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Interfaces with Other Disciplines

Corporate credit risk counter-cyclical interdependence: A systematic analysis of cross-border and cross-sector correlation dynamics

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ABSTRACT

Sectoral corporate credit risk interlinkages constitute a highly topical issue for the systemic risk considerations of policymakers and market practitioners. We reveal the macroeconomic drivers of dynamic correlations between European and US sectoral Credit Default Swaps (CDS) markets. The CDS conditional equicorrelations are explained by common macro-financial and news proxies. Our results demonstrate the counter-cyclical behaviour of the time-varying sectoral CDS interdependence, that is elevated sectoral correlations are associated with higher economic policy and financial uncertainty, stronger infectious disease news impact on equity markets, tighter credit conditions, economic activity slowdown, and negative sentiment. We further focus on economic policy uncertainty (EPU) as a potent catalyst of the CDS markets integration process and conclude that EPU magnifies the macro effects across credit risk correlations. Moreover, crisis events play a crucial role in the time-varying impact of the correlation macro drivers. Both financial and health crises amplify the influence that the macro factors exert on the evolution of credit risk correlations, leading to credit risk contagion and threatening financial stability. Lastly, we show that understanding the credit contagion mechanisms has clear implications for operational research applications on risk and portfolio management.

1. Introduction

The recent Covid-induced turmoil has reignited research and regulators' interest in studying risk spillovers and contagion mechanisms. Such mechanisms act as transmitters for the spread of economic shocks across markets and industries. The domino effects of a crisis event starting from a single country, corporate sector, or asset market are rapidly disseminated to further economies, industries, and financial markets with a magnifying propagating power. The markets' connectedness, mostly exacerbated during weaker economic conditions, constitutes a major threat to financial stability, leading to contagion and systemic risk build-ups. Therefore, market practitioners and policymakers closely investigate such co-movements, which are considered to be crucial early warning signs of upcoming crises or post-crisis systemic risk diagnostics. In this vein, motivated by the importance of risk spillovers, we explore credit markets' interdependence by focusing on corporate credit risk contagion across different sectors and economies. The onset of the 2008 global turmoil was attributed to a credit crunch caused by the meteoric rise in US sub-prime mortgage defaults. Hence, loan and bond delinquency has been shown to behave as a potent catalyst for credit squeeze episodes and subsequent globally spread financial crashes. Periods of exuberance with lax lending standards and, often, enormous funding supply from banks and bond markets are followed by contraction phases of financial stress. Common features of stress periods are large concentrations and transmission (cross-border and cross-sector) of corporate bankruptcies, which are the direct outcome of elevated counterparty credit risk materialisation and contagious defaults.

Against this backdrop, we hereby delve into default risk interlinkages quantified by conditional correlations and explain the time-varying behaviour of the credit correlation pattern with eco-

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nomic fundamentals and news diffusion effects. The primary objective of the present study, in particular, is to investigate the dynamic correlations between European and North American sectoral corporate credit risk and identify the determinants of credit correlation dynamics. Making use of daily sectoral Credit Default Swaps (CDS) indices as the corporate credit risk proxies for each economic sector, we reveal the common forces that drive cross-country and -industry credit risk co-movements and analyse the sensitivity of the correlation trajectory to the economic uncertainty channel and crisis periods. Both aspects, the credit risk correlations at the corporate sector level and their evolution across the business cycle, are topics overlooked by the finance literature. Besides the widely documented pro-cyclical behaviour of credit flows (see, for example, (Jordà, Schularick, & Taylor, 2013), the extant CDS and, more widely, credit risk literature has also provided ample evidence on the macro-relevance of default risk, which is mainly magnified during business cycle downturns (see, among others, Alexander & Kaeck, 2008; Chortareas, Magkonis, & Zekente, 2020, and the literature therein). However, research on corporate credit risk comovements, as examined by CDS connectedness studies, lacks evidence on the macro drivers of their dependence dynamics. Therefore, we fill a notable gap in the literature with our novel results on cross-country and cross-sector CDS interdependence and on the main drivers of this interdependence, which is also found remarkably vulnerable to the ubiquitous feelings of uncertainty and crisis shocks.

Using the Dynamic Equicorrelation (DECO) model of Engle & Kelly (2012), we measure the time-varying linkages (correlation pairs) between fifteen European Union (EU) and US sectoral credit markets: Automotive, Banks, Basic Resources, Chemicals, Construction Materials, Food & Beverage, Industrial Goods & Services, Insurance, Media, Oil & Gas, Retail, Technology, Telecommunications, Travel & Leisure, and Utilities. Our multivariate DECO specification estimates the mean equation of the CDS indices with cross effects and the significant macro environment's impact. The variance (time-varying GARCH) equation incorporates asymmetries, shock and leverage spillovers, and the crisis impact on the conditional variance dynamics. Using the matrix inequality constraints derived in Karanasos, Xu, Yfanti, Zopounidis, & Christopoulos (2021), we employ the constrained quasi maximum likelihood estimation, recently introduced in the aforementioned paper. Apart from the cross-country (EU-US) connectedness of each economic sector over a long 17-year period (2004–2020), we also estimate the overall correlations among all fifteen sectoral CDS indices for each economy separately. Next, we explain the correlation evolution with economic policy and financial uncertainty, infectious disease news impact on stock market volatility, sovereign and corporate credit conditions, economic activity, and news sentiment. Our results demonstrate the counter-cyclical correlation pattern since contractive economic forces (higher uncertainty, tighter credit, weak economic activity) and negative news sentiment exacerbate CDS interdependence.

The sensitivity analysis further shows the susceptibility of sectoral co-movements to policy uncertainty and crisis events, which both magnify the macro and news impact on CDS correlation evolution. We also notice remarkable differences in the correlation trajectory across sectors and countries. European sectoral credit interlinkages are tighter but less macro-sensitive than the US ones. Although macros and news play a key role in moving all correlations, in the cross-border case, certain sectors' CDS correlations are more affected by fundamentals and crisis events than others. The crisis impact on cross-sector (same-country) credit risk comovements is more significant than on the cross-country ones. The pandemic-induced turmoil is found to be the most contagious shock (for the majority of sectoral combinations) compared to the other two shocks from the financial crises investigated (the 2008 global financial crