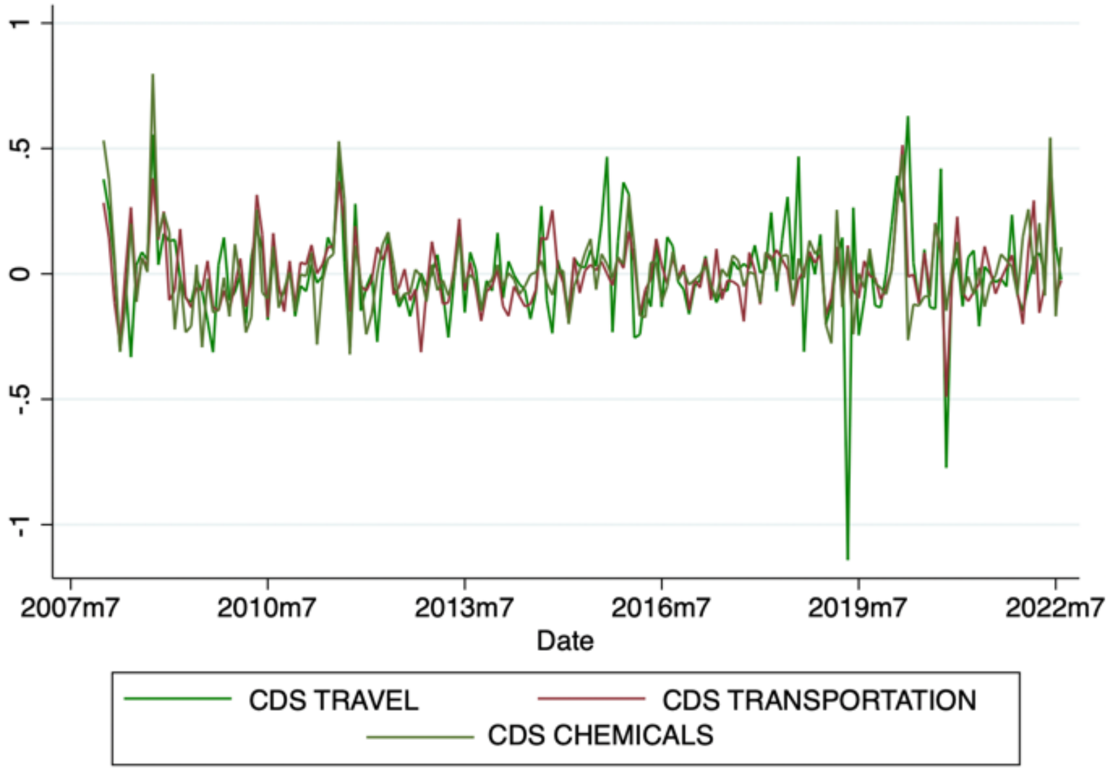

Figure 5: Percentage change of European credit default swap indices by industry between 2007-2022. Abbreviations used in the figure are the following: Leisure and travelling industry (CDS TRAVEL), Transportation industry (CDS TRANSPORTATION), Chemical industry (CDS CHEMICALS).

In figure 6 there are presented the oil and gas, as well as the electricity as a power -industries. Both of said industries are a vital part of the global economy, and therefore understanding the risks associated with them can be valuable for both investors and the industries' professionals. The fluctuations seen in figure 6 are mostly similar between the two industries, peaking during the global financial crisis as well as in 2012 and 2015. The oil and gas industry peaked also in the beginning of the Covid-19 pandemic and both industries peaked in the beginning of the Russian invasion of Ukraine.

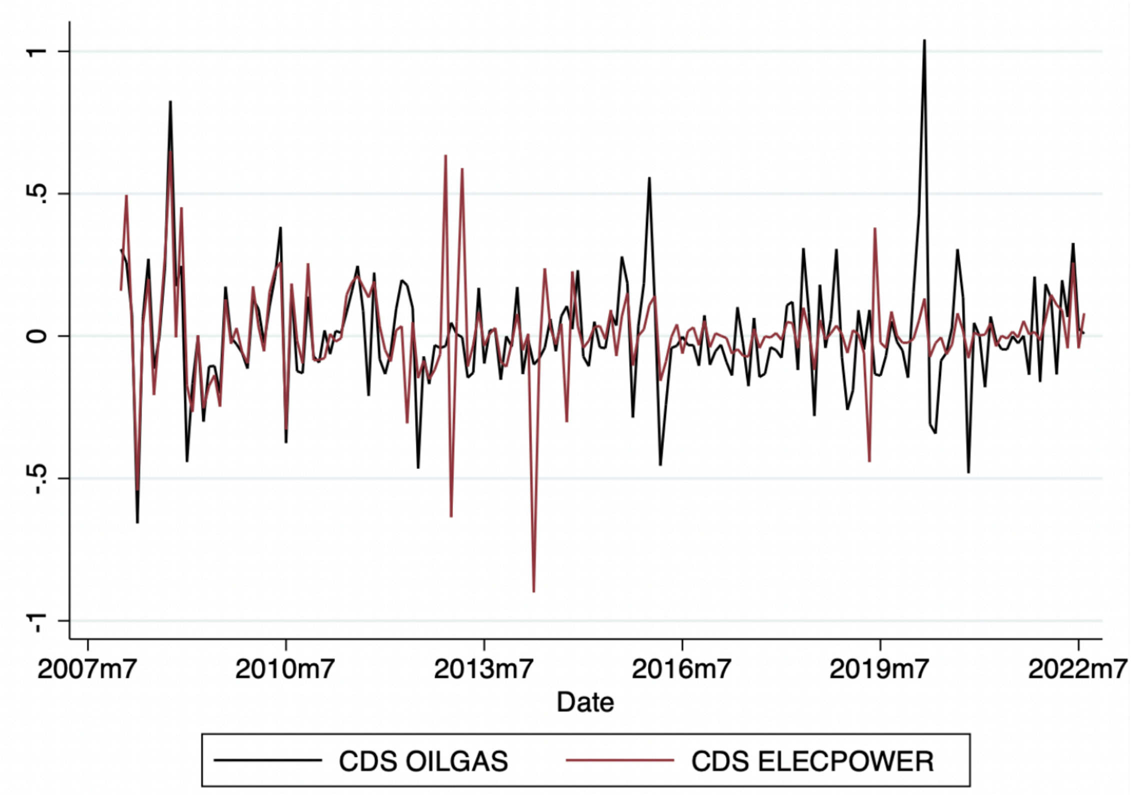

Figure 6: Percentage change of European credit default swap indices by industry between 2007-2022. Abbreviations used in the figure are the following: Oil and gas industry (CDS OILGAS), Electricity as a power industry (CDS ELECPOWER).

Figure 7 illustrates the trends in short-term and long-term interest rate yields in Europe between 2007 and 2022. The line graph shows how the long-term yields have been significantly above short-term yields, except for during the last few years, starting in 2019, when the yield curves began to approach one another. Both curves increased during the global financial crisis, and the long-term yield had a significant fall during the European sovereign debt crisis in 2014-2015. The short-term yield remained rather stable during the 2010s, ending in a sharp rise at the end of the decade, exceeding the long-term yield curve for the first time in nearly 15 years.

