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CDS spreads and COVID-19 pandemic

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ABSTRACT

US corporate credit default swap (CDS) spreads have significantly increased since the beginning of the COVID-19 global pandemic. This paper shows that the magnitude of the pandemic measured by the number of COVID-19 cases and deaths both in the US and globally are positively linked to the CDS spreads, an effect both economically and statistically significant. However, there is a significant heterogenous effects across sectors, in which banking, travel & leisure, transportation, airlines, and restaurants are the hardest hit sectors. The analysis also documents that the COVID-19 pandemic increases corporate CDS spreads via increased firms' distress levels transmission channels.

1. Introduction

Corporate credit default swaps (CDS) are credit derivative contracts designed to allow investors to buy protection to swap/transfer credit risks on bonds or loans. The CDS buyer pays a premium to the seller to compensate the buyer if a specific credit event occurs, typically the default of a third debtor. Just like in insurance contracts, the buyer pays a periodic premium to a CDS seller in return for compensation should the credit event (accident) occurs. The natural buyers of corporate CDS would be large bondholders or banks that wish to enhance the creditworthiness of their loan portfolios. The price or spread of CDS reflects the probability of a firm failing to repay their debts in full, serving as an important indicator of firms' credit risks, especially during periods of uncertainty (Chiaramonte and Casu, 2013). Therefore, a better understanding of the nature of CDS prices and their determinants are crucial to many decision makers in macroeconomic policy, investment/production decisions, consumption, management risks, and portfolio management. The ability to accurately gauge the CDS spreads can support both retail and institutional investors on the design of effective investment strategies i.e., to assess and select firms to collaborate with or invest in or adjust their investment portfolios if certain firms/sectors become unstable. In addition, CDS spreads can also act as an early warning indicator to alarm and assist managers to prevent the occurrence of credit failure.

The recent literature has contributed substantially to comprehend the causes of CDS spread fluctuations. The typical strategy is to search factors that could alter a firm's value and its ability to meet debt repayments, and hence, its default probability. Most studies find that CDS spreads respond to various firm-specific and macroeconomic variables, such as credit rating, profitability, liquidity, stock returns and their volatility (Abid and Naifar, 2006; Corò et al., 2013). It is also widely accepted that CDS spreads are affected by macroeconomic conditions and the business cycle (Kim et al., 2017; Pereira et al., 2018). The ongoing COVID-19 pandemic is not only a health crisis, but also a social, economic, and political catastrophe. The global economy has been suffering from the effects and many

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economies have been led into recession (Ludvigson et al., 2020). According to IMF's World Economic Outlook, the global economy is predicted to suffer a 4.4% contraction in global GDP, which is far worse than the 2008–2009 financial crisis (−0.1%). The US unemployment rate reached to 15% for the second quarter of 2020[1]; the UK economy suffered a shocking 10% contractions[2] and Japan economy diminished 4.8% in 2020.[3] Hence, it is not surprising that researchers have begun to link the impact of COVID-19 on CDS spreads. The worsened financial soundness on both macro-level and firm-level can increase the risk of default in debt, therefore, the spread of CDS can respond positively to the severity of COVID-19 pandemic (Bosio et al., 2020; Didier et al., 2021). The goal of our paper aims to build upon on this strand of the literature. In particular, it empirically examines the relationship between US corporate CDS spreads and COVID-19 pandemic shocks, while accounting for heterogeneity and transmission channels.

The COVID-19 pandemic can transmit its effect onto the CDS market through its impact on firms' future cash flows and discount rate channels. The radial steps imposed by administrations (e.g., lockdowns, border shutdowns, social distancing, travel restrictions) to halt the spread of the pandemic have sparked, among other things, tremendous undesirable consequences on demand, firms' profitability and growth, income, and productivity. The COVID-19 pandemic has sparked a massive spike in uncertainty and causing stock market volatility risen to levels that have rarely been seen since the Great Moderation (Baker et al., 2020). The behavioural finance and psychology literature argues that economic agents behave differently in times of turbulences and fear as opposed to periods of prosperity and calm (Akerlof and Shiller, 2009). For instance, managers may fail to identify best investment opportunities to standstill on new business formation, R&D expenditures, human capital investments due to unwillingness to bear risks, or equally, due to a shift in their preferences (Bloom et al., 2007; Caglayan and Xu, 2016a; Baker et al., 2020). Fear and panic triggered by COVID-19 can reduce firms' profitability and growth from the demand side via a steady decline in customers' physical attendances (Liu et al., 2021).

Households may increase their precautionary savings and smooth their consumptions in response to positive pandemic shocks as they perceive a greater chance of future unemployment (Jordà et al., 2020). Furthermore, the interconnectedness among financial institutions, firms, households, and governments can accelerate the transmission effects of the pandemic shocks into the CDS market (e.g., Brei et al., 2020; Barua and Barua, 2020). For instances, banks face withdrawals of deposits, funds and credit from businesses and households because their deteriorated current financial conditions and anticipated forthcoming cash flow concerns caused by the sustained pandemic shocks. On the other hand, firms/households with serious liquidity problem are more prone to default will reflect onto the banking system later causing banks holding lower quality assets (e.g., Bosio et al., 2020; Didier et al., 2021). Taking all these together, the COVID-19 can have substantial negative impact on the financial institutions' ability to offering credits to private sector, efficiency and operational performance, and adversely affects the stability of the financial system (Baum et al., 2021; Caglayan and Xu, 2016b).

Furthermore, pandemic shocks can adversely affect CDS prices through the discount rate channel as monetary policy makers tend to carry out aggressive expansionary policies to combat the recession and kept interest rate low (Bernanke et al., 2005). All these, in return, will impact firms' default probability and ultimately CDS spreads.

Our paper incorporates important innovations relative to previous literature. First, by employing both global and local COVID proxies to measure the severeness of the pandemic, it provides new insights on the turmoil effect of COVID-19 on the US corporate CDS market. Despite all businesses are likely to experience significant economic losses due to the pandemic, it is crucial to reflect the heterogeneous effects across sectors. Furthermore, there is limited attention on searching for different transmission channels of COVID-19 pandemic on the spread of CDS.

To carry out our investigation, the analysis constructs a large panel of US corporate CDS data collected from Bloomberg. The final dataset that we employ in our analysis is comprised of 386 firms with a sample of 66,392 daily observations. The analysis covers the period between February 2020 to September 2020. The findings can be summarized as follows. First, we show that the magnitude of the pandemic is positively linked to the US corporate CDS spreads, an effect both economically and statistically significant. The results highlight the heterogenous effects across sectors, in which banking, travel & leisure, transportation, airlines, and restaurants are the hardest hit sectors in the US. By identifying the heterogeneity of sectoral sensitivities to the pandemic implies that some sectors can provide a channel for diversification during further waves of pandemic cases and fatalities. For example, if the cases and deaths are expected to increase in the future, investors may use this information to devise their investment strategies by taking short positions in banking, transportation, airlines, restaurants, and long positions in media, technology, telecommunications, pharmaceutical, information and data technology firms.

