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The Determinants of CDS Spreads During the COVID-19 Pandemic

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Abstract

This paper investigates the determinants of CDS spreads in the US, following the spread of the COVID-19 pandemic in early 2020. The pandemic led to an increased volatility and credit risk, as supply and demand suffered. By introducing measures related to COVID-19 we try to explain changes in CDS spreads in the US during the pandemic. The results show that the magnitude of the pandemic, measured by the number of COVID-19 cases, COVID-19 deaths and stringency index in the US, are linked to CDS spreads. However, we cannot prove all COVID-19 variables caused an increase in CDS spreads in all sectors.

Keywords: *Credit Default Swap, CDS spreads, Credit Risk, COVID-19*

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1 Introduction

The market for credit derivatives, explained as the market for contingent claims that allows the trade of default risk independently of other sources of uncertainty, has had tremendous growth since the mid-nineties. At the beginning of 2008, the market had reached a notional principal of more than 35 trillion US dollars (Bank for International Settlements, 2018). However, due to the following financial crisis, the credit derivative market was greatly affected by a massive decline in trading volume. After the peak in 2008, the demand for credit derivatives cooled off. Yet, credit derivatives are still actively traded today and make up for an extensive part of the financial market (Bank for International Settlements, 2021). In June 2021, derivative contracts' gross market trading volume equalled 12.6 trillion US dollars (Bank for International Settlements, 2021).

The *credit default swap* (CDS) is the most commonly traded credit derivative contract within the credit derivative market, accounting for a majority of the total credit derivative market as of 2021 (Bank for International Settlements, 2021). The price, or the spread, of a CDS contract can give valuable insight in the financial health of a firm, due to its close relation to the credit- and default risk (Merton, 1974). CDS spreads can be interpreted as the rate at which the buyer pays a protection fee to the seller, in order to transfer the risk of a credit event (Annaert, De Ceuster, Van Roy, & Vespro, 2013). Analyzing CDS spreads is therefore a valuable tool in understanding the financial reliability of a firm (Annaert et al., 2013).

Through its impact on firms' future cash flows and outlooks, the COVID-19 pandemic heavily affected financial markets worldwide. Measures implemented by administrations, such as lockdowns, country borders closing and social and economic distancing, have among other things had large negative consequences for demand, supply, firms' profitability and growth, income, and productivity. Thus, stock market volatility rose to crisis levels as markets declined by over 30% in March 2020 (OECD, 2020).

Not only do economic agents act differently in times of turmoil and fear, as could be seen during the pandemic and previous crises, but it furthermore has other implications for firms and businesses (Akerlof & Shiller, 2010). Due to their unwillingness to bear risk when the economic outlook is shaky, firms may fail to identify investment opportunities. Henceforth, R&D expenditures and human capital investments are being decreased (Baker, Bloom, Davis, & Terry, 1992). Moreover, consumer demand, affected by fear and panic caused by COVID-19, led to a steady decline in customers' physical attendance, resulting in reduced firm profitability and growth (Liu, Qiu, & Wang, 2021). The American population was hit hard by the COVID-19 pandemic, and 19% of adults reported losing their job or getting work hours cut, within the first months of the pandemic (**?**). Financially, nearly one-fourth of adults in the US were worse off compared to 12 months earlier (**?**). For the aforementioned reasons, and the fact that S&P made almost the same amount of credit ratings downgrades by July 2020 as in 2009, we expect that COVID-19 impacted CDS spreads (Jones, 2020). Thus, in this paper we investigate the effect of COVID-19 on CDS spreads in the US.

The purpose of this thesis is to explain changes in determinants for CDS spreads in the US during the COVID-19 pandemic. In order to do this, we also investigate the period leading up to the pandemic. Furthermore, it covers new ground by introducing variables related to the COVID-19 pandemic, as well as exploring new sub-samples. Moreover, the main thing companies can do to protect themselves from potential financial losses, is to understand and learn how to manage credit risk. Thus, managing credit risk is important for businesses of all sizes. By learning about credit risk, it is possible to get an indication of what causes the market's view of financial health and what drives changes in it. This knowledge can help businesses make sound credit decisions, set credit limits, and price their products or services (Apergis, Danuletiu, & Xu, 2022).

What drives changes in credit risk is a well-researched question. However, there is still a lack of consensus. Some studies suggest that credit risk is driven by firm-specific factors, while others suggest that it is driven by market factors. However, most studies find that both these factors are useful when analyzing CDS spreads (Apergis, Danuletiu, & Xu, 2022). Thus, this paper contributes to the existing literature surrounding credit risk by providing new insights into potential underlying structural changes during the COVID-19 pandemic, as well as providing a further understanding of the driving forces behind changes in CDS spreads during the COVID-19 pandemic in the US. In order to do so, the following hypothesis has been set and will be the focus of the investigation of this study.

Hypothesis: COVID-19 has positively affected CDS spreads in the US.

The main scope of the research paper is based on the initial COVID-19 wave that hit the US in early 2020, since we expect the initial reaction to be far more susceptible to the virus, as shown by the large sell-off that hit financial markets in March 2020 (OECD, 2020). Moreover, the scope of this paper is based on the examination of sector-specific changes in CDS spreads for US-listed companies. This implies that all CDS spreads have corporate bonds as underlying assets. Changes in CDS spreads are measured by sub-indices to the Markit CDX NA Investment Grade index, due to liquidity and availability. Moreover, the scope of the sample period for this essay is the period between January 2016 and April 2022, divided into sub-samples preceding and during the initial infection wave following the COVID-19 pandemic.

The remainder of the paper is structured as follows. Section 2 presents the literature review. Section 3 presents the conceptual framework. Section 4 presents data and variables. Section 5 presents and discusses the methodology and results. Section 6 concludes the thesis.

2 Literature Review

Research regarding determinants of credit default swaps and changes in CDS spreads are considered broad. Due to its characteristics and close relation to the Merton (1974) model, the majority of studies evoke by including proxies related to explanatory variables from this model, as described by Annaert et al. (2013). Di Cesare & Guazzarotti (2010) furthermore shows that variables related to the Merton (1974) model could explain up to 48% of the variation in CDS spreads when looking at the time period spanning 2002–2009. One of the earliest attempts to explain changes in CDS spreads were Hull, Predescu, & White (2004) who were able to explain changes in credit default swap spreads of 32 corporate bonds in the US by looking at changes in the credit rating. Hull, Predescu, & White (2004) also found a relationship between bond yield spreads and CDS spreads.

Furthermore, Byström (2005) were early on in exploring the relationship between stock return volatilities and CDS spreads. He studied the European iTraxx CDS index market, focusing on specific sector CDS indices and their corresponding stock index. Moreover, Byström (2005) found significant results for a close relationship between CDS spreads, stock index returns, and stock returns volatility, in line with previous theoretical literature. In addition to Byström (2005)'s research, Alexander & Kaeck (2008) showed that the iTraxx Europe indices are extra sensitive to volatility in the stock market during periods of a turbulent CDS market.

Galil, Shapir, Amiram, & Ben-Zion (2014) showed that three factors outperformed others in explaining CDS spreads for a US database of 718 firms. The variables were stock return, change in stock return volatility and changes in median CDS spread for the rating class. Samaniego-Medina, Trujillo-Ponce, Parrado-Mart inez, & di Pietro (2016) and Galil et al. (2014) also showed the occurrence of a structural change in determinants during the *great* *financial crisis* (GFC). Samaniego-Medina et al. (2016) also showed a structural difference in determinants of CDS spreads for European banks- when comparing the period before and after the GFC. Di Cesare & Guazzarotti (2010) also showed that a firm's leverage contributed more to the explanation of CDS spreads during the GFC than before, attributed to an increase in awareness for individual risk factors from investors, when looking at the US market. Furthermore, Naumer & Yurtoglu (2020) investigated if corporate news on costs of financing had any influence on European and US CDS spreads. Their results suggests that ESG- and non-ESG-related news influenced CDS spreads. They also concludes that the influence primarily originates from positive ESG news, showing the effect news can have on these types of derivatives.

In recent years, studies have examined whether COVID-19 related variables might affect CDS spreads, where Kartal (2020) introduced numbers of deaths from COVID-19 and similar COVID-19 related factors in order to explain CDS spreads in Turkey. He found that determinants of CDS spreads differed, when looking at before and during the pandemic, where the number of new COVID-19 cases proved to have explanatory power. Similarly, Apergis, Danuletiu, & Xu (2022), examined whether COVID-19 had any effect on US CDS spreads. They concluded that US and global COVID-19 metrics positively affects CDS spreads and that COVID-19 increases corporate CDS spreads. Furthermore, they found that banking, travel, transportation, airlines and restaurants were the most affected sectors. Similarly, Daehler, Aizenman, & Jinjarak (2021) examined if unpleasant news about COVID-19 had any negative effect on sovereign credit risks. They came to the conclusion that emerging market spreads are driven largely by global/regional factors in risk-on environments. The authors also found that spreads at peak COVID-19, around March 2020, were primarily driven by traditional country-specific factors.

Romanyuk (2021) tested the predictability for 6 CDS sectors on the US market during the COVID-19 pandemic. His results showed that only the financial sector, excluding banks, showed a drop in predictability when applying exogenous macroeconomic and market factors during the pandemic.

3 Conceptual Framework

This section will include two main parts. The first part will be a theoretical background to credit risk, aiming to provide the readers with a foundation and understanding of the field of investigation. The second part will explain the COVID-19 pandemic and business climate in relation to financial markets and CDS spreads.

3.1 Credit Risk

A CDS is a financial contract between two parties in which one party agrees to make payments to the other party in the event of a credit default. A CDS contract can therefore be seen as insurance, the buyer of the contract pays a premium to the insurer in exchange of compensation if a default occurs, often referred to as the spread. Cases of default could be failure to pay, bankruptcy and restructuring (Chan-Lau & Kim, 2004).

The difference between an insurance contract and a CDS is in the case of insurance, where the buyer of the contract gets compensated only for the actual loss from the default. In contrast, it is possible to buy or sell protection against credit events independently from the real exposure to the risk of default via a CDS. One can use CDS for more than simply hedging credit risk, it can also be used for speculative positions as with future and forwards contracts. This is an extensive difference from the bond market, whereas the CDS markets allow for high levels of liquidity, by for instance allowing investors to more easily sell credit risk (European Central Bank, 2009). Furthermore, CDS spreads indicate the difference between ask and bid prices. Therefore, CDS spreads are often seen as a measure of credit worth- since they directly represent the cost of covering losses in the case of a default (Duffie, 1999).

The last decade has implied substantial amount of empirical research on credit-sensitive instruments, primarily focusing on corporate bonds. In terms of its theoretical foundation, this work can be divided into different approaches. The approach of interest in this study is the structural approach, which is based on models that have evolved around the Merton (1974) model. It is one of the most popular models for credit risk and pioneered the subject in the early 70s. It considers the possibility of a credit event, such as a company going bankrupt, and includes variables such as volatility of stock price, equity, assets, debts and risk-free interest rate (Merton, 1974).

The Merton (1974) model is a useful tool for understanding credit risk and allows for a practical approach to determining the equity and debt value of a firm. Credit-risky instruments are priced using this approach based on the economic factors determining financial distress and loss given default. These models suggest that financial leverage, volatility, and the risk-free term structure are the primary determinants of the likelihood and severity of default (Merton, 1974). Despite its intuitive appeal and simplicity, the model has some limitations as well as having in previous empirical studies performed poorly. One could say those firm value models are fundamentally flawed, since some of the input parameters to the equation are unobservable. For instance, in the original Merton (1974) model, the firm's assets, total liabilities and volatility are unobservable (Benkert, 2004).

One of the major shortcomings of the model is that it only recognizes that the firm defaults at the maturity of the debt. Before maturity, the asset value of the firm is not considered in the assessment of credit risk. In other words, if a firm's value falls below the level of debt, but it is able to recover and make payments before maturity, these facts are ignored by the Merton (1974) model. Furthermore, the capital structure of a firm is more complex than the one assumed in the Merton (1974) model, which only considers one type of debt. As an example, debt is not constant over time, as it is seen in the model (Casimiro, 2015).

Perhaps because of the difficulty in implementing structural models in practice, a more direct approach to this has been suggested by Collin-Dufresne, Goldstein, & Martin (2001) and Eichenbaum, Rebelo, & Trabandt (2021), who use the structural approach to identify the theoretical determinants of corporate bond credit spreads. In contrast, this model implies that the variables are used as explanatory variables in regressions for changes in corporate credit spreads, rather than inputs to a particular structural model. Collin-Dufresne, Goldstein, & Martin (2001) conclude that the explanatory power of the theoretical variables is modest, and that a significant part of the residuals is driven by a common systematic factor, not captured by the theoretical variables (Ericsson, Jacobs, & Oviedo, 2009).

3.2 The COVID-19 Pandemic

The COVID-19 pandemic started in China in late 2019 and was followed by a worldwide pandemic, resulting in over 514 million confirmed cases and 6.22 million deaths as of May 8th 2022 (World Health Organization, 2020).

Following the assessment by WHO in early 2020 the pandemic led to lockdowns and bankruptcies in countries that were initially hit. The COVID-19 pandemic struck economies worldwide and led to severe disruption and hardship in almost every business sector in the US, following the first reported case on the 21st of January 2020 (Holshue, DeBolt, Lindquist, Lofy, Wiesman, Bruce, Spitters, Ericson, Wilkerson, Tural, Diaz, Cohn, Fox, Patel, Gerber, Kim, Tong, Lu, Lindstrom, Pallansch, Weldon, Biggs, Uyeki, & Pillai, 2020). The pandemic resulted in business closures and a worldwide decline in demand, which had a negative effect on manufacturing (Bowman, 2020). COVID-19 and its following measures by governments inflicted massive harm on the economy, in the form of large redundancies, bankruptcies and massive output losses (Pagano, Wagner, & Zechner, 2020). The effects on the economy due to the COVID-19 pandemic has been widely researched, and Eichenbaum, Rebelo, & Trabandt (2021) concludes that pandemics affect the economy negatively through a large reduction in both demand and supply.

Bosio, Djankov, Jolevski, & Ramalho (2020) report that on a firm level, loss of demand and increased uncertainty about future growth prospects caused a severe negative impact on liquidity. Furthermore, the authors examined the survival time of different sectors during economic crises, by looking at how long it would take for savings to run out in case of no revenue. They concluded that the retail sector had the shortest survival time and the manufacturing sector had the highest, as profit margins tend to be higher. According to Pagano, Wagner, & Zechner (2020), certain sectors have been more resilient than others to the effects of the COVID-19 pandemic. Sectors that were hit the hardest were for example travel, tourism and restaurants and the ones who were able to handle it better were the high-tech sector. According to Pagano, Wagner, & Zechner (2020) one reason for this difference was that high-tech companies were able to adapt to social distancing more easily than other sectors, for example, travel and tourism. The authors also found that there was a large difference between the high-tech sector and travel sector when it came to expected return and required risk-premia for investors. In a risk-premia context, the expected return of for example United Airlines and Royal Caribbean Group were around 40% and 60% respectively, while the same measures for Microsoft and Apple was 4% and 3%. In other words, the market appeared to price exposure to the pandemic risk (Pagano, Wagner, & Zechner, 2020).

It is also important to take the impact on the financial sector in general, and banks in particular, into account. Almost all firms were facing liquidity problems during the crisis, and their ability to operate depended much on their access to bank credits. In other words, company withdrawals increased due to financial instability and uncertainty about future cash flow and growth prospects, induced by the pandemic (Li, Strahan, & Zhang, 2020). Furthermore, banks also faced an increase in withdrawals from households, due to uncertainty and a decrease in working hours (Li, Strahan, & Zhang, 2020). Conclusively, the banks was affected by liquidity, market risk and credit risk, showing the strong link between firms and banks regarding financial risks (Li, Strahan, & Zhang, 2020).

Furthermore, CDS spreads are higher for low-rated banks than for high-rated ones. It applies to banks that rely heavily on short-term funding as well. Andries, Ongena, Sprincean, Billio, & Varotto (2020) examine the impact of the lockdown measures on the CDS spreads of European banks. The authors provide evidence of increases in sovereign and bank CDS spreads when lockdown measures are implemented, and the number of new confirmed cases seems to be the most critical factor for the perception of risk associated with bank investments (Andries et al., 2020). Furthemore, Romanyuk (2021) found that the financial sector (excluding banks) performed well compared to other sectors during COVID-19.

Increased energy prices, unpaid bills by households, delays in the supply chain, and increased operational costs caused a large drop in demand for the utility sector, as described by Gollakota & Shu (2022). Furthermore, the drop in demand for energy resulted in many fossil fuel production facilities being forced to close (Gollakota & Shu, 2022). In the industrial sector, the pandemic had a negative effect through its impact on the construction sector. The industrial sector and the construction sector it's closely related. The construction sector is sensitive to the economic cycles and the COVID-19 had a forceful effect on the sector. However, due to the construction sector's potential to create jobs, the sector usually recovers faster than other sectors (International Labour Organization, 2021). Overall, the S&P predicted in July 2020, that almost 16% of US junk-rated bonds could default in less than a year, following the effects of the pandemic (Jones, 2020).

3.3 Business Climate

There are many empirical papers that find that there are residuals in their model containing common variation when exploring the explanatory power of credit risk variables for CDS spreads. The reason for this might be missing common factors, according to Collin-Dufresne, Goldstein, & Martin (2001). This common variation is likely to be linked to economic conditions and the general market. The business cycle may have an impact on CDS spread for at least two reasons. The first one is that the general default risk depends on the economic environment and economic circumstances. Therefore, the CDS should reflect this. Furthermore, risk aversion is also known to vary through the business cycle, which should affect the risk premia investors would require to take on credit risk (Berndt et al., 2005). Changes in the credit spreads can occur due to changes in the expected recovery, even if the probability of default for a firm is constant. The overall business climate has a large impact on the recovery rate. Where, improvement in the market conditions increase the recovery rate and reduces the probability of default (Collin-Dufresne, Goldstein, & Martin, 2001).

4 Data and Variables

4.1 Data

Our sample consists of US CDS spreads index with 5-year maturities for investment grade companies, available via Bloomberg during the sample period January 2016 to April 2022. The sectoral factors, market-wide factors and COVID-19 variables are similarly collected from Bloomberg. The sample period allows for distinguishing between the relative calm period preceding the COVID-19 pandemic and the period following community spread in the US. We expect a positive relationship between CDS spreads and all COVID-19 measures. Since the goal of this paper is to explain changes in CDS spreads rather than predict them, contemporaneous explanatory variables are used, as previously discussed by Annaert et al. (2013).

The data we are analyzing is panel data, in which we analyze CDS Spread in different sectors in the cross section dimension through time. According to Park (2011), panel data has a lot of advantages. One of them being the fact that panel data is usually good at dealing with omitted variables and heterogeneity within the data. Panel data can also provide greater variability by combining cross-sectional unit variations with variations over time, eliminating some multicollinearity problems. Furthermore, a panel dataset provides more information than a cross-sectional dataset (Park, 2011). Finally, panel data allows for performing a better analysis of dynamic adjustments since cross-sectional data by themselves are not enough to capture dynamics. To obtain more accurate estimates of dynamic trends, a very long time series data would be needed (Kennedy, 2008).

4.2 Variables

The CDS spreads are, as previously presented, reported as index values measured in bps for the different sectors constituting the CDX North American Investment Grade index. This proxy allows for separation between six sectors; energy, communication services, information technology, financials, industrials and utilities. The selection of an investment grade index means only firms with credit ratings Baa3/BBB- or better are included. Closing prices for the indices are selected on a daily basis, allowing to distinguish changes even in shorter time periods.

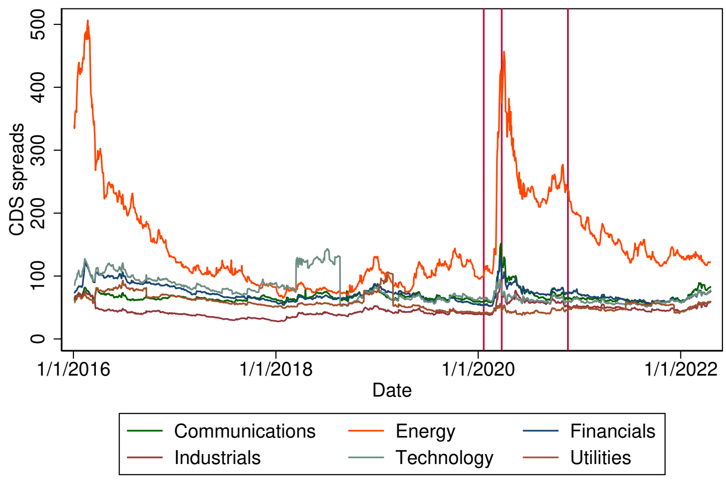

Figure 4.1: CDS spreads for all sectors, full sample. Time periods indicated by red lines.

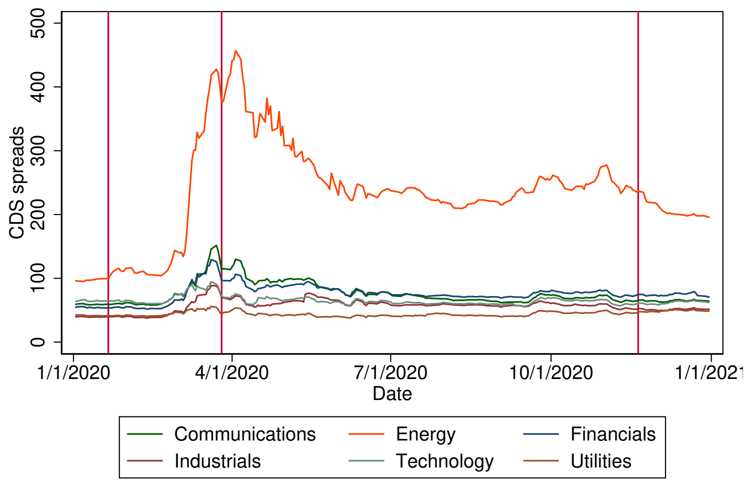

Figure 4.2: CDS spreads for all sectors, 2020–2022. Time periods indicated by red lines.

Greatrex (2008) shows that econometric variables commonly used for determining CDS spreads are often non-stationary in levels, resulting in potential high values for R^2 as well as inefficient estimates for coefficients and invalid significance tests (Granger & Newbold, 1974). To overcome this, Greatrex (2008) also shows variables are stationary in first differences. Due to the potential problems arising with levels data, we transform the data using logarithmic and first-differencing, resulting in daily change in percentage for CDS spreads.

$$\Delta CDS_{i,t} = ln(CDS_{i,t}/CDS_{i,t-1})$$

Where $CDS_{i,t}$ denotes CDS spread for sector i on day t. In a similar fashion, sector returns, VIX index, FED total assets and stringency index are also transformed using this method. Following the work by Kartal (2020), in order to get more consistent data for COVID-19 measures, the number of cases and deaths is measured by taking the weekly change on a daily basis. In order to capture any reaction to the COVID-19 pandemic, we implement weekly change on a daily basis for confirmed cases and deaths, following the work by Kartal (2020). For this procedure, the transformation looks as following:

$$\Delta CASES_t = ln(CASES_t/CASES_{t-7})$$

Where $CASES_t$ denotes percentage change over week on a daily basis for COVID-19 cases. This transformation also applies to COVID-19 deaths. As a third measure of COVID-19, we implement the stringency index, retrieved from Bloomberg. The stringency index is a composite measure of school closures, workplace closures, cancellation of public events, stay-at-home requirements, information campaigns and restrictions on internal movements and international travel. The index is calculated as the mean of these metrics and take on a value between 1-100, where a higher value indicates a stricter response (Hale, Angrist, Goldszmidt, Kira, Petherick, Phillips, Webster, Cameron-Blake, Hallas, & Majumdar, 2021).

Improvements in the business climate, such as a positive change in stock returns index, will affect the probability of default and the recovery rates. As the stock index increases, the probability of default will decrease and the recovery rate will increase, following the fundamentals of the Merton (1974) model. Higher stock returns indicate an increase in asset value, and theoretically should decrease the CDS spreads. Henceforth, a negative relationship between stock return and CDS spread is expected, also presented by Galil et al. (2014). With this theory in mind, choosing a market-wide stock index return as a control variable is reasonable and also common in other similar papers (see e.g. Collin-Dufresne, Goldstein, & Martin, 2001; Ericsson, Jacobs, & Oviedo, 2009; Duffie, 1999). However, instead of choosing a more general index like the S&P 500, we choose sector-specific sub-indices as control variables. The reason for this is to capture the sectoral changes in a better way and give a better picture of performance and growth prospects for each of the sectors. It also allows for a more direct proxy for asset value, and Zhu (2006) has specifically shown that CDS spreads are quite responsive to changes in stock return.

Due to the specific returns index chosen, and due to limitations in data, leverage is not included as an explanatory variable, as it is expected the potential effect is already captured by the individual returns index, hence it can be seen as a proxy for financial leverage (Annaert et al., 2013). Financial leverage is valuable due to the characteristics of the Merton (1974) model, which interprets equity as a call option for the firm's assets. Similarly, debt is regarded as a short put option for the firm's assets, and default is defined as when asset value is lower than the value of debt at the time of maturity (Merton, 1974). With this in mind, it's clear that the probability of default can be interpreted as a function of the firm's capital structure (Greatrex, 2008). However, following a similar path, company performance in the form of stock returns, can be suspected to incorporate effects induced by firm leverage. Following a similar procedure as with CDS spreads, sector return indices are also retrieved via Bloomberg as sub-indices to the broadly used S&P 500 index.

The sub-indices we have included in our model are the following: Information technology, Communication services, Utilities, Financial, Industrials, and Energy Index. Investigating on a sector level allows us to distinguish between sectoral differences, and the use of these indices also allows us to explain business climate more accurately for every sector. The S&P 500 consists of different sectors, where we have selected the ones matching the constituents of the CDX index. The six different sectors are listed below:

- **S&P 500 Energy:** The S&P 500 Energy composes the companies included in the S&P 500, classified as members of the GICS for the energy sector. The greatest companies in this index are: Occidental Petroleum Corporation, Marathon oil company, Devon energy company and Exxon Mobil Corporation. These companies relate to supplying or producing energy (S&P Global, 2020).

- **S&P 500 Information & Technology:** The S&P 500 information and technology composes the companies that are included in the S&P 500, classified as members of the global index classification standard (GICS) for the information and technology sector. The ten greatest companies within S&P 500 information and technology are; Apple Inc., Microsoft Corp, Nvidia Corp, Visa Inc A, Mastercard Inc A, Broadcom Inc, Cisco Systems Inc, Accenture plc A and Adobe Inc (S&P Global, 2020).

- **S&P 500 Communication services:** The S&P 500 communication service comprises the companies included in the S&P 500, classified as members of the GICS for the communication service sector. Some of the greatest companies within S&P 500 communication service are; Alphabet Inc. (Google), Meta Platforms, Verizon Communications, Twitter, Meta Platform, Netflix and AT&T (S&P Global, 2020).

- **S&P 500 Utilities:** The S&P 500 utilities composes the companies included in the S&P 500, classified as members of the GICS for the utilities sector. Some companies within S&P 500 utilities are; NextEra Energy Inc, Duke energy corporation, Dominion energy, Sempra, American Water works, Dte Energy company and Entergy Corp (S&P Global, 2020).

- **S&P 500 Financials:** The S&P 500 financials composes the companies included in the S&P 500, classified as members of the GICS for the finance sector. The ten greatest companies within S&P 500 financials are; Berkshire Hathaway B, JP Morgan Chase & Co, Bank of America Corp, Wells Fargo & Co, S&P Global Inc, Morgan Stanley, American Express Co, Goldman Sachs Group Inc, Charles Schwab Corp and Citigroup Inc (S&P Global, 2020).

- **S&P 500 Industrials:** The S&P 500 industrials composes the companies included in the S&P 500, classified as members of the GICS for the industrial sector. Companies in this index are for example: Caterpillar Inc, Deere & Company, General

Electric Company, Honeywell International Inc, Lockheed Martin Corporation, 3M Company, Raytheon Technologies Corporation and Union Pacific Corporation (S&P Global, 2020).

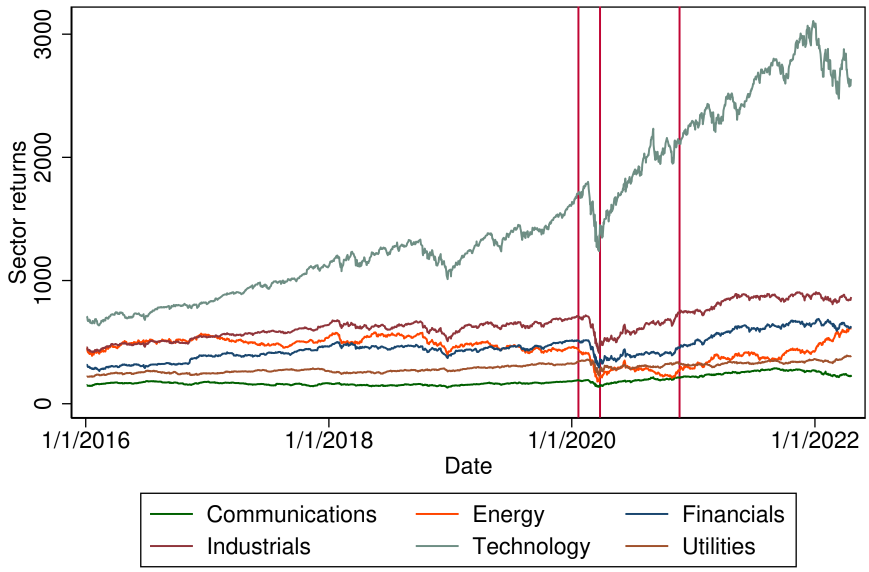

Figure 4.3: Sector performance, full sample. Time periods indicated by red lines.

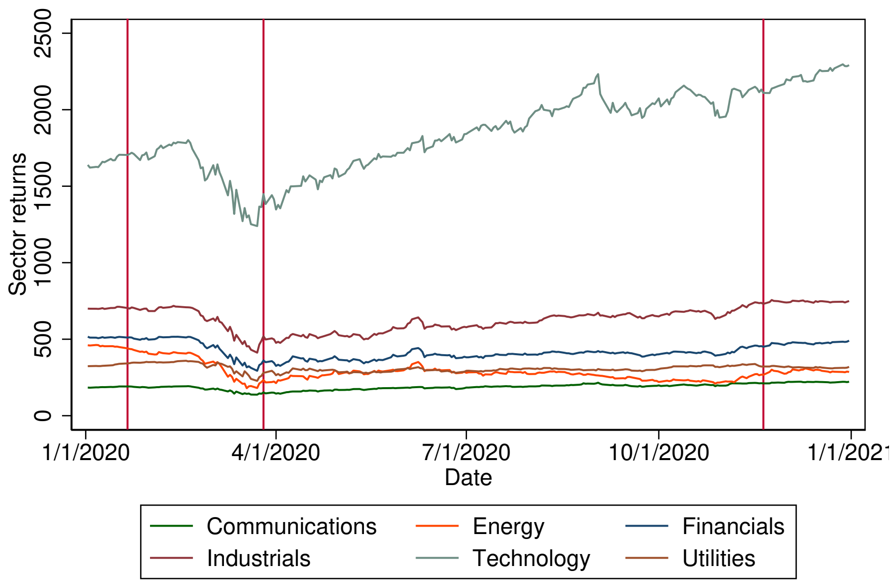

Figure 4.4: Sector performance, 2020–2022. Time periods indicated by red lines.

There has long been an acceptance that the central bank's monetary policy has an impact on macroeconomic outcomes and that the slope of the term structure is widely acknowledged as a business cycle predictor (see e.g. Bernanke & Mishkin, 1992; Estrella &

Mishkin, 1997). Higher slopes indicate improved growth. Therefore, a negative relationship is expected with credit spreads. Litterman & Scheinkman (1991) find that the slope and level of the term structure are the two most important factors affecting interest rates. Increasing the slope of the yield curve would result in higher interest rates.[1] Furthermore, since the slope indicates future interest rate levels, there is a negative relationship between the slope and the credit spread. In other words, a higher slope indicates a lower credit risk, based on the arguments above. Avramov, Jostova, & Philipov (2007), on the other hand, means that the effect on credit spread changes is an empirical question, hence it's unsure whether a positive or negative coefficient is expected for this variable. There is no theoretical answer to which points the term structure should be used to measure slope. There have been a wide variety of combinations suggested in the literature (see e.g. Collin-Dufresne, Goldstein, & Martin, 2001). We consider the difference between the 10 year and 5 year yield to maturity for US government bonds, following the work by Annaert et al. (2013).

The contingent-claims approach implies that debt claims have features similar to short positions in put options according to Breeden & Litzenberger (1978). The authors' model predicts that credit spreads will increase with volatility since option values rise with volatility. That makes intuitive sense: higher volatility means more defaults, also in line with the arguments presented by Merton (1974). With this said, the assumption is that higher volatility implies higher uncertainty about the economic prospect. Moreover, this can also be assumed as an indicator of investment risk aversion, as proposed by Pan & Singleton (2008). Thus, an increase in CDS spreads is expected as volatility rises.

We use the VIX index as a proxy for volatility, which is based on the expectations of the stock market S&P 500's volatility (Annaert et al., 2013). This variable has previously been widely used for similar research (see e.g. Galil et al., 2014; Di Cesare & Guazzarotti, 2010; Corò, Dufour, & Varotto, 2013). Data for the VIX index is retrieved through Bloomberg, and following the previous discussion, we expect a positive sign for the VIX index.

[1] The slope of the Term structure is more commonly known as the yield curve.

According to Merton (1974), the drift in the risk-neutral world is constituted by the risk-free rate. With this said, higher risk-free rates result in decreasing credit spreads, as default risk decreases, as previously proposed by Ericsson, Jacobs, & Oviedo (2009). This relationship can also be explained by macroeconomic factors, where economic growth is linked with interest rate and a higher growth rate results in lower default risk (Annaert et al., 2013). As a proxy for risk-free rate the 10-year US government bond rate (Treasury) has been considered and retrieved from Bloomberg, following the work by Ericsson, Jacobs, & Oviedo (2009). Although Annaert et al. (2013) did not use this, they tested it and proved it yielded similar results as any other bond. Similarly, measures for proxies to the risk-free rate have previously been implemented by e.g. Corò, Dufour, & Varotto (2013). The 10-year Treasury fell to an all-time low on March 6th 2020, as investors fled riskier assets and concerns grew over the persistence of the coronavirus (Franck, 2020).

Although the US was hit particularly hard during the initial wave of COVID-19 the swift and drastic response from the US central bank, the Federal Reserve (FED), had markets bounce back and consequently, the S&P 500 ended the year with positive returns. The FED implemented unprecedented measures beginning in early March 2020, leading to an enormous capital injection in US companies and a following positive response from the stock market (Board of Governors of the Federal Reserve System, 2020). Following this argument, we expect a negative relationship between FED's total assets and CDS spreads. Similar measures as proxies for government intervention have previously been implemented by e.g. Zhang, Zhou, & Zhu (2009). The total assets of the Federal Reserve are considered as a measure of central bank intervention during the crisis. This data is not seasonally adjusted. Data is retrieved through FRED and transformed using first difference and log.

Before proceeding with the regression models, we first check for multicollinearity between the independent variables. In the case of multicollinearity, it is impossible to calculate with confidence the effect that one variable has on another independent variable when using ordinary least squares (OLS) estimating procedures (Kennedy, 2008). In Table 4.1, correlation exceeding >0.7 can be seen between several variables. Due to this, these explanatory variables are not included in regressions simultaneously. Even though correlation matrices for sub-sample time periods are not reported, they are thoroughly investigated and a similar approach to avoid multicollinearity is performed. Since regression analysis is performed on transformed variables, they are reported as such in the correlation matrix below.

	CDS	Returns	S&P 500	VIX	Bond	Curve	FED	Cases	Deaths	Stringency
CDS	1.00									
Returns	-0.36	1.00								
S&P 500	-0.40	0.80	1.00							
VIX	0.25	-0.52	-0.68	1.00						
Bond	0.03	0.01	-0.01	0.00	1.00					
Curve	-0.03	0.03	0.03	-0.01	-0.08	1.00				
FED	-0.01	0.02	0.02	0.00	-0.08	-0.04	1.00			
Cases	0.02	-0.06	-0.07	0.01	-0.27	-0.17	0.38	1.00		
Deaths	-0.02	-0.02	-0.01	-0.02	-0.28	-0.17	0.37	0.95	1.00	
Stringency	0.07	-0.24	-0.30	0.13	-0.05	-0.08	0.26	0.39	0.27	1.00

Table 4.1: Correlation matrix for full sample.

4.3 Descriptive Statistics

Below we report the descriptive statistics for the entire sample (2016-01-01—2022-04-22) as well as the sub-samples. Table 4.1 provides certain basic summary statistics. The average daily CDS spreads in our sample is 78 basis points with the lowest at 28 and the highest at 507 for the full sample. Following the full sample we present summary statistics for the sub-samples.

	Mean	SD	Min	Max	N
Dependent variable					
CDS (index)	78	49.78	28	507	9,450
Market factors					
Returns (index)	590	524.48	131	3,107	9,450
S&P 500 (index)	3,020.48	771.17	1,829.08	4,796.56	9,450
VIX (index)	18.32	8.25	9.14	82.69	9,450
Bond (yield)	1.93	0.69	0.51	3.24	9,450
Slope (curve)	0.35	0.19	-0.17	0.85	9,450
FED (MUSD)	5,444,657	1,720,464	3,759,946	8,965,487	9,450
Covid-19 factors					
Cases (units)	28,254,232	24,567,551	1	80,801,712	3,384
Deaths (units)	454,706	307,927	0	990,208	3,378
Stringency (index)	57.02	17.70	0.00	75.46	3,408

Table 4.2: Summary of variables, full sample.

	Energy	Communications	Technology	Financials	Utilities	Industrials
CDS	152.22	67.46	76.96	72.12	56.26	45.28
	(82.15)	(9.54)	(20.58)	(12.81)	(12.35)	(9.77)
Returns	447.20	184.58	1516.92	454.44	290.19	646.68
	(91.51)	(39.29)	(677.48)	(99.31)	(36.30)	(122.85)

Table 4.3: Summary statistics with mean and SD for different sectors, full sample.

	Mean	SD	Min	Max	N
Dependent variable					
CDS (index)	77	46.09	28	507	6,072
Market factors					
Returns (index)	501	314.88	131	1,706	6,072
S&P 500 (index)	2,559.38	340.66	1,829.08	3,329.62	6,072
VIX (index)	14.72	4.13	9.14	37.32	6,072
Bond (yield)	2.29	0.47	1.36	3.24	6,072
Slope (curve)	0.32	0.16	0.09	0.61	6,072
FED (MUSD)	4,285,096	231,957	3,759,946	4,501,695	6,072

Table 4.4: Summary of variables, 2016-01-01–2020-01-20.

	Mean	SD	Min	Max	N
Dependent variable					
CDS (index)	85	69.71	38	428	282
Market factors					
Returns (index)	586	483.38	138	1,802	282
S&P 500 (index)	3,030.53	361.10	2,237.40	3,386.15	282
VIX (index)	34.16	22.29	12.85	82.69	282
Bond (yield)	1.29	0.35	0.54	1.77	282
Slope (curve)	0.22	0.08	0.06	0.46	282
FED (MUSD)	4,392,927	403,079	4,145,912	5,811,607	282
Covid-19 factors					
Cases (units)	6,803	18,584	1	86,693	282
Deaths (units)	136	367	0	1,785	276
Stringency (index)	18.93	24.01	0.00	72.69	282

Table 4.5: Summary of variables, 2020-01-21–2020-03-26.

	Mean	SD	Min	Max	N
Dependent variable					
CDS (index)	98	78.32	38	457	942
Market factors					
Returns (index)	601	584.04	144	2,233	942
S&P 500 (index)	3,167.44	257.18	2,470.50	3,580.84	942
VIX (index)	30.60	7.46	21.35	65.54	942
Bond (yield)	0.68	0.08	0.51	0.92	942
Slope (curve)	0.37	0.06	0.21	0.50	942
FED (MUSD)	6,933,813	297,958	5,811,607	7,243,080	942
Covid-19 factors					
Cases (units)	4,158,026	2,814,582	105,383	10,208,150	942
Deaths (units)	139,995	63,305	2,304	240,107	942
Stringency (index)	68.38	3.71	62.50	72.69	942

Table 4.6: Summary of variables, 2020-03-27–2020-11-09.

5 Methodology and Empirical Analysis

This section starts with a brief introduction to the fixed effects estimator, followed by a discussion about the methodology, time periods and the empirical analysis.

5.1 Panel Data and Fixed Effects

Regressions will be done using a fixed effects estimator on balanced panel data and computed using Stata SE 17.0. We resort to the fixed effects model, commonly used for panel data in general and financial data in particular. Using the fixed effects model allows for fixing the model in cross section dimension, therefore making it possible to analyze changes in the relationship among sectors through time. This approach allows for a workaround for omitted variable bias (Best & Wolf, 2013). Although a majority of previous papers have employed the fixed effects models when looking at firms in specific, we apply a similar framework to sectors. We resort to the fixed effect model in this case, because we want to examine if intercepts vary across groups or time periods, whereas a random effect model explores differences in error variance components across individuals or time periods (Park, 2011).

To ensure the robustness of our proposed variables, we first examine the proposed explanatory variables using a pooled OLS (not reported), with S&P 500 as a replacement for sector specific returns. In this model, we assigned dummy variables to sectors. This model reported similar results as the fixed effects. However, the estimation results reported in the following chapter and the analysis of these results are based on the fixed effects estimator, posing several pros in relation to the pooled OLS (Best & Wolf, 2013). We also examined the entire sample period for the baseline model to ensure robustness, yielding similar results as presented in the results section, and further discussed in the next chapter.

5.2 Empirical Analysis and Regression Specification

Since the aim of this paper is to: 1) distinguish any changes in determinants for CDS spreads from before and during the COVID-19 pandemic and 2) investigate if variables related to the COVID-19 pandemic positively affected changes in CDS spreads, it is focused around the time period leading up to the COVID-19 pandemic. The pre COVID-19 period is followed by an investigation of the peak and late COVID-19 period, based on major milestones related to the development of the virus. This allows for distinguishing between different phases of the pandemic, and is in line with previous research on the pandemic but also for previous investigations of financial crises (see e.g. Liu, Qiu, & Wang, 2021; Samaniego-Medina et al., 2016; Kartal, 2020).

Time period 1, pre COVID-19 2016-01-01–2020-01-20: As a baseline for the study the first analysis is based on the relative calm period spanning from the beginning of the sample on the 1st of January 2016 to the first case of COVID-19 was detected in the US on the 20th of January 2020. Even though COVID-19 already started to spread in China during this period there were no signs of widespread infections in the US, or indications that a pandemic was underway to unfold. This leads us to believe that analyzing a pre COVID-19 time period as an introduction is a relevant beginning. Using a pre-event time period is also in line with both studies conducted during the COVID-19 pandemic but also during previous crises, e.g. the GFC (Samaniego-Medina et al., 2016).

The baseline model, will be used as a foundation for the rest of the models and used to compare the results with our later introduced extended models, containing COVID-19 variables. The model uses fixed effects and clustered standard errors on the highest aggregated level, sectors. This procedure is in line with the framework presented by (Abadie, Athey, Imbens, & Wooldridge, 2017), and ensures that potential problems related to heteroscedasticity and autocorrelation do not need to be taken into consideration. Moreover, similar clustering is also reoccurring in previous literature (see e.g. Annaert et al., 2013; Liu, Qiu, & Wang, 2021; Augustin, 2018). We estimate model 1, our baseline model, using previously presented explanatory variables to explain changes in CDS spreads for the first time period, spanning 2016-01-01–2020-01-20.[1] Model 1, the baseline model, looks as follows:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta Returns_{i,t} + \beta_2 \Delta VIX_t + \beta_3 \Delta Slope_t + \beta_4 \Delta Bond_t + \beta_5 \Delta FED_t + \varepsilon_{i,t} \quad (1)$$

Where $\Delta CDS_{i,t}$ denotes the percentage change in CDS spread for sector i for day t. $\Delta Sector_{i,t}$ denotes sector returns for sector i for day t. ΔVIX_t denotes the percentage change in VIX for day t. Δ *Slope* denotes the percentage change in the slope of the term structure for day t. $\Delta Bond_t$ denotes the the percentage change in Treasury bond for day t. ΔFED_t denotes the percentage change in FED's total assets for time period t.

Our empirical analysis seeks to investigate the relationship between CDS spreads and explanatory variables as well as try to explain why and how. We start off by reporting the baseline model for the pre COVID-19 time period, spanning 2016-01-01–2020-01-20.

	Model 1
Δ Returns	-0.398***
	(0.097)
Δ VIX	0.031***
	(0.007)
Δ Slope	0.123
	(0.209)
Δ Bond	0.123***
	(0.014)
Δ FED	-0.040
	(0.126)
$R^2 within$	0.058
$R^2 between$	0.354
$R^2 overall$	0.058

*Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. Dependent variable:* ΔCDS.

Table 5.1: Baseline model results for time period 1, pre COVID-19 2016-01-01–2020-01-20.

[1]Before proceeding with the regression we conduct the Augmented Dickey-Fuller unit root test for variables in levels and after log first difference. Our results confirm that a majority of the explanatory variables exhibit unit roots in levels, but can reject the null Hypothesis for all variables after transformation, confirming that we do not have unit roots.

During the pre COVID-19 time period, the proposed relationship is in play between sector returns, volatility and CDS spreads. As previously explained, increased asset value, in the form of sector returns, is expected to decrease company default risk and hence its credit risk, following the Merton (1974) model. Accordingly, the VIX index also exhibits the expected sign and significance, following the explanation that increased volatility implies increased uncertainty about the future and more defaults, as proposed by both Merton (1974) and Breeden & Litzenberger (1978).

However, quite surprisingly, the Treasury bond shows significance for having a positive effect on CDS spreads, not in line with previous results (see e.g. Annaert et al., 2013; Apergis, Danuletiu, & Xu, 2022; Collin-Dufresne, Goldstein, & Martin, 2001). However, worth noting is that the US 10 year Treasury yield has stayed quite stable throughout the time period spanning 2016–2019, which might imply other factors closely correlated to the Treasury yield, not discussed here, might have an impact on the change of CDS spreads. Also worth noting is that the Treasury bond lacks significance when performing the baseline regression for the entire sample period (not reported), although the coefficient carries the expected sign (-). However, Raunig & Scheicher (2009) also found inconsistency when looking at the sign related to the risk-free rate. This relationship might be worth researching further, since one can suspect a structural change in the way US Treasury bonds are interpreted for this time period.

Time period 2, peak COVID-19 2020-01-21–2020-03-26: Time period 2 starts on the 21st of January 2020, the day after the first case of COVID-19 was detected on US soil. The time period reaches until the 26th of March 2020, when the US became the most infected country in the world, surpassing both China and Italy in COVID-19 cases (McNeil Jr., 2020). The same period has previously been researched by Liu, Qiu, & Wang (2021). When investigating this time period, and to evaluate the effect COVID-19 related variables have on CDS spreads, number of cases of COVID-19 for US, total number deaths with COVID-19 for US and stringency index are introduced and transformed to daily percentage change, using log and first difference. This gives us four models to evaluate for the given time period. COVID-19 variables are not introduced simultaneously since they are highly correlated and different proxies for a pandemic-wide effect.[2] We start off by introducing cases to the baseline model, resulting in the following model:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta Returns_{i,t} + \beta_2 \Delta Slope_t + \beta_3 \Delta FED_t + \beta_4 \Delta Cases_t + \varepsilon_{i,t} \quad (2)$$

Where $\Delta CDS_{i,t}$ denotes the percentage change in CDS spread for sector i for day t. $\Delta Returns_{i,t}$ denotes sector returns for sector i for day t. $\Delta Slope_t$ denotes the percentage change in slope of the yield curve for day t. ΔFED_t denotes the percentage change in FED's total assets for day t. $\Delta Cases$ denotes the percentage change in new COVID-19 cases in US for day t. Following a similar procedure, the model for COVID-19 deaths looks as follows:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta Returns_{i,t} + \beta_2 \Delta Slope_t + \beta_3 \Delta FED_t + \beta_4 \Delta Deaths_t + \varepsilon_{i,t} \quad (3)$$

Where $\Delta CDS_{i,t}$ denotes the percentage change in CDS spread for sector i for day t. $\Delta Returns_{i,t}$ denotes sector returns for sector i for day t. $\Delta Slope_t$ denotes the percentage change in slope of the yield curve for day t. ΔFED_t denotes the percentage change in FED's total assets for day t. $\Delta Deaths$ denotes the percentage change in new COVID-19 deaths in US for day t. As a final COVID-19 measure, we introduce the daily percentage change in stringency index as an explanatory variable. This model looks as follows:

$$\Delta CDS_{i,t} = \beta_0 + \beta_1 \Delta Returns_{i,t} + \beta_2 \Delta Slope_t + \beta_3 \Delta FED_t + \beta_4 \Delta Stringency_t + \varepsilon_{i,t} \quad (4)$$

Where $\Delta CDS_{i,t}$ denotes the percentage change in CDS spread for sector i for day t. $\Delta Returns_{i,t}$ denotes sector returns for sector i for day t. $\Delta Slope_t$ denotes the percentage change in slope of the yield curve for day t. ΔFED_t denotes the percentage change in FED's total assets for day t. $\Delta Cases$ denotes the percentage change in the stringency index in US for day t.

[2] Worth noting for these models is the that VIX and Bond have been excluded from this time period, in order to avoid multicollinearity problems.

	Model 1	Model 2	Model 3	Model 4
Δ Returns	-0.711***	-0.690***	-0.429***	-0.739***
	(0.080)	(0.065)	(0.066)	(0.076)
Δ Slope	-6.338**	-10.721*	33.520***	-15.011*
	(2.344)	(4.930)	(7.551)	(6.258)
Δ FED	0.080	0.059	-0.075*	0.151*
	(0.053)	(0.043)	(0.036)	(0.071)
Δ Cases		0.005		
		(0.004)		
Δ Deaths			-0.075***	
			(0.015)	
Δ Stringency				-0.072*
				(0.028)
$R^2 between$	0.870	0.788	0.080	0.799
$R^2 within$	0.406	0.419	0.505	0.447
$R^2 overall$	0.407	0.418	0.490	0.441

*Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. Dependent variable:* ΔCDS.

Table 5.2: Model results for time period 2, peak COVID-19 2020-01-21–2020-03-26.

All four models in Table 5.2 contains sector returns, slope of term structure and FED's total assets. Model 2 consists of COVID-19 cases, model 3 includes COVID-19 deaths, model 4 includes stringency index. As shown in 5.2, sector returns and the slope of term structure is statistically significant for all four models. We observe that there is a negative relationship between sector indices and CDS spreads, as anticipated. Also worth observing is the fact that the coefficient for sector returns is almost twice as large in this time period, compared to the previous one. We reckon this is due to the fact that we have not included the VIX index for this time period, hence its potential effect is expected to be captured by changes in sector returns, due to the correlation between these terms. It could also be to the fact that CDS spreads are more sensitive to changes in assets when volatility increases on the stock market.

Furthemore, we notice that there is a significant negative relationship between the slope of the term structure and the CDS spread in model 1, model 2 and model 4. We expect this result, due to the fact that higher slopes in the term structure indicate improved economic growth, which in turn has a negative relationship with CDS spreads (Annaert et al., 2013). This relationship between the slope of the term structure and CDS spreads is not significant for the pre COVID-19 period, potentially related to a market more sensitive to changes in the yield curve. Regarding model 3, the relationship between the term structure is significant but positive in this case. In line with the findings of Avramov, Jostova, & Philipov (2007), which mention "the realized effect of changes in the term structure slope on credit-spread changes is an empirical question" there seems to be no consensus on which sign to expect and the explanation behind it.

In Table 5.2, we can also see that COVID-19 deaths in model 3 and stringency index in model 4 have a significant negative effect on CDS spreads. This relation seems unreasonable due to the negative impact the pandemic had on the economy, which would imply an increase in CDS spreads. However, this result may depend on the fact that the number COVID-19 deaths lagged behind COVID-19 cases, which means that the initial reaction of the market could have been based on the increase of COVID-19 cases, and not on the number of increased deaths. One can suspect the market anticipated deaths to increase as cases started to increase.

It is also suspected that after the FED announced their stimulus package in March 2020, the sentiment shifted, confidence rose and the market's response to increased COVID-19 deaths faded - although the number of people dying from COVID-19 continued to rise. Looking at the VIX movements from mid-March and onwards confirms this theory, where it slowly declines to pre COVID-19 levels after the high close on March 18th 2020. The FED total assets variable has a significant negative effect on CDS spreads in model 3. This means that, as the FED continued to buy assets to support the economy, we saw a decrease in CDS spread, which can strengthen the explanation above. (Hasan, Marra, To, Wu, & Zhang, 2021) also show that country-level policies in the form of income support packages etc. helped alleviate the pandemic's negative impact on credit risk. However, we cannot see the same results in model 4, and the sign unexpectedly changes. Going back to COVID-19 measures, our results are in contrast to previous results achieved by Kartal (2020) when looking at Turkey. He found that the number of new COVID-19 deaths and cases increased CDS spreads. Moreover, worth noting is that Turkey exhibited the

6th highest CDS spreads in the world at this moment, hence its market was probably more sensitive to shocks. In addition, he did not examine the same time period, which is understandable due to the fact different countries were hit in different time periods.

We further discussed this finding but we also decided to test with different combinations of variables in our regression. Moreover, we tested different time periods to see whether our result was unique for our time period or not. We could conclude was that our result, with the chosen method, was the same, independent of time period or combination of variables. Finally, we gathered data from another data source to determine whether our results were unique for that particular data, which it wasn't.

However, we can't see any significant relationship between COVID-19 cases and CDS spreads during this period. Although Kartal (2020) found this factor to be positively related to changes in CDS spreads for Turkey, the lack of explanatory power for the US might indicate a higher resilience to shocks. This conclusion is in line with observations done by MSCI, which concludes that the CDS market in the US showed high resilience during the COVID-19 pandemic (Fekete & Janosik, 2020). Moreover, Fekete & Janosik (2020) also showed that buyers insuring companies with single-name swaps had to pay a higher price, which might indicate an interesting extension of this research paper, via looking at single names with different credit ratings.

R^2 during this period is relatively high in all four models presented in the table compared to previous periods. This finding is consistent with the ones reported previously by Annaert et al. (2013), Chiaramonte & Casu (2013) and Samaniego-Medina et al. (2016) which all show an increase in explanatory power during crisis periods. Moreover, model 3 explains a tiny portion of the variation between sectors, but has the highest explanatory power of all models when looking at variation within. After this relationship is investigated, we move on to evaluate potential differences between sectors by the use of interactions. All COVID-19 related variables are interacted with each specific sector, in order to denote any differences between sectors. This is done for time periods where COVID-19 measures are applicable, hence it's not performed during the first time period.

	Model 1	Model 2
Δ Returns	-0.682***	-0.438***
	(0.064)	(0.066)
Δ Slope	-10.852*	33.588***
	(5.069)	(7.895)
Δ FED	0.060	-0.074
	(0.044)	(0.038)
Energy $\times$ Δ Cases	0.019***	
	(0.001)	
Communications $\times$ Δ Cases	0.007***	
	(0.001)	
Technology $\times$ Δ Cases	-0.003	
	(0.001)	
Financials $\times$ Δ Cases	0.005**	
	(0.001)	
Utilities $\times$ Δ Cases	-0.003*	
	(0.001)	
Industrials $\times$ Δ Cases	0.006***	
	(0.001)	
Energy $\times$ Δ Deaths		-0.033**
		(0.010)
Communications $\times$ Δ Deaths		-0.101***
		(0.009)
Technology $\times$ Δ Deaths		-0.063***
		(0.009)
Financials $\times$ Δ Deaths		-0.096***
		(0.009)
Utilities $\times$ Δ Deaths		-0.067***
		(0.009)
Industrials $\times$ Δ Deaths		-0.090***
		(0.009)
$R^2 between$	0.986	0.003
$R^2 within$	0.444	0.530
$R^2 overall$	0.452	0.217

*Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. Dependent variable: ΔCDS.*

Table 5.3: Interaction models for time period 2, peak COVID-19 2020-01-21–2020-03-26.

Table 5.3 reports the result from the interaction models between the COVID-19 variables and CDS spreads in each sector for time period 2, spanning 2020-01-21–2020-03-26. We can see that COVID-19 cases have a significant positive effect on the CDS spreads in the energy, communications, financial and industrial sector. In other words, as COVID-19 cases increased, the CDS spreads in each of the above sectors increased as well. The COVID-19 cases effect on the energy sector (0.019) can be explained by the massive drop in demand for energy due to the pandemic. Many fossil fuel production facilities were forced to close due to the drop in demand, which had a large effect on the sector (Gollakota & Shu, 2022). Stringency showed similar coefficients to COVID-19 deaths, but with less significance (not reported).

Furthermore, the COVID-19 cases also had a positive significant effect on the financial sector. It seems reasonable, as the sector was affected greatly by the pandemic. As many firms were facing liquidity problems during the peak COVID-19 time period, company withdrawals increased due to uncertainty about future cash flow. This in turn, affected the financial sector in terms of both market risk and credit risk (Li, Strahan, & Zhang, 2020).

Moreover, COVID-19 cases have a significant negative effect on CDS spread in the utilities sector. This result is not expected, as the utilities sector experienced a large drop in demand and supply due to increased prices in energy and increased prices in cost of operation (Gollakota & Shu, 2022). In other words, we would expect a positive relationship between COVID-19 cases and CDS spreads. The reason for this unexpected result might be due to the fact that we look at the index, capturing only the biggest firms in the sector. As one might expect, the smallest companies with the weakest financials in the sector were affected the most, which is something we don't capture in our statistical analysis. However, the coefficient is low and is only significant for the 0.10 level. Furthermore, COVID-19 deaths have a significant negative effect on CDS spread in all sectors. We believe that this result is due to the same reason mentioned in the previous discussion.

Time period 3, late COVID-19 2020-03-27–2020-11-09: To further extend on previous literature the period following peak COVID-19, reaching from the 27th of March

2020, to the announcement of a vaccine with over 90% efficacy by Pfizer, on the 9th of November 2020 is also investigated (Pfizer Inc, 2020).

	Model 1	Model 2	Model 3	Model 4
Δ Returns	-0.343***	-0.347**	-0.346***	-0.344***
	(0.081)	(0.086)	(0.085)	(0.083)
Δ VIX	0.007	0.005	0.005	0.006
	(0.006)	(0.007)	(0.007)	(0.006)
Δ Slope	-2.782**	-3.969	-4.440*	-2.783**
	(0.760)	(2.143)	(2.022)	(0.765)
Δ FED	-0.274**	-0.255*	-0.234*	-0.274**
	(0.095)	(0.102)	(0.107)	(0.095)
Δ Cases		-0.003		
		(0.004)		
Δ Deaths			-0.004	
			(0.003)	
Δ Stringency				0.011
				(0.036)
$R^2 between$	0.011	0.011	0.011	0.011
$R^2 within$	0.099	0.101	0.102	0.099
$R^2 overall$	0.098	0.100	0.102	0.098

*Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. Dependent variable: ΔCDS.*

Table 5.4: Model results for time period 3, late COVID-19 2020-03-27–2020-11-09.

Table 5.4 includes similarly, as Table 5.2 all four models for this time period.[3] As seen in the late COVID-19 period spanning 2020-03-27–2020-11-09, both COVID-19 cases and deaths have no significant effect on CDS spreads. In model 2, model 3 and model 4, the R^2 has dropped to levels not seen since before the pandemic, which might indicate the initial COVID-19 cases had the largest shock effect on the financial markets as this result captures the COVID-19 late impact, as previously discussed. Furthermore, the sector returns are statistically significant for all four models, where we can see it has a negative effect on CDS spreads. Moreover, the slope of the term structure has a statistically significant negative effect for CDS spreads in model 1 and model 4. In Table 5.2, we can also see that the FED balance sheet in model 2, model 3 and model 4 have a significant negative effect on CDS spreads.

[3]Bond has been excluded as an explanatory variable, in order to avoid multicollinearity.

	Model 1	Model 2
Δ Returns	-0.358***	-0.357***
	(0.075)	(0.074)
Δ Slope	-3.955	-4.422*
	(2.158)	(2.041)
Δ FED	-0.257*	-0.236*
	(0.105)	(0.110)
Energy × Δ Covid-19 cases, US	0.003	
	(0.002)	
Communications × Δ Covid-19 cases, US	-0.004	
	(0.002)	
Technology × Δ Covid-19 cases, US	-0.007**	
	(0.002)	
Financials × Δ Covid-19 cases, US	-0.006**	
	(0.002)	
Utilities × Δ Covid-19 cases, US	0.003	
	(0.002)	
Industrials × Δ Covid-19 cases, US	-0.010***	
	(0.002)	
Energy × Δ Covid-19 deaths, US		0.000
		(0.001)
Communications × Δ Covid-19 deaths, US		-0.004**
		(0.001)
Technology × Δ Covid-19 deaths, US		-0.005**
		(0.002)
Financials × Δ Covid-19 deaths, US		-0.005**
		(0.002)
Utilities × Δ Covid-19 deaths, US		-0.000
		(0.001)
Industrials × Δ Covid-19 deaths, US		-0.008***
		(0.002)
$R^2 between$	0.022	0.025
$R^2 within$	0.106	0.105
$R^2 overall$	0.104	0.104

*Significance levels are indicated as follows: * Significant at the 10% level. ** Significant at the 5% level. *** Significant at the 1% level. Dependent variable: ΔCDS.*

Table 5.5: Interaction models for time period 3, late COVID-19 2020-03-27—2020-11-09.

Table 5.5 shows the interaction models for the late COVID-19 time period. It presents the result from the interaction models between the COVID-19 variables and the CDS spreads, in each sector. COVID-19 cases have a significant negative effect on the CDS spreads in the information technology sector, financial sector and the industrials sector. In other words, as COVID-19 cases increase, the CDS spread in each of the above sectors is expected to increase. Although significant in many interactions, the coefficients are low, indicating a lower impact on CDS spreads. Stringency showed similar coefficients to COVID-19 deaths, but with less significance (not reported).

Moreover, the sector that COVID-19 cases have the most significant negative effect on in this time period, is the industrial sector. The industrial sector is made up of companies that relate to supplying or producing machinery, equipment and supplies used in manufacturing and construction (S&P Global, 2020). This sector was clearly affected by the COVID-19 pandemic because demand for equipment and machinery decreased as the manufacturing and construction business faced less demand for their products. However, smaller businesses within the industrial sector have shorter survival time and were therefore affected more by the pandemic compared to more financially healthy firms, which are more resilient (Bosio et al., 2020). This might explain the above result, due to the fact that the sub-indices we are looking at are made up by the biggest companies in each sector, with longer survival times. Regarding the COVID-19 deaths, our results show that the variable has a significant negative effect on CDS spreads in the communications, technology, financial and industrial sectors.

Noteworthy, since we look at investment grade companies, with good financial health and high credit ratings, one might also expect that any potential effect on these companies might be delayed, due to longer survival times than their high yield counterparts. One limitation to the empirical analysis is sector specification, as one company could be operating within more than one sector. Hence, this could limit the ability to draw conclusions, as the company sector isn't necessarily onefold. However, it is argued we can still draw conclusions based on the results of this essay, due to the large number of firms included.

For further investigation, the inclusion of a leverage proxy could provide an interesting addition to the foundations proposed by this paper. Although leverage poses a key role in the Merton (1974) model, and is reoccurring in similar papers (see e.g. Collin-Dufresne, Goldstein, & Martin, 2001; Galil et al., 2014; Zhang, Zhou, & Zhu, 2009) it has been excluded from this paper due to lack of data. However, to some extent, we still believe potential effects captured by leverage could still be included in the study and captured by stock returns, due to their high correlation, as presented by Galil et al. (2014). It is still believed a better proxy for leverage, and the introduction of firm-specific financial measures could further increase the accuracy and explanatory power. Moreover, future research regarding both sector differences and country differences could provide insights into regional differences and open doors to widen the topic. Since the impact of COVID-19 on financial markets had a large effect on firms in the US, we suggest future researchers also investigate the high yield constituents of the CDX index, to gain insights into the effect financial health has on CDS spreads.

6 Conclusion

This research studies the changes in CDS spreads in the US during the time period 2016-2020. It examines the relationship between COVID-19 variables, market variables and sector-specific changes in CDS spreads. The paper further contributes to previous research by investigating the changes in CDS spreads drivers during the COVID-19 pandemic in the US market. We did this by dividing the data into sub-samples for the time period before the COVID-19 pandemic, during the COVID-19 pandemic and up until the announcement of a vaccine by Pfizer/BioNTech in November 2020. During the pre COVID-19 period, we could see a significant relationship between sector returns, volatility and CDS spreads.

Following the investigation of the peak COVID-19 period we observe an even larger relationship between sector returns and CDS spreads, implying the market is more sensitive to movements in the stock market during volatile times. More surprisingly, we found that COVID-19 variables have a significant negative effect on CDS spreads. We believe this can be related to both a more resilient market in the US overall, but also due to central bank interventions. In the late COVID-19 period, we found results that might indicate that the initial COVID-19 cases had the largest shock effect on financial markets, as our models explanatory power decreased during this time period and which we also expected. Moreover, we found some interesting results regarding the CDS spreads for the different sectors. The fact that COVID-19 cases had a negative effect on the CDS spread of the industrial sector was in particular interesting. This result was not expected, however, we discuss the possibility of the sector's long survival time as a reason for this unexpected result.

In conclusion, our result provided evidence of sector-specific changes in CDS spreads in relation to the COVID-19 variables. However, these factors are found to fluctuate over different time periods. In this paper, we also study investment grade companies, which might indicate a higher overall resilience to shocks, compared to their high yield counterparts. We believe this could prove an interesting follow-up for further research, as well as the investigation of different regional effects across countries. All in all, we could see that COVID-19 variables had a significant effect on CDS spreads in the US, but not in a positive way in the entirety of our study.

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