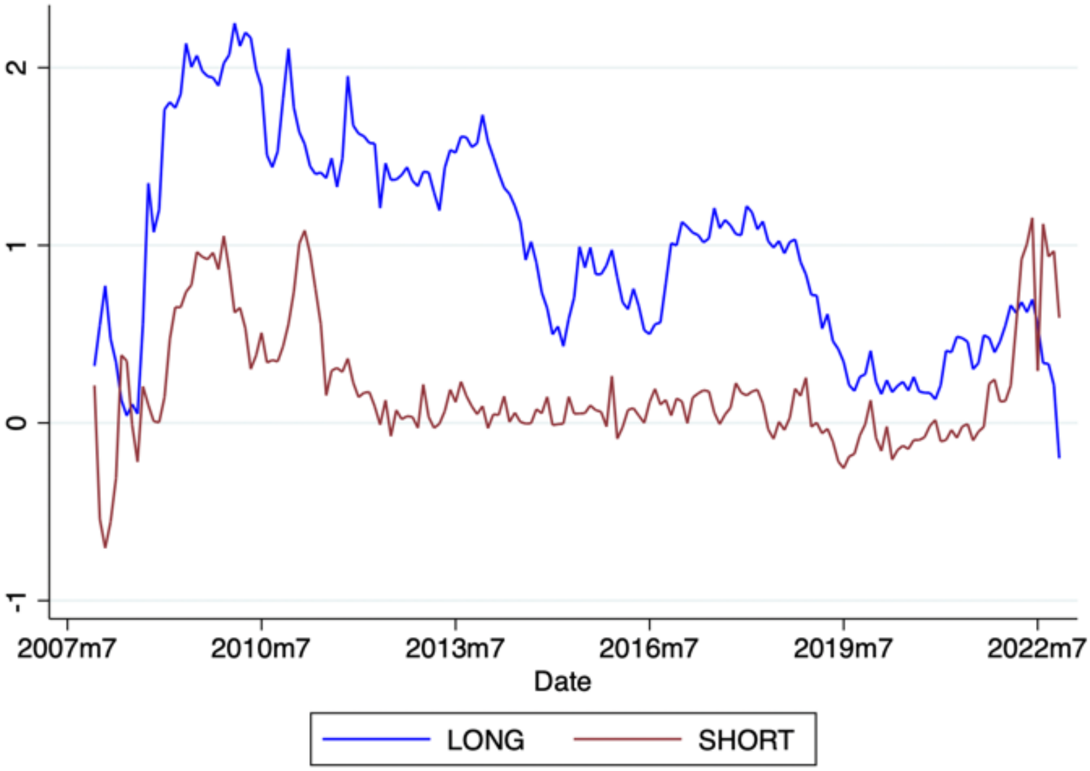

Figure 7: Long and short interest yield curves in the Euro area between 2007-2022. Abbreviations used in the figure are the following: Long interest yield curves: 10 years – 2 years (LONG), short interest yield curves 2 years – 3 months (SHORT).

4.3 Methodology

The methodology chapter in this thesis describes the research method and technique used to gather and analyze data. In this section, the methodology used in this thesis is described. It is based on ordinary least squares (OLS) and linear regression.

Linear regression is a statistical method that is used to model the relationship between a dependent variable and explanatory variables (Stock & Watson, 2020). In this thesis, three separate regression models are used. The first regression was used to model the relationship between CDS indices of a specific industry in Europe and several explanatory variables as can be seen from equation 2:

$$Y_i = B_1 + B_2X_{2i} + B_3X_{3i} + B_4X_{4i} + B_5X_{5i} + B_6X_{6i} + B_7X_{7i} + B_8X_{8i} + B_9X_{9i} + B_{10}X_{10i} + B_{11}X_{11i} + B_{12}X_{12i} + B_{13}X_{13i} + B_{14}X_{14i} + B_{15}X_{15i}\varepsilon_i \quad (2)$$

Where

Y = the industry specific CDS index
B_1 = the estimated intercept
$B_2 \ldots B_{12}$ = the estimated coefficients
X_{2i} = lagged industry specific CDS index
X_{3i} = the logarithmic difference in industry specific stock index
X_{4i} = the logarithmic difference in gold prices
X_{5i} = the logarithmic difference in oil prices
X_{6i} = the logarithmic difference in the European volatility index
X_{7i} = Euro area risk
X_{8i} = the logarithmic difference in European Central Bank assets
X_{9i} = the short interest rate
X_{10i} = the long interest rate
X_{11i} = the Euribor 3M rate
X_{12i} = the Geopolitical risk index (GPR)
X_{13i} = the Covid-19 variable (percentage growth of cases)
X_{14i} = the Covid-19 dummy variable for March 2020
X_{15i}= the Covid-19 dummy variable for April 2020
ε = the error term

The linear regression model is estimated using the ordinary least squares (OLS) method. The OLS is a commonly used method for estimating the coefficients of a linear regression model. The method minimizes the sum of the squared differences between the observed values of the dependent variable and the predicted values of the dependent variable based on the estimated coefficients (Stock & Watson, 2020).

The relationship between the dependent variable and the explanatory variables presented above is investigated using linear regression. The dependent variable, industry specific CDS indices in Europe, is the primary interest in this thesis, and reflects the cost of insuring against credit default for a specific industry. It can provide insight into market perceptions of credit risk within the industries. The industries chosen for this thesis are covered more thoroughly above.

Another important variable, in addition to the dependent variable, is the industry specific stock index. It can be used to examine the relationship between stock market performance and credit risk within a specific industry. A strong performance of the stock market can be associated with lower credit risk and therefore lower CDS spreads. Stock market returns have been used as a key variable also in previous studies researching changes in CDS spreads (see Aman, 2019; Apergis et al., 2022).

Commodity prices, such as gold and oil prices can also be included as potential drivers of CDS spreads, as these prices might have a significant impact on the economy and therefore on credit risk. In addition, the European volatility index is beneficial in capturing market sentiment and overall uncertainty in the economy. High volatility can be linked to higher credit risk and therefore higher CDS spreads. Market volatility is also a commonly used variable when studying CDS spreads (see Aman, 2019; Apergis et al., 2022; Stulz, 2010).

Euro risk variable is constructed by subtracting Italy's ten-year interest rate from Germany's ten-year interest rate to measure the overall risk of the Euro area. Both the short-term and long-term interest rates are included in the analysis to examine the relationship between interest rates and credit risk. Short-term interest is calculated by subtracting the three-month interest rate of Germany government bonds from the two-year interest rate.

Respectively, the long-term rate is calculated by subtracting the German two-year rate from the ten-year rate. Adding these variables into the regression is interesting, as higher interest rates might be associated with lower credit risk and therefore lower CDS spreads. Euro Interbank Offered Rate for a 3-month deposit, or Euribor 3M, is a benchmark interest rate that reflects the average rate at which banks lend money to each other in the Eurozone. This is why it can be used as a proxy for the overall interest level in the area. Euribor 3M is often used as a benchmark rate for derivative pricing, that includes CDS, therefore including it in the regression can account for variation in the derivative prices. The rate can also be used as an indicator of the overall risk in the financial system.

Another interesting variable included in the regression is assets held by the European Central Bank, ECB. It can offer information on the overall health and stability of the financial health of the European economy. Using ECB assets as a variable is beneficial as its monetary policy decisions can have significant impacts on individual industries, which is controlled for including it in the regression. The level of ECB assets can be seen as an indicator for the overall level of economic activity and risk in an area.

The two main variables of the topic of this thesis, answering the research questions, are the geopolitical risk index and the Covid-19 pandemic cases. Geopolitical risk is measured using three separate variables in this thesis: the overall global geopolitical risk index, geopolitical risk acts and geopolitical risk threats. The index is based on a measure that searches "adverse geopolitical events and associated risks based on a tally of newspaper articles covering geopolitical tensions, and examine its evolution and economic effects since 1900" (Caldara & Iacoviello, 2022). High geopolitical risks are often associated with higher credit risk, and therefore increased CDS spreads.

Lastly in the regression are the pandemic variables: the percentage growth of Covid-19 cases, and two dummy variables that mark the two months in 2020 when the pandemic truly began to spread. As the pandemic started to spread in the early 2020 and businesses and public places began to shut down, uncertainty in the economy began to increase. The uncertainty grew larger when businesses began to go bankrupt, and people began to lose their jobs. This increase in uncertainty was a major factor in increasing credit risks, which is linked to increased CDS spreads.

The second regression is presented in equation 3, where the two main variables, the pandemic, and the geopolitical risks, that are in the center of this thesis are being more thoroughly researched in their own regression. Using fewer variables in a linear regression can be beneficial in feature selection, as the most important variables are more effortless to identify as there are fewer options. Using fewer variables can also improve interpretability of the regression. This regression is completed for each nine industries selected for this thesis. The regression therefore also includes the logarithmic differences in industry specific stock indices. The regression 3 is presented below.

$$Y_i = B_1 + B_2X_{2i} + B_3X_{3i} + B_4X_{4i} + B_5X_{5i} + B_6X_{6i} + B_7X_{7i} + \varepsilon_i \quad (3)$$

Where

Y = the industry specific CDS index
B_1 = the estimated intercept
$B_2 \ldots B_{12}$ = the estimated coefficients
X_{2i} = lagged industry specific CDS index
X_{3i} = the logarithmic difference in industry specific stock index
X_{4i} = the Geopolitical risk index (GPR)
X_{5i} = the Covid-19 variable (percentage growth of cases)
X_{6i} = the Covid-19 dummy variable for March 2020
X_{7i} = the Covid-19 dummy variable for April 2020
ε = the error term

For each regression, both AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) selection criterion tools are used. They take into account the complexity of the model and the goodness of fit of the model to the data. Both AIC and BIC are calculated in Stata. Their advantages come from their ability to account for the complexity of a model, while balancing the trade-off between model fit and model simplicity. These methods however assume asymptotic normality of the estimator and fail to consider prior information about the data. (Kuha, 2004; Burnham & Anderson, 2004). The results of the regressions and AIC and BIC are presented in the next chapter.

Lastly, a third linear regression is completed, where the focus is on identifying the most significant variables to the dependent variable, industry specific CDS indices. This happens by starting with all variables included, as in equation 2. One by one, the least significant variable is omitted from the regression, until only two variables remain. This is beneficial because some explanatory variables might be correlated with each other. This method also utilizes a variance-covariance matrix estimation of the regression coefficients, as well as a heteroskedasticity-robust standard error condition, in which the variance of the error term is not constant across all levels of the explanatory variable.

The results for all three regressions covered in this chapter are presented and discussed in the following chapter 5.