Furthermore, the empirical results confirm the prediction that the pandemic adversely affects the CDS market through several transmission channels. To be more specific, the analysis provides strong supportive evidence of pandemic measures for increasing firms' likelihood of default considerably.

The rest of the paper is organised as follows. Section 2 reviews a brief review of prior literature. Section 3 presents the econometric methodology and describes the data employed. Sections 4 and 5 present the empirical results, robustness checks and discuss the economic significance of the findings. Finally, Section 6 concludes.

[1] https://fred.stlouisfed.org/series/UNRATE.

[2] https://www.independent.co.uk/news/business/uk-economy-latest-gdp-recession-ons-b1801277.html.

[3] https://www.bbc.co.uk/news/business-56066065#:~:text=Japan's%20economy%20surged%20in%20the,negative%20growth%20for%20the%20year.&text=Japan's%20economy%20shrank%204.8%25%20over,its%20first%20contraction%20since%202009.

2. Literature review

The investigation relates to several strands of earlier studies that have examined the CDS markets. This section highlights some of the major studies along these lines.

2.1. The determinants of CDS

Researchers have expended a considerable effort on identifying the key determinants of CDS spreads. Most studies find that both firm- and market-specific factors are useful in explaining CDS prices. Abid and Naifar (2006), for example, find that credit ratings, CDS contract maturity, stock volatility, risk-free interest rates, and yield curves explain 60% of the variation in European CDS pricing, where credit ratings were considered as the most influential factor. Chiaramonte and Casu (2013) investigate five-year senior bank CDS spreads' determinants using several key performance indicators (e.g., return on equity (ROE)) and return on assets (ROA)), along with balance sheet indicators (e.g., net loan/deposits, liquid assets/deposits). They find that liquidity variables appear to have the most significant impact on banks' CDS pricing.

Following the 2008 financial crisis, several researchers have begun to explore the interrelations between risk and CDS spreads. Corò et al. (2013) study the role of credit and liquidity factors in explaining corporate CDS price changes during normal and crisis periods. They find that liquidity plays a critical role in driving the CDS price fluctuations during the 2007–2009 financial crisis. Baum and Wan (2010) examine how US CDS spreads respond to macroeconomic uncertainty measured by GDP growth, and firm-specific characteristics (e.g., stock values, volatility and returns, ROE, dividend pay-outs, credit ratings). Their findings highlight that macroeconomic uncertainty generates tight credit restrictions for firms, by affecting firms' leverage and increasing the default risk of firms, while the effects of dividend pay-outs and ROE on the CDS spread differ greatly according to issuers' credit rating. Kim et al (2017) also show that business macroeconomic conditions and business cycles can determine changes in CDS spreads. Several authors focus on examining the role of uncertainty about the probabilities of future outcomes in addition to risk. For instance, Augustin and Izhakian (2019) explore the impact of the ambiguity on CDS spreads, while they find a negative impact on CDS spreads since major counterparties in CDS markets are net buyers of CDS protections. They also highlight that the effects of ambiguity and risk on CDS spreads are more pronounced in longer horizon contracts.

Another strand of literature focuses on exploring the relative importance of CDS spreads' determinants as the economy evolves over time and across markets. The general conclusion is that after controlling for firm-specific effects, market factors have a greater explanatory power, especially during periods of crises, as well as in post-crisis periods (Galil et al., 2014; Pereira et al., 2018; Fu et al., 2020). Additionally to business cycles, Fu et al. (2020) show that the relative importance of explanatory variables (e.g., Tobin-Q coefficient, risk-free rates, stock market returns, and stock market volatility) of CDS spreads varies across US, Japan and UK markets. Aman (2019) finds that the long-run factor of the yield curve is a negatively significant determinant of the CDS premia, regardless of the sector and market states. The CDS spreads in the financial sector exhibit strong sensitivity to the yield rate in extreme market states.

2.2. The COVID-19 pandemic crisis

In contrast to other natural disasters, COVID-19 is considered as a multi-period event that is almost synchronized within and across countries, with several health, social and economic implications for a prolonged period of time (Ludvigson et al., 2020). Hence, it is not surprising to see a recent lively debate about the impact of COVID-19 on business survival and credit risk. Most studies document a significant negative impact on firms' liquidity across the globe due to loss of demand and increased uncertainty (Bosio et al., 2020; Didier et al., 2021). The heterogenous sectoral reaction has been highlighted by Pagano et al. (2020) according to which, certain industries (e.g., high-tech) seem to be more resilient, while others (e.g., travel, tourism, and restaurant), appear to be hit harder by the pandemic. The financial markets reflect the level of resilience through the assets prices channels. Choi (2020) also illustrates the different impact industries across regions (airlines, oil and gas, and consumer-facing industries) are suffering in North America and Europe, automotive in North America, apparel and shoes in Europe. The lack of government support has accelerated the number of business bankruptcies for low income- and lower-middle-income countries (Didier et al., 2021). Banerjee et al. (2020) pinpoint that further bankruptcies and unemployment are expected to increase after the withdrawal of government-aid schemes for business in advanced economies.

The study is also related to the literature concerning the impact of crisis on banking activities. Most firms are facing severe liquidity problems and their growth substantially depends on the extend of the access to bank credit during the COVID-19 pandemic. To be more specific, firms draw funds from their banks because of their current financial disruptions and anticipated declines in future cash flows induced by the pandemic (Li et al., 2020). In contrast, banks also face important withdrawals of deposits, especially from households and SMEs, as a response to the rise of uncertainty, forcing them to reduce lending activities (Brei et al., 2020). The complex implications of COVID-19 pandemic for banking activities are analysed by Barua and Barua (2020), who emphasize that banks face interest rate, liquidity, credit and market risks because of the close linkages among firms, households and governments. It is believed that some firms will face substantial liquidity problems, reflecting onto the banking system later on, implying a major threat to banks' stability, as they are holding riskier assets, calling for imminent actions in support of the banking system. Moreover, in case of the low-rated banks, CDS spreads rise more than in the case of high-rated ones. The same also holds in the case of banks that are more dependent on short-term funding. Andrieş et al. (2020) investigate the impact of the lockdown measures on the European bank's CDS spreads. They provide evidence that both sovereign and bank CDS spreads increase due to lockdown measures, while the number of new confirmed cases seems to be the most important indicator that affects the perceived risk associated with bank investments. Banerjee et al. (2020) predict that in the case of advanced economies, a rise of about 20% of bankruptcies in 2021 vis-a-vis 2019, as well as a rise in unemployment are highly expected. Both negative effects could also be stimulated by the financial system in case that as the result of a low perceived quality credit, the access of firms to bank credit is restricted.

3. Methodology and data

3.1. Empirical approach

Our model assumes that variations in CDS spreads depend both on its own characteristics and on the environment within which it operates (e.g., Tang and Yan, 2007; Acharya and Johnson, 2007; Pires et al., 2011):

$$CDS_{i,t} = \alpha + \beta_1 COVID\mathrm{Cases}_t + \beta_2 COVIDDeaths_t + \gamma \cdot \mathbf{Z}_{i,t} + i.time + \nu_i + \epsilon_{i,t} \tag{1}$$

where the dependent variable, $CDS_{i,t}$ represents the CDS spread of firm i at time t. The key explanatory variables, $COVID\mathrm{Cases}_t$ and $OVIDDeaths_t$, are two metrics to reflect the magnitude of COVID-19 pandemic, both in the US and on global scale. We expect to find a positive relationship between COVID-19 severity and corporate risks measured by CDS spreads. $\mathbf{Z}_{i,t}$ is a vector of three firm-level and macroeconomic control variables including stock market prices ($stock_{i,t}$) to reflect firm's current performance and its future prospects; US stock market volatility (VIX_t) to capture US macroeconomic risks; and risk-free interest rates ($Tbill_t$) to capture the state of the economy; $i.time$ denotes daily dummies; ν_i captures firm fixed effects, and $\epsilon_{i,t}$ is the error term. Given that there is high likelihood for the presence of endogeneity of certain variables included in the Z vector [i.e., stock prices (Ngene and Hassan, 2012; Du et al., 2013; Eyssell et al., 2013), interest rates (Longstaff et al., 2004; Ericsson et al., 2009), and stock market volatility (Gatev et al., 2006; Dotz, 2007)], the analysis will be making use of the General Method of Moments (GMM) method. As a result, Eq. (1) can be written as:

$$CDS_{i,t} = \sum_{k=1}^{K} a_i CDS_{i,t-k} + \sum_{k=0}^{K} \beta_{1i} COVIDCases_{i,t-k} + \sum_{k=0}^{K} \beta_{2i} COVIDDeaths_{i,t-k} + \sum_{k=0}^{K} \gamma_i Z_{i,t-k} + v_i + \varepsilon_{i,t} \tag{2}$$

where $\mathrm{E}[v_i] = \mathrm{E}[\varepsilon_{i,t}] = \mathrm{E}[\mu_i\varepsilon_{it}] = 0$. The disturbance term has two orthogonal components, i.e. the fixed effects, v_i and the idiosyncratic shocks, ε_{it}. We assume that ε_{it} are not serially correlated. The lagged dependant variable is still endogenous, since $CDS_{i,t-1}$ term in $CDS_{i,t-1}$-$CDS_{i,t-2}$ correlates with $\varepsilon_{i,t-1}$ in ε_{it}-$\varepsilon_{i,t-1}$. Therefore, the analysis needs to use instrumental variables to deal with the problem of endogeneity. From Eq. (1), natural candidates for the dependent variable are higher lags, such as $CDS_{i,t-2}$ and so on. Z may also contain endogenous variables and, weakly and strictly exogenous variables. In our case, we have the following additional moment conditions, using weak exogenous variables:

$$E\left[CDS_{i,t-j} \bullet \left(\varepsilon_{it} - \varepsilon_{i,t-1}\right)\right] = 0 \mathrm{and} \mathrm{E}\left[Z_{i,t-j} \bullet \left(\varepsilon_{i,t} - \varepsilon_{i,t-1}\right)\right] = 0 \mathrm{for} j \geq 2, t = 3, \cdots, T.$$

From Eq. (1), it is possible to increase efficiency of the Arellano-Bond estimator through a great number of instruments. Arellano and Bover (1995) recommend the idea of a transformation of the system of equations, which favors the use of more information from observations. They develop an approach that transforms the instruments to make them exogenous to the fixed effects. They assume that changes in any instrumenting variable are uncorrelated with the fixed effects in Eq. (1). From mathematical perspective, we get:

$$E\left[CDS_{i,t+p} \bullet v_i\right] = \mathrm{E}\left[\mathrm{CDS}_{i,t+q} \bullet v_i\right]$$

and

$$E[Z_{i,t+p} \bullet v_i] = \mathrm{E}[Z_{i,t+q} \bullet v_i]$$

for all p and q.

Eq. (1) means that $\mathrm{E}[CDS_{i,t-1}\,\mu_i]$ and $\mathrm{E}[Z_{it}\,\mu_i]$ are time-invariant. In this case, ($CDS_{i,\,t-1}$- $CDS_{i,t-2}$) is a valid instrument for $CDS_{i,t-1}$ and ($Z_{i,t-1}$-$Z_{i,t-2}$). Thus, we have the following additional moment conditions:

$$E[(CDS_{i,t-1} - CDS_{i,t-2}) \bullet (v_i + \varepsilon_{it})] = 0$$

and

$$E[(Z_{i,t-1} - Z_{i,t-2}) \bullet (v_i + \varepsilon_{it})] = 0$$

The above expressions hold because we assume that ε_{it} are not serially correlated. If Z is endogenous, ($Z_{i,t-1}$ - $Z_{i,t-2}$) may be used as an instrument, because ($Z_{i,t-1}$ - $Z_{i,t-2}$) should not be correlate with ε_{it}. If Z is predetermined, the contemporaneous (Z_{it} - $Z_{i,t-1}$) is also valid, since $\mathrm{E}[Z_{it}\,\varepsilon_{it}] = 0$. This permits to derive an extended 'system' GMM estimator. System GMM estimator uses lagged differences of CDS_{it} as instruments for equations in levels and lagged levels of CDS_{it} as instruments for equations in first differences. The number of such instruments can be easily determined through certain criteria, such as the Akaike criterion, thus generating consistent and efficient parameters estimates.

Arellano and Bond suggest two specification tests to address consistency issues of the GMM estimators. First, the Sargan/Hansen test of over-identifying tests for joint validity of the instruments. The null hypothesis is that the instruments are not correlated with the residuals. Second, the test for autocorrelation examines the hypothesis that the idiosyncratic disturbance ε_{it} is not serially correlated (the full disturbance $\mu_i + \varepsilon_{it}$ is presumed autocorrelated since it contains fixed effects). To examine for autocorrelation aside from the fixed effects, the test is applied to the residuals in difference. We know that $\varepsilon_{i,t}$-$\varepsilon_{i,t-1}$ is mathematically related to $\varepsilon_{i,t-1}$-$\varepsilon_{i,t-2}$ via the shared term $\varepsilon_{i,t-1}$. Thus, we expected a first-order serial correlation in differences. To examine first-correlation in levels, the interest goes to the second-order correlation in differences, because we consider that this will detect correlation between the $\varepsilon_{i,t-1}$ in ($\varepsilon_{i,t}$-$\varepsilon_{i,t-1}$) and the $\varepsilon_{i,t-2}$ in ($\varepsilon_{i,t-2}$-$\varepsilon_{i,t-3}$).

Finally, given that the moment conditions never hold exactly, the GMM weighting matrix has an impact on the parameter estimates. The estimation analysis uses a pre-specified weighting matrix in the GMM minimization process. The matrix describes a linear combination of the moments, and GMM is trying to minimize this linear combination where the moments are weighted in a flat mode (Newey and West, 1994; Bonnal and Renault, 2001).