5 RESULTS

This chapter presents the results of this study that examines the impact of geopolitical tensions on industry specific CDS indices in Europe. The study utilizes a sample of CDS index and stock index data in various industries, including banks, manufacturing, and electricity over a 15-year time period. The data is analyzed using several linear regressions and completed using a statistical software, Stata. The goal is to identify any significant relationships between geopolitical tensions, in this thesis the Covid-19 pandemic and the Russian war in Ukraine, on European CDS indices.

The findings of this study have the potential of having important implications for policymakers, investors, and industry leaders, as they can inform decision-making related to risk management and investment strategy. The findings of this study also contribute to the existing literature of the relationship between geopolitical tensions and CDS spreads, as those have not been studied yet from this perspective to the author's current knowledge.

Table 3 presents results for the first regression, which includes all 12 explanatory variables. In the table coefficients of explanatory variables are presented with significance marked, as well as the number of observations, constant term, and the explanatory power. For each regression, two information criteria are also measured: Akaike Information Criterion (AIC) as well as Bayesian Information Criterion (BIC).

TABLE 3: Linear regression results for all variables

CDS	Bank	Auto	Chem	Elec	Ind	Tran	Trav	Tele	Oilg
L CDS	0.938***	0.685***	0.843***	0.771***	0.738***	0.828***	0.818***	0.761***	0.765***
Stock	-64.123	15.257	-46.042	-58.475	-15.256	-16.938	-112.65	7.191	2.329
Gold	-11.045	17.730	98.856	5.956	43.013	68.120	95.848	24.452	-11.155
Oil	6.090	-25.735	-47.644	-20.210	-79.119*	-1.096	-63.296	-17.610	-35.151
ECB	-103.246	-31.575	-14.528	-68.661	-52.459	5.594	-166.477	0.453	-23.288
Eur 3M	3.574	11.553*	7.272*	2.650	12.701**	6.492	7.000	8.759*	1.803
Long	2.358	8.194	5.161	-1.510	12.103	-4.664	-14.621	5.651	-1.233
Short	3.968	5.366	1.125	5.620	-13.413	15.260	28.623	4.393	7.060
Vstoxx	0.098	0.866*	0.667	0.300	2.371	0.872	2.180	0.483	0.316
EurRisk	0.413	13.102*	0.550	9.685	0.503	16.395*	2.907	14.555*	1.652
GPR	-0.010	0.011	0.065	0.080**	0.101	-0.002	-0.238	0.009	0.041
Covid	0.001	0.006	0.001	0.001	0.000	0.008**	0.011	0.002	0.002
March	5.259	-68.064	3.675	-16.515	-0.862	-37.414	-177.075	-12.223	62.871
April	-14.181	-83.886	-99.759	-48.496	-171.143	-20.386	222.892	-52.223	-72.746
N	175	175	175	175	175	175	175	175	175
Const	4.298	-36.951	-4.807	-3.551	-35.090	-2.989	54.524	-13.761	5.440
R^2	0.943	0.911	0.926	0.840	0.890	0.908	0.806	0.906	0.752
AIC	1663.53	1721.857	1599.966	1615.302	1839.722	1790.799	2118.719	1697.299	1535.857
BIC	1710.988	1769.328	1647.437	1662.744	1887.194	1838.251	2166.191	1744.771	1583.329

Notes: Abbreviations used in the table are the following: Logarithmic differences of industry CDS indices for following industries: Bank (Bank), auto (Auto), chemical (Chem), travel and leisure (Trav), industrial (Ind), transportation (Tran), telecommunications (Tele), oil and gas (Oilg), and electricity as a power (Elec). Lagged CDS index for a specific industry (L CDS). Logarithmic differences of industry specific stock indices for a specific industry (Stock). European volatility stock index (Vstoxx), Euro area risk measure (EurRisk). Logarithmic differences of European Central Bank assets (ECB), gold (Gold), and oil (Oil). Percentage growth of covid-19 cases (Covid), a dummy variable for March of 2020 (March), a dummy variable for April of 2021 (April), geopolitical risk index (GPR). Long European interest rate (Long), short European interest rate (Short). Euribor three-month rate (EUR 3M). Number of observations (N), constant term of the regression (Const), measure of explanatory power of the regression model (R^2). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC). Statistical significance of the coefficients: * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

As can be seen from table 3, all lagged CDS indices are significant coefficients at 1 % significance level, and for all industries the coefficient lies slightly below 1. The stock index return coefficients are negative for all industries except for the auto, telecommunications and oil and gas industries, meaning that for those industries the CDS spreads do not decrease as the stock index returns increase. For other industries it is the opposite: as the industry performs better and stock index returns increase, the CDS spreads the industry faces decreases. CDS spread can be considered as a measure of credit risk.