Despite the literature has shown more firm-specific and macroeconomic factors played an important role in explaining the variations in CDS spreads, our model only embodies with only four variables can be measured daily as the main emphasis of our paper is to explore the impact of the COVID19 pandemic on the CDS spreads from February 2020 to September 2020. Firstly, we incorporate *stock market prices* as a proxy to reflect firms' current performance and future prospects. We expect a negative relationship between stock prices and the CDS spreads (Abid and Naifar, 2006; Galil et al., 2014). Recall that CDS is an insurance policy on the default risk of a bond or loan. A higher (lower, respectively) stock market price signals that firms are performing well (worse, respectively), hence, the default risk associated with their debt payments is expected to be lower (higher, respectively). Secondly, we expect *stock market volatility* positively linked to CDS spreads. Our expectation follows Collin-Dufresn et al. (2001), Doshi et al. (2013), and Galil et al. (2014) who have included the CBOE Volatility Index (VIX) that represents stock market volatility. As stock market volatility increases, the related option values also increase, and this can lead to a greater probability of default and results in higher CDS spreads. Furthermore, *risk-free interest rates* is believed to have a negative impact on the CDS spreads, because an increase in the risk-free rate reduces risk-adjusted default probabilities and hence, CDS spreads fall (e.g., Collin-Dufresn et al., 2001; Abid and Naifar, 2006; Ericsson et al. 2009; and Doshi et al. 2013).

3.2. Data

Daily data are sourced from *Bloomberg* and perform applicable calculations to generate the required variables. The full sample covers the period from February 2020 to September 2020. The data set includes CDS spreads and stock market prices. The sample includes all 5-year CDS spread data, but we omit any firms that did not have data spanning the entire sample period. This leaves us with 386 firms and a final sample of 66,392 total daily observations in a balanced panel format. The daily closing bid-ask quote information is retrieved for the time span of our study. Moreover, daily data on the US VIX volatility index, 3-month T-bill interest rates, and on corresponding stock prices are also sourced from Bloomberg. Finally, COVID-19 data on confirmed cases and deaths both in the US and worldwide are obtained from *DataStream*.

3.3. Descriptive statistics

Table 1 provides variable definitions and sources, while Table 2 presents certain basic summary statistics. The positive skewness and kurtosis with respect to the CDS spreads imply fat tails. The average daily CDS yields in our sample is 280.68 basis points with the lowest at 118.309 and the highest at 649.274.

Table 1
Variable definition.

Variable	Description	Source
A. CDS		
CDS Spreads	This is US dollar nominated five-year CDS data for each firm.	Bloomberg
B. Firm-level variables		
Stock prices	Logarithmic first difference of US firms' stock prices.	Bloomberg
Loans spreads	This measures the difference between the all-in spread drawn of loan facility included facility fees and LIBOR rate.	Bureau van Dijks BankScope
Market Cap	Market capitalization is computed by multiplying daily share prices with the number of shares outstanding. (US$ millions)	CRSP
Volume	This refers to the daily number of shares traded in each stock. (100,000 s)	CRSP
Shares per trade	This is measured by the number of shares executed per trade.	CRSP
C. Market variables		
VIX	VIX reflects the forward-looking stock market volatility implied by options on the S&P 500 index.	Bloomberg
T-bills	Three-month US Treasury Bills.	
D. COVID measures		
COVID-19 (US cases)	Confirmed number of COVID-19 cases in the US.	Datastream
COVID-19 (US Death)	Confirmed number of COVID-19 death in the US.	Datastream
COVID-19 (World cases)	Confirmed total number of COVID-19 cases across the globe.	Datastream
COVID-19 (World Death)	Confirmed total number of COVID-19 death across the globe.	Datastream

Table 2
Summary statistics.

Variables	Mean	Standard Deviation	Min	Max	Skew	Kurt
CDS yields	280.68	112.329	118.309	649.274	0.727	0.055
VIX	32.765	13.489	13.68	82.69	1.487	2.404
Stock prices	69.721	29.556	22.374	80.841	−0.658	−0.196
T-Bills	0.793	0.294	0.498	1.649	1.929	2.472
Loans spreads	0.263	0.418	−0.208	0.589	−1.378	0.177
Market cap ($M)	13.68	13.62	0.51	79.85	1.236	1.084
Volume (100,000 s)	192.14	158.75	11.74	1,401.46	0.884	1.219
Shares per trade	122.63	69.28	57.25	1,281.09	−1.063	0.347
COVID-19 (US cases)	2,895,591	2,655,629	8	8,263,362	0.523	−1.152
COVID-19 (US deaths)	101,846	75,330	0	220,061	−0.099	−1.389
COVID-19 (World cases)	12,316,642	12,408,142	11,955	41,196,846	0.791	−0.681
COVID-19 (World deaths)	454,837	363,857	258	1,130,600	0.25	−1.243
No. of obs. (firms)	66,392					
No. of obs. (COVID-19)	172					

4. Empirical analysis

In the first part of the empirical analysis, we make use of the cross-sectional dependence (CD) statistic by Pesaran (2004) to test the cross dependence of our panel. Under the null hypothesis of cross-sectional independence, the CD test statistic follows asymptotically a two-tailed standard normal distribution. The results, reported in Table 3, uniformly reject the null hypothesis of cross-section independence, providing evidence of cross-sectional dependence in the data, given the statistical significance of the CD statistics.

Next, a second-generation panel unit root test is employed to determine the degree of integration of the respective variables. The Pesaran (2007) panel unit root test does not require the estimation of factor loading to eliminate cross-sectional dependence. The null hypothesis is a unit root for the Pesaran (2007) test. The results of this test are reported in Table 4 and support the presence of a unit root across all panel variables.

We estimate Eq. (1) using the systems General Method of Moments (GMM) estimator set forth by Arellano and Bover (1995) and Blundell and Bond (1998). The key merits of the GMM estimator approach is the allowance for firm-specific effects, which may reflect the differences across firms in their riskiness level. We also employ a cluster-robust estimator to allow for arbitrary heteroscedasticity and autocorrelation in the error term. Note that, cross-sectional dependence (CD) is a common problem in cross-country panels with various cross sections (firms). To test for CD in the model residuals, we apply the Breusch–Pagan Chi-square, the Pearson LM Normal, and the Pearson CD Normal tests. The GMM results are reported in Table 5. All three tests generate a p-value test of 0.00; hence, we can reject the null hypothesis of cross-sectional dependence and use the GMM approach to generate efficient estimators. In addition, to test for the validity of the instruments, we compute Hansen's J-statistic and report the associated p-value in the tables.

The results conclude that there is a positive association between CDS and the metrics of pandemic event. More specifically, the US corporate CDS market seems to have been substantially affected by the presence of pandemic metrics that denote the presence of certain costs that can materialise through both supply and demand effects. For instance, the corporate section suffers from workers who may limit social interactions by reducing both labour supply and consumption. These results confirm the findings reported in the literature. For instance, Arnold et al. (2006) found these detrimental effects. Similarly, Fan et al. (2016) highlighted the importance of mortality costs and the reduction of the labour force because of pandemic events, thus, lowering returns to capital and slowing the pace of capital accumulation and GDP growth. Moreover, aggregate demand side effects could also negatively impact the corporate sector of the economy. Jordà et al (2020) showed that pandemics are usually followed by low natural interest rates for an extended period of time, due to higher precautionary saving and depressed investment opportunities. Furthermore, there is ample evidence on financial institutions' reluctance to extend loans when uncertainty reaches extreme levels, because, in general, lenders can suffer more from asymmetric information issues that affecting their judgements on the expected returns from lending and enlarged monitoring costs as businesses are more prone to default (Caglayan and Xu, 2016a). Therefore, the presence of the COVID-19 pandemic with millions of confirmed cases and deaths informs the corporate CDS markets that the economic loss can be substantially high and persistent, implying negative spillovers in firms' profitability and growth. Additional uncertainty is also transmitted to the sector when the most noteworthy characteristic of COVID-19 is its rapid transmission, resulting in large-scale containment policies, not only in the US, but also around the globe, leading to a global sudden stop in overall economic activity. The combination of a large fraction of global economic activity to a synchronised standstill and the presence of heightened financial market turbulence, amplified the impact of the pandemic shock, as financial markets came to grips with a historical global sudden stop. The presence of bankrupt firms, potentially disrupting supply chains, and unemployed workers, losing their skills, long-term relationships with firms, and lower labour productivity, seem just to have added to higher levels of uncertainty and higher CDS spreads.

Finally, relevant diagnostics are also reported in Table 5. In particular, for the validity of the instruments, the results need to reject the test for second-order autocorrelation, AR(2), in the error variances. Moreover, they also need to reject the null hypothesis of difference-in-Hansen tests of the exogeneity of instruments. The regression has explicitly used 11 and 24 instruments across the two

Table 3
Cross dependence tests.

Variables	p-values
CDS yields	0.00
COVID-19 (US cases)	0.00
COVID-19 (US deaths)	0.00
COVID-19 (world cases)	0.00
COVID-19 (world deaths)	0.00
Stock prices	0.00
VIX	0.00
T-bill rates	0.00

Table 4
Panel unit root test.

H_0 : Contains a unit root		
CIPS		
Variables	Levels	1st Differences
CDS yields	−1.128	−5.806***
COVID-19 (US cases)	−0.885	−5.977***
COVID-19 (US deaths)	−1.019	−6.874***
COVID-19 (World cases)	−1.114	−6.652***
COVID-19 (World deaths)	−0.966	−6.804***
Stock prices	−1.329	−6.741***
VIX	−1.235	−5.996***
T-bill rates	−1.552	−6.426***

***: $p \leq 0.01$.

respective model specifications, where as instruments have been used two lags and one lead from the control variables that ensure the validity of the instrument tests. It is evident that both the test for AR(2) of disturbances and the difference-in-Hansen tests fail to reject the respective nulls. Thus, these tests support the validity of the instruments used, while difference-in-Hansen tests imply the exogeneity of the instruments employed. The table also reports the Hansen test for overidentifying restrictions. In the estimation process, eleven instruments have been used. As the number of instruments was by far lower than the number of observations, it did not create any identification problem, as reflected in the Hansen test.

5. Sectoral estimates

In this part of the analysis, we repeat the above estimates by making use of sectoral CDS spreads. The sectors considered are: automobiles, banking, basic resources, chemicals, construction materials, financial services, health care, insurance, media, personal and household, retail, technology, telecommunications, travel and leisure, food and beverages, industrial, oil and gas, transportation, airlines, electronics, machinery, pharmaceutical, publishing, real estate, tobacco, information and data technology, metals and mining, textile, conglomerate manufacturing, restaurants, and health care supply, with corresponding data also coming from Bloomberg. Table 6 reports the number of firms in each sector.

The (sectoral) GMM estimates are reported in Table 7 (where again standard errors are clustered by firm). To save space only the COVID-19 estimates are reported, while those in relevance to the remaining drivers are available upon request. The findings clearly illustrate the presence of differentiated effect on CDS spreads. In particular, there have been certain sectors, such as restaurants and airline transportation, that have experienced a strong increase in CDS spreads to the pandemic virus, while other sectors did not feel any impact. The results can be explained through the work by Ozili and Arun (2020) who examined the impact of the corona pandemic across all sectors in the economy and shows that the COVID-19 outbreak led to spillovers into major sectors of the global economy. The banking sector has been one of the sectors that have been hit hard by the COVID-19 crisis. As a result, funding conditions are tight and long-term rating outlooks have been revised to negative for many banks, while actual ratings and corresponding CDS spreads are catching up with this trend, with more downgrades to be expected as the financial prospects of banks' borrowers deteriorate (e.g., Drehmann et al., 2020; Andrieş et al. 2020). The pandemic can generate a significant threat to the sustainability of banks, as higher levels of Non-Performing Loans, calling for imminent actions in support of the banking system (Barua and Barua, 2020).

6. Identifying a channel of transmission

The COVID-19 pandemic enters its second consecutive year, businesses have been serious damaged due to the strict government measurements and anxiety from public. There has been a record number of businesses filed for bankruptcies across the world since the beginning of the pandemic. It is difficult to predict the amount and length of continued government support and the depth of the ongoing economic slowdown (Wang et al., 2021). It is projected that a rise of 20% of insolvencies are expected after the withdrawal of government-aid schemes in advanced economies (Didier et al., 2021; Banerjee et al., 2020). For example, a recent survey of businesses

Table 5
Baseline results on the CDS and COVID-19 link (All CDSs are considered).

Variables	(1)	(2)
Constant	5.459**	4.893**
	[0.04]	[0.05]
ΔCDS(-1)	0.521***	0.439***
	[0.00]	[0.00]
ΔStock prices	−2.588***	
	[0.00]	
ΔStock prices(-1)	−0.973**	
	[0.05]	
ΔVIX	11.895***	
	[0.00]	
ΔT-bills	−14.509***	
	[0.00]	
ΔUS:COVID-19(cases)	2.348***	1.974***
	[0.01]	[0.01]
ΔUS:COVID-19(deaths)	2.871***	2.236***
	[0.00]	[0.01]
ΔW:COVID-19(cases)	4.309***	4.082***
	[0.00]	[0.00]
ΔW:COVID-19(deaths)	4.952***	4.347***
	[0.00]	[0.00]
Diagnostics		
R^2-adjusted	0.53	0.62
No. of instruments	11	17
AR(1)	[0.00]	[0.00]
AR(2)	[0.43]	[0.51]
Hansen test	[0.53]	[0.58]
Difference Hansen test	[0.46]	[0.52]
Firm fixed effects	YES	YES
Time fixed effects	YES	YES
Wald F-test (cases)	[0.00]	
Wald F-test (deaths)	[0.00]	
No. of instruments	11	24
No. of obs. (firms)	66,392	
No. of obs. (COVID-19)	172	

Column (1) reports the results when the information set contains only the COVID-19 variables, while Column (2) presents the findings when both the COVID-19 and the remaining drivers are included. The number of lags in the was determined through the Akaike criterion. AR(1) is the first-order test for residual autocorrelation. AR(2) is the test for autocorrelation of order 2. Hansen is the test for the overidentification check for the validity of instruments. The difference-in-Hansen test checks the exogeneity of the instruments. Figures in brackets denote p-values. **: $p \leq 0.05$; ***: $p \leq 0.01$.

found almost 15% of UK businesses are at-risk of permanently closing by the start of April 2021.[4] As expected, we find that during periods of volatility, businesses are more prone to bankruptcies as the variance of expected future returns from an investment would increase and access to external funds would diminish (Caglayan and Xu, 2019).

This section examines whether the COVID-19 pandemic affects the CDSs through a particular transmission channel. More specifically, the channel is associated with the information transmitted from the COVID-19 metrics to the *distressed characteristics* of the 386 firms participating in the analysis. In other words, it will provide the first analysis of the capacity of the pandemic on individual firms to act as a signal of the firms' financial condition. The literature has provided evidence of faster information processing ability in the CDS market associated with the financial condition of firms. Acharya and Johnson (2007) and Berndt and Ostrovnaya (2014) found that CDS markets reveal information in advance of the equity market for corporate entities that experience (or are likely to experience) adverse credit events. Moreover, Subrahmanyam et al. (2014), provided evidence that firms with a CDS market on their debt tend to default more. Relatedly, Colonnello et al. (2017) showed that firms with strong shareholders are more likely to default, because their creditors are more likely to purchase credit protection to avoid renegotiation. This part of the analysis also touches the literature that considers various aspects of the CDS-credit market nexus. Saretto and Tookes (2013) documented that CDS referenced firms have higher leverage ratios and borrow on longer debt maturities. Subrahmanyam et al. (2017) found that CDSs lead firms to increase their cash holdings to avoid funding constraints in times of distress.

Furthermore, this part is related to the literature that considers the role of natural disasters and pandemics on corporate default. There are two dominant views that attempt to explain how creditors interpret and respond to information about natural disasters, known chiefly as the debt default risk view and the creative destruction view. According to the former, the occurrence of natural

[4] https://www.ons.gov.uk/businessindustryandtrade/business/businessservices/bulletins/businessinsightsandimpactontheukeconomy/latest.

Table 6
Sectors and number of firms.

Sectors	Number of firms
Automobiles	7
Banking	13
Basic Resources	11
Chemicals	13
Construction Materials	15
Financial Services & Insurance	18
Health Care	15
Media	19
Retail	23
Technology	15
Telecommunications	14
Travel and Leisure	15
Food and Beverages	22
Oil and Gas	13
Transportation	14
Airlines	10
Electronics	18
Machinery	15
Pharmaceutical	16
Publishing	13
Real Estate	11
Tobacco	12
Information and Data Technology	17
Metals & Mining	12
Textile	15
Restaurants	22
TOTAL	**386**

disasters increases a firm's debt default risk due to increased operational risk (Elnahas et al., 2018), which comes in the form of disruptions to both the supply and demand side of the local market. Furthermore, any disruption of the supply chain may result in the temporary or permanent termination of the buyer–supplier relationship (Wagner and Bode, 2006). The latter view refers to the predicted positive economic effect of a natural disaster occurrence (Cuaresma et al., 2008). Natural disasters cause more damage to country's (physical) capital stock, which is most likely made up in large part by outdated equipment, thus motivating the replacement of outdated (physical) destroyed capital stock with capital stock that embodies the latest technology, thereby inducing a positive productivity shock that leads to higher GDP growth rates (Okuyama et al., 2004). Hence, natural disasters might provide economic opportunities for surviving firms who hope to replace outdated production technologies with new production technologies and/or shift from physical capital investments with a relatively lower return toward more human capital investments with a relatively higher return (Tanaka, 2015). Moreover, Queiroz et al. (2020), Ivanov (2020) and Sarkis et al. (2020) discuss that pandemic and epidemic events can seriously wreak havoc on supply chains, thus leading to extensive corporate defaults.

The set of the COVID-19 measures are used to investigate whether they can help in explaining firms' financial distress, i.e. likelihood of default. The analysis defines the measure of firm distress and firm failure employed. This measure of financial distress captures the point at which a firm is downgraded by a major rating agency (Fitch, Moody's or Standard and Poor's). The measure defined is binary, taking a value of one when a firm is categorised as failed or downgraded, and a value of zero, otherwise. From a total of 386 US firms, we have 65 firms which failed over the time span under consideration. To explore the explanatory power of the COVID-19 measures for firm failure, the analysis follows Shumway (2001) and Chava and Jarrow (2004) and estimates the probabilities of failure using a logit model. In particular, it assumes that the marginal probability of failure follows a logistic distribution given by:

$$P_{i,t}(Y_{i,t+1}) = \frac{1}{1 + e^{-a-bX_{i,t}}} \tag{3}$$

where $P_{i,t}$ is the probability at time t that firm i will fail, $Y_{i,t+1}$ is a dummy variable taking on the value of 1 (0, respectively) if the firm failed (did not fail, respectively) in period $+1$, X_{it} is the vector of five explanatory variables (i.e., COVID-19 measures and equity returns) at the end of period t , a and b represent the constant and slope parameters characterizing the logistic function, respectively. The models are estimated via maximum likelihood. Note that a higher value of $a + bX_{i,t}$ indicates a higher probability of failure. The model is formed such that only information available at time t is employed to understand the probability of failure of an individual firm during the subsequent period $+1$. Finally, to avoid potential endogeneity problems, the regression is estimated through Instrumental Variables (IV) Logit method (Chintagunta, 2001; Shugan, 2004).

The analysis uses two modelling specifications for Eq. (2). Specification/column (1) includes only the COVID-19 measures as the explanatory variables, while specification/column (2) includes these four COVID-19 metrics, as well as the control variables from Eq. (1), i.e. US stock market volatility, risk-free interest rates, and stock returns of the underlying firms. To instrument the probability of default, we have considered CDS spreads as potential instruments.

Table 7
Sectoral estimates.