Gold returns only have a negative coefficient with CDS spreads of bank and oil and gas industries. For other industries the coefficient is positive, indicating an increase in gold prices increases the CDS spreads. Oil prices have the strongest negative coefficients on the industrial, travel and leisure, and the oil and gas industries, as one can expect.

The size of the European Central Bank assets has a highly strong negative coefficient on the bank industry, which can be due to lowering interest rates by buying securities, which helps banks to increase their lending activity. Three-month Euribor rates have the strongest coefficient on the industrial and the auto industries and those coefficients are significant at 10% level.

The volatility index had the strongest positive impact on the industrial and transportation industries, indicating that overall volatility leads to an increased credit risk on these industries. Euro risk has the highest positive coefficients on the auto, transportation, and telecommunication industries, and smallest on banking and industrial industries.

The geopolitical risk (GPR) index does not have strong coefficients on any of the selected industries CDS spreads. The highest positive coefficients it has on industrial, chemical, and electricity as a power industries. These are industries where investments are often large and therefore credit risk is a crucial measure of the industry's success. Negative, but small, coefficients the GPR index has on the bank, transportation and travel and leisure industries.

The first covid-19 pandemic variable, Covid, measures the percentage change in cases, and as the pandemic only started in 2019, it has a very small coefficient on all dependent variables, as the data starts from December 2007. The dummy variable for March (March 2020=1) has stronger coefficients on the industry CDS indices, and the strongest negative coefficient it has on travel and leisure industry, as expected. Leisure travelling nearly stopped during the first months of the pandemic, which had a major impact on the industry. Other industries affected by the Covid-19 cases of March 2020 are auto and transportation industry, for which the coefficient is negative, indicating an increase in CDS spreads. Decrease in CDS spreads was found for oil and gas, bank, and chemical industries for March 2020.

For the April dummy (April 2020=1) the coefficient for travel and leisure industry has drastically changed from -177.08 to 222.90. This might be a correction movement from the market after such a dramatic change in the CDS spreads. In April, the industrial industry was also hit with a sharp increase in CDS spreads, as did auto, chemical, and oil and gas industries. For all regressions, the explanatory power of R-squared is slightly below 1, strongest being the bank industry and the weakest oil and gas industry.

It can be concluded that the impact of geopolitical risk index on industry specific CDS spreads is not especially strong, and only significant on the electricity as a power industry on 5% level. The two dummy variables, March and April of 2020 had vastly strong coefficients on most industries, while the bank industry had the smallest coefficients, indicating that it is the most resistant for the pandemic from these selected industries, when it comes to credit risk and CDS spread variation. The great majority of these results are not significant, and therefore not generalizable.

Table 4 presents results for the second regression, which includes variables for the Covid-19 pandemic as well as the geopolitical risk index. In addition to those, lagged CDS index and the stock index for a corresponding industry CDS is used as explanatory variables. In the table coefficients of explanatory variables are presented with significance marked, as well as the number of observations, constant term, and the explanatory power. For each regression, two information criteria are also measured: Akaike Information Criterion (AIC) as well as Bayesian Information Criterion (BIC).

TABLE 4: Linear regression results for the most important variables

CDS	Bank	Auto	Chem	Elec	Ind	Tran	Trav	Tele	Oilg
L CDS	0.963***	0.936***	0.938***	0.899***	0.913***	0.949***	0.873***	0.944***	0.838***
Stock	-67.770*	-33.457	-125.037	-91.453*	-243.705*	-101.044	-219.255	-41.842	-42.181
GPR	-0.023	-0.020	0.002	0.051	-0.022	-0.019	-0.242	-0.030	0.038
Covid	0.000	0.003	0.002	0.002	-0.000	0.007	0.012	0.001	0.002
March	18.775	22.474	-2.759	-18.959	30.393	-11.694	-143.773	10.395	64.806
April	-31.407	-37.915	-37.701	-24.165	-84.828	-23.553	319.259	-30.121	-25.787
N	175	175	175	175	175	175	175	175	175
Const	8.226	12.546	6.707	8.126	18.490	16.1967	78.320	10.863	10.071
R^2	0.940	0.885	0.904	0.825	0.866	0.900	0.796	0.896	0.726
AIC	1656.675	1750.233	1629.328	1615.006	1858.812	1790.26	2111.383	1699.533	1536.001
BIC	1678.829	1772.387	1651.48	1637.16	1880.965	1812.414	2133.536	1721.686	1559.155