Variables	US: COVID-19(cases)	US: COVID-19(deaths)	W: COVID-19(cases)	W: COVID-19(deaths)	No. of obs.
Automobiles	2.109***	2.677***	4.257***	4.605***	1,204
	[0.01]	[0.00]	[0.00]	[0.00]	
Banking	6.519***	6.924***	8.733***	8.982***	2,236
	[0.00]	[0.00]	[0.00]	[0.00]	
Basic Resources	2.114***	2.345***	3.996***	4.227***	1,892
[0.01]	[0.00]	[0.00]	[0.00]		
Chemicals	1.435**	1.662**	2.917***	3.273***	2,236
[0.04]	[0.03]	[0.01]	[0.00]		
Construction materials	3.684***	3.975***	4.662***	4.949***	2,580
	[0.00]	[0.00]	[0.00]	[0.00]	
Financial services & insurance	2.004***	2.116***	3.659***	4.014***	3,096
[0.01]	[0.01]	[0.00]	[0.00]		
Health care	4.762***	4.986***	5.592***	5.991***	2,580
[0.00]	[0.00]	[0.00]	[0.00]		
Media	0.655	0.738	0.709	0.750	3,268
[0.37]	[0.32]	[0.34]	[0.28]		
Retail	5.309***	5.873***	5.552***	6.101***	3,956
[0.00]	[0.00]	[0.00]	[0.00]		
Technology	0.713	0.746	0.652	0.673	2,580
[0.27]	[0.24]	[0.33]	[0.31]		
Telecommunications	0.426	0.442	0.419	0.428	2,408
[0.41]	[0.39]	[0.44]	[0.42]		
Travel & leisure	7.893***	8.229***	7.614***	7.955***	2,580
[0.00]	[0.00]	[0.00]	[0.00]		
Food & beverages	3.914***	4.118***	3.657***	3.826***	3,784
[0.00]	[0.00]	[0.00]	[0.00]		
Oil & gas	3.661***	4.048***	4.373***	4.516***	2,236
[0.00]	[0.00]	[0.00]	[0.00]		
Transportation	7.497***	7.918***	7.805***	8.349***	2,408
[0.00]	[0.00]	[0.00]	[0.00]		
Airlines	10.326***	11.084***	10.802***	11.241***	1,720
[0.00]	[0.00]	[0.00]	[0.00]		
Electronics	0.922	1.016	0.973	1.029	3,096
[0.35]	[0.28]	[0.31]	[0.26]		
Machinery	4.184***	4.459***	4.372***	4.810***	2,580
[0.00]	[0.00]	[0.00]	[0.00]		
Pharmaceutical	0.352	0.326	0.392	0.411	2,236
[0.42]	[0.45]	[0.38]	[0.33]		
Publishing	0.535	0.492	0.429	0.441	2,236
[0.37]	[0.42]	[0.49]	[0.45]		
Real estate	5.328***	5.861***	5.695***	6.024***	1,892
[0.00]	[0.00]	[0.00]	[0.00]		
Tobacco	0.603	0.682	0.574	0.598	2,064
[0.36]	[0.33]	[0.42]	[0.36]		
Information and data technology	0.549	0.522	0.526	0.509	2,924
[0.37]	[0.40]	[0.40]	[0.43]		
Metals & mining	0.916	0.937	0.949	1.083	2,064
[0.28]	[0.26]	[0.25]	[0.22]		
Textile	1.268	1.573	1.367	1.629	2,580
[0.18]	[0.13]	[0.15]	[0.11]		
Restaurants	16.082***	16.975***	16.773***	17.329***	3,784
[0.00]	[0.00]	[0.00]	[0.00]		

Figures in brackets denote p-values. **: $p \leq 0.05$; ***: $p \leq 0.01$.

The results in Table 8 report a highly significant positive coefficient for all four COVID-19 measures across both specifications. The estimates are significant at the 5% significance level, confirming strong evidence that pandemic measures impound additional information for equity markets. The observed pseudo R-squared values are found to be substantially high, recommending that logit models would have had high explanatory power during the pandemic crisis. Moreover, to test whether the instrument is correlated with the predictor, the analysis conducts first-stage robust F-statistic test. A significant robust F-statistic, which is higher than a rule of thumb value of 10, indicates that the instrument is not weakly correlated with the predictor (Cameron and Trivedi, 2010). To test that the instrument is not weakly correlated to the predictor, the analysis computes the minimum eigenvalue statistics and compares them to the Stock and Yogo's critical values. The minimum eigenvalue statistics values reported for both IV logit models are higher than Stock and Yogo's critical values, implying that the instrument is not weakly correlated with the predictor. Finally, to test whether the instrument is not jointly correlated with the outcome variable, we provide estimates of the Sargan (Sargan, 1958). The estimates indicate non-significant χ^2, implying that the instrument is not jointly correlated with the outcome variable.

In addition to logit regression estimations, we also employ a Cox proportional hazards model as an alternative method to analyse

Table 8
Logit regressions of COVID-19 on firm failure indicator.

Variables	(1)	(2)
Constant	−2.02*	−1.79*
	[0.08]	[0.09]
US: ΔCOVID-19 confirmed cases	2.97**	2.80**
	[0.04]	[0.04]
US: ΔCOVID-19 confirmed deaths	3.62**	3.29**
	[0.02]	[0.03]
W: ΔCOVID-19 confirmed cases	2.97**	2.83**
	[0.05]	[0.05]
W: ΔCOVID-19 confirmed deaths	3.44**	3.36**
	[0.05]	[0.05]
ΔStock prices	−2.17**	
	[0.04]	
ΔVIX	3.36**	
	[0.02]	
ΔT-bill	−1.93**	
	[0.05]	
Pseudo R-squared	0.52	0.74
Log likelihood	−3249.17	−3774.92
Wald χ^2 test statistic of equality of all regression coefficients	[0.00]	[0.00]
Robust F-statistic	[0.00]	[0.00]
Minimum eigenvalue statistic	398.14	406.51
Stock and Yogo's statistic	42.85	48.69
Sargan	[0.28]	[0.35]

Figures in brackets denote p-values. Pseudo R-squared is the value of the McFadden R-squared. Figures in brackets report the z-statistics by adjusting standard errors using the Huber-White method. *: $p \leq 0.10$; **: $p \leq 0.05$.

the impact of the fitted pandemic CDS spreads for firm failure. The dependent variable is the time to default, with Table 9 containing the estimation results (for the same specifications as in Table 8). Both modelling specifications confirm that these pandemic CDS spreads are significantly associated with default, in line with the results obtained from the logit regressions.

7. Forecasting performance

In light of the results reported, this step of the empirical analysis evaluates the (in-sample) forecasting performance of Eq. (1). The forecasting exercise uses a rolling sample of the past CDS spreads. By recursive substitution of the spreads, forecasts for up to 15 periods are constructed. The forecasting performance was compared against the model with the two COVID-19 variables. Table 10 reports the forecasting results which highlight that the model with the COVID-19 factors (Panel I with respect to the world confirmed cases and confirmed deaths and Panel II with respect to the US confirmed cases and confirmed deaths) outperforms the forecasts compared to the model excluding the COVID-19 factors. The mean absolute forecast error (MAFE) and the mean squared forecast error (MSFE) are used to assess forecast accuracy. The model with the COVID-19 variables displays smaller MAFE and MSFE metrics, than that without the COVID-19 metrics in both panels. It is also imperative to assess whether any reductions in the two measures are statistically significant. Thus, the Diebold and Mariano (1995) test of equal forecast accuracy is presented. The results, also reported in Table 10, reject the null

Table 9
Hazard model estimates.