Notes: Abbreviations used in the table are the following: Logarithmic differences of industry CDS indices for following industries: Bank (Bank), auto (Auto), chemical (Chem), travel and leisure (Trav), industrial (Ind), transportation (Tran), telecommunications (Tele), oil and gas (Oilg), and electricity as a power (Elec). Lagged CDS index for a specific industry (L CDS). Logarithmic differences of industry specific stock indices for a specific industry (Stock). Percentage growth of covid-19 cases (Covid), a dummy variable for March of 2020 (March), a dummy variable for April of 2021 (April), geopolitical risk index (GPR). Number of observations (N), constant term of the regression (Const), measure of explanatory power of the regression model (R^2). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC). Statistical significance of the coefficients: * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

Table 4 highlights the importance of the explanatory variables that are the most central for this thesis: Covid-19 and the geopolitical tensions that have increased due to the Russian invasion of Ukraine. In this regression, the lagged CDS indices are also included, which all have a near to one coefficient with significance at 1 % level. In this regression, unlike in the previous one, all stock index returns have a negative coefficient on the CDS indices of the selected industries. The strongest negative coefficients are on the industrial and travelling industries.

The geopolitical risk index has small but negative coefficients on the bank, auto, industrial, transportation, travel and leisure, and telecommunications industries, indicating an increase in geopolitical tensions has potentially decreased the CDS spreads in these industries. Positive coefficients GPR index has on chemical, electricity as a power, and oil and gas industries, meaning that for these industries CDS spreads have slightly increased with the GPR index.

As discussed for the first regression, the percentage growth of Covid-19 cases variable “Covid” does not have strong coefficients on any industry. However, the dummy variables for March and April of 2020 do. March has positive coefficients on bank, auto, industrial, telecommunications and oil and gas industries, indicating increased CDS spreads and credit risk during that beginning month of the pandemic. Negative coefficients March had on chemical, electricity as a power, transportation and travel and leisure industries. This means that during March, these industries did not suffer from increased credit risk and CDS spreads.

For April 2020 the coefficients look very different for most industries. Bank, auto, industrial, telecommunications and oil and gas industries went from having a positive coefficient in March to a negative coefficient in April, meaning a decrease in CDS spreads. The only industry that had the opposite happen was travel and leisure industry, with a sharp increase in CDS spreads during April, as the coefficient went from -143.77 in March to 319.26 in April.

In conclusion, the results fail at being generalized due to their low significance. Neither the GPR index nor the pandemic variables have significant results in this regression. Especially the dummy variables for the first months of the pandemic are unexpectedly not significant, even though they could be expected to have significance.

Table 5 presents results for a regression for each of the selected industry specific CDS indices with the two most significant variables. This was conducted by starting with all explanatory variables and eliminating the least significant variable one by one. Like in the two previous linear regression tables, the two information criterion measures (AIC and BIC), as well as the R squared are included.

TABLE 5: Linear regression results for the most significant variables

CDS	Bank	Auto	Chem	Elec	Ind	Tran	Trav	Tele	Oilg
L CDS	0.950***	0.854***	0.871***	0.905***	0.853***	0.946***	0.893***	0.947***	0.807***
Oil							-174.075*		
ECB									2.319
Eur 3M	4.459**		8.659*		14.741**				
Vstoxx		1.527							
GPR				0.047					
Covid						0.007***		0.002*	
N	176	176	176	176	176	176	176	176	176
Const	6.577	-12.102	9.217	7.672	19.273	14.870	48.840**	7.759	15.807*
R^2	0.939	0.889	0.909	0.819	0.872	0.897	0.787	0.894	0.676
AIC	1675.881	1745.705	1620.817	1622.342	1852.144	1796.24	2110.664	1703.103	1567.177
BIC	1667.392	1755.217	1630.329	1631.854	1861.655	1805.751	2120.159	1712.615	1576.688

Notes: Abbreviations used in the table are the following: Logarithmic differences of industry CDS indices for following industries: Bank (Bank), auto (Auto), chemical (Chem), travel and leisure (Trav), industrial (Ind), transportation (Tran), telecommunications (Tele), oil and gas (Oilg), and electricity as a power (Elec). Lagged CDS index for a specific industry (L CDS). Logarithmic differences of European Central Bank assets (ECB) and oil (Oil). Percentage growth of covid-19 cases (Covid), geopolitical risk index (GPR). Euribor three-month rate (EUR 3M). Number of observations (N), constant term of the regression (Const), measure of explanatory power of the regression model (R^2). Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC). Statistical significance of the coefficients: * denotes $p < 0.05$, ** denotes $p < 0.01$, *** denotes $p < 0.001$.

As can be expected, for each industry CDS index the lagged CDS index is the most significant variable with p-values of 0.000 and values varying from 0.807 to 0.950. Three-month Euribor rate is another most significant variable for three industries, bank, chemical and industrial industries. Of them, chemical industry is significant at 10 % level, whereas bank and industrial are significant at 5 % level. For all these industries the coefficient is positive, indicating an increase in the CDS spreads with an increase in the Euribor three-month rate. Industrial industry has the strongest coefficient.

Another variable that is the other most significant is the Covid-19 variable, being a significant explanatory variable for the transportation and telecommunications industries. The coefficient however is very small for both industries, which means that no real conclusion can be drawn from these results.

For the travel and leisure industry, oil has a strong positive coefficient with a 10 % significance. The coefficient is stronger compared to the regression that includes all explanatory variables. The result indicates a decrease in CDS spreads of the industry as oil prices increase. The European volatility index is the another most significant variable for the auto industry with a slight positive coefficient.

Oil and gas industry has ECB assets as its another most significant variable with a positive coefficient of 2.32, meaning that as the ECB increases the amount of its assets, the CDS spreads of the oil and gas industry increase. However, this result is not significant and therefore not generalizable. Lastly, the another most significant variable of electricity as a power industry is the geopolitical risk index. However, the coefficient is very small and not significant, and therefore it faces the same limitations as the oil and gas industry regression.

The results of the third linear regression that are presented in table 5 are the most significant of the linear regressions conducted, however they are not all significant at 5 % or even at 10 % level.

6 CONCLUSIONS

The aim of this thesis was to examine the impact of geopolitical tensions on industry specific credit default swap (CDS) indices in Europe. The study utilized monthly data of CDS and stock indices as well as geopolitical index and Covid-19 pandemic cases, as well as several other financial variables over a sample period of 15 years. The data was analyzed using three separate linear regression models to identify any significant relationships between geopolitical tensions and European CDS indices. The conclusions chapter summarizes the main findings of the study, discuss their implications, as well as make suggestions for future research topics.

This thesis has begun to fill the existing gap in the literature focusing on the relationship between these specific global crises of the Covid-19 pandemic as well as the Russian war in Ukraine on European CDS spreads. To the author's current knowledge, studies related to this relationship do not yet exist.

As an answer to the first research question, it can be concluded that the most significant variable in explaining the CDS indices is the lagged CDS index. Another variable that has some significance is the three-month Euribor rate.

To answer the second research question, the results of the study show that geopolitical tensions do not have a strong impact on industry specific CDS indices in Europe. The findings indicate that companies in industries that are more susceptible to geopolitical risks, such as the travelling and leisure industry, can potentially experience a greater increase in CDS spreads during periods of increased geopolitical tensions. The results are not significant, which limits the ability to draw straightforward conclusions. The existing literature highlights the importance of considering geopolitical risks in managing risk and making investment strategies.

The results also show strong, yet unsignificant results for the Covid-19 variables and industry specific European CDS spreads. For April 2020, the second month of the widespread pandemic, the results show that most industries faced a decrease in CDS spreads. An exception is the travelling and leisure industry, that had a dramatic increase in CDS spreads.

Some limiting factors in this thesis are the non-significance of most results, which can be interpreted as unexpected. More significant and measurable results for the geopolitical risk for this thesis would have been available if the GPR index was not global, but European, as the object of the thesis was to examine European CDS indices. In addition, using linear regression has its limitations to interpreting the data in the most comprehensive matter, as it assumes linearity in the relationship between the independent and dependent variables.

This thesis has aimed to examine the impact of geopolitical tensions on industry specific CDS spreads in Europe. While the study provided some insights into the relationship between geopolitical tensions, more specifically, the Covid-19 pandemic and the Russian war in Ukraine, and CDS spreads, still many questions remain unanswered. One possible area of future research is to expand the scope to include other countries and areas as well. As the war in Ukraine is linked to food safety and supply chains, it would be interesting to study its impacts on Asian and African countries as well. By including more countries, the regional or country specific differences could be examined in more detail.

Another potential route for future research would include examining how the relationship between geopolitical tensions and CDS spreads varies over time, and to use forecasting models such as autoregressive moving average (ARMA) to create a prediction for future values of CDS spreads. The scope of the study could also be widened to include more financial instruments, other than CDSs to allow for a more complete understanding of the implications of geopolitical tensions.

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