Variables	(1)	(2)
US: ΔCOVID-19 confirmed cases	3.06**	2.83**
	[0.04]	[0.04]
US: ΔCOVID-19 confirmed deaths	3.29**	3.05**
	[0.03]	[0.04]
W: ΔCOVID-19 confirmed cases	3.17**	2.87**
	[0.04]	[0.04]
W: ΔCOVID-19 confirmed deaths	3.48**	3.22**
	[0.03]	[0.03]
ΔStock prices	−2.40**	
	[0.05]	
ΔVIX	2.64**	
	[0.05]	
ΔT-bill	−1.72*	
	[0.06]	

Figures in brackets denote p-values. *: $p \leq 0.10$; **: $p \leq 0.05$.

Table 10
Forecasting performance of the model with COVID-19.

Forecasting Horizon (days)	I. World cases and deaths				II. US cases and deaths				
	Without COVID-19	With COVID-19	days	Without COVID-19	With C With COVID-19				
	MAFE	MSFE	MAFE	MSFE		MAFE	MSFE	MAFE	MSFE
1	0.1751	0.0736	0.1109	0.0432	1	0.1511	0.0603	0.1132	0.0367
4	0.1768	0.0758	0.1134	0.0464	4	0.1545	0.0642	0.1174	0.0389
8	0.1799	0.0791	0.1173	0.0595	8	0.1589	0.0778	0.1202	0.0428
15	0.1824	0.0819	0.1206	0.0628	15	0.1625	0.0798	0.1239	0.0453
DM test					DM test				
MAFE: [0.00], MSFE: [0.00]					MAFE: [0.00], MSFE: [0.00]				

MAFE and MSFE represent mean absolute forecast error and mean squared forecast error, respectively. DM is the Diebold-Mariano test statistic, using MAFE and MSFE as the error criterion. Figures in brackets denote p-values. The results are based on 15 out-of-sample forecasts.

hypothesis of forecasting accuracy across both cases of the COVID-19 definitions.

8. Causality tests

Based on a reviewer's suggestion, a statistically significant parameter does not mean that the independent variable is economically linked to the dependent variable, especially when using time series for short periods. To this end, this part of the empirical analysis does run a panel Granger causality test. In particular, to show causation this part of the analysis makes use of the Dumitrescu and Hurlin (2012) Granger non-causality test, which is suitable for heterogeneous panelized data frameworks which consider individual unit fixed effects and is based on a bootstrap procedure that takes care of cross-sectional dependence challenges. It takes into account the following methodological framework:

$$CDS_{i,t} = \sum_{k=1}^{K} \beta_{1i} COVIDCases_{i,t-k} + \sum_{k=1}^{K} \beta_{2i} COVIDDeaths_{i,t-k} + \sum_{k=1}^{K} \gamma_i Z_{i,t-k} + v_i + \varepsilon_{i,t} \tag{4}$$

with all the variables being defined as in Eq. (1). The test approach puts forward that the null hypothesis is assumed to have no causality for any units available in the panel. Therefore, if the null hypothesis, H_0, is rejected, then causality from the independent variables to the dependent variable does exist. The average statistic $W_{N,T}$ which is associated with the null hypothesis yields:

$$W_{N,T} = 1/N \sum_{i=1}^{N} W_{i,T} \tag{5}$$

where $W_{i,T}$ illustrates the individual Wald statistics in relevance to the ith cross-section unit to match the individual null hypothesis. Table 11 presents the findings of the Granger causality test outcomes generated through a bootstrap application technique. The findings clearly document that across all COVID-19 metrics, the null hypothesis of non-causality is rejected, while the reverse does not hold, indicating the presence of univariate causality running from the COVID-19 metrics to CDS spreads.

9. Conclusion

The COVID-19 crisis has created an enormous uncertainty shock with magnitude similar to the Great Depression of 1929–1933. This massive increase in uncertainty has a profound adverse effect on business profitability, mew business formation, R&D, investments, and other factors that affect productivity over the medium and long-term (Baker et al., 2020). Given CDS spreads act as an important indicator of firm's credit risk, there is a surge on researchers' intensified effort on gauging the market's ability to correctly price this risk induced by COVID-19. This paper complements this line of literature, by examining the extent to which pandemic measured by both global and local COVID-19 proxies affects US corporate CDS spreads. In contrast to the literature, the analysis provided evidence from both aggregate and sectoral CDS markets sought to understand how the pandemic transmitted its effects on CDS spreads. To carry out the analysis, a comprehensive panel dataset comprised of 386 US firms with a sample of 66,392 daily observations was employed, spanning the period between February 2020 to September 2020.

The results documented strong evidence for the relevance of the severeness of the pandemic on US corporate CDS spreads. Consistent with our prior belief, the COVID-19 drove up the price of CDS, where both the magnitude and significance were heterogenous across sectors. To be more specific, banking, travel & leisure, transportation, airlines and restaurants were the worst affected sectors, while media, technology, telecommunications, pharmaceutical, information, and data technology firms were spared from the pandemic. Furthermore, the results confirmed three pandemic effects transmission channels that contributed to larger CDS spreads. The analysis also found that COVID-19 measures increased the probability of firms' financial distress that captured the point at which a firm had been downgraded by a major rating agency. In addition, a forecasting exercise clearly indicated the forecasting superiority of the modelling approach that explicitly introduced the COVID-19 metrics, potentially indicating the substantial role of uncertainty associated with the pandemic crisis for correctly pricing CDS spreads.

Table 11
Dumitrescu-Hurlin Granger causality tests.

Null hypothesis	W-statistic
World confirmed cases do not Granger cause CDS spreads	20.95[0.00]
World confirmed deaths do not Granger cause CDS spreads	21.64[0.00]
US confirmed cases do not Granger cause CDS spreads	18.26[0.00]
US confirmed deaths do not Granger cause CDS spreads	18.99[0.00]
CDS spreads do not Granger cause World confirmed cases	4.59[0.28]
CDS spreads do not Granger cause World confirmed deaths	4.91[0.25]
CDS spreads do not Granger cause US confirmed cases	3.71[0.36]
CDS spreads do not Granger cause US confirmed deaths	3.42[0.34]

Figures in brackets denote p-values.

In sum, the findings provide useful information for macroeconomic policymaking, consumption, capital investments, management risk, and portfolio management. The impact of COVID-19 crisis is large, it requires central banks to carry out aggressive policies to maintain the financial stability and to minimize the number of business failures. By identifying the heterogeneity of industry sensitivities to the pandemic implies that some sectors can provide a channel for diversification during further waves of pandemic cases and fatalities. For example, if there is an anticipated increase cases and deaths, investors may use this information to devise their investment strategies, such as taking short positions in COVID-sensitive sectors (e.g., banking, transportation, airlines, restaurants), and long positions for firms in insensitive sectors (e.g., technology, telecommunications, pharmaceutical, information and data technology). One interesting (future) question will be to examine the impact of COVID-19 on other heavily affected countries.

CRediT authorship contribution statement

Nicholas Apergis: Conceptualization, Data curation, Formal analysis, Methodology, Project administration, Software, Supervision, Validation, Writing – original draft, Writing – review & editing. **Dan Danuletiu:** Investigation, Resources, Software, Validation, Writing – original draft, Writing – review & editing. **Bing Xu:** Investigation, Project administration, Validation, Visualization, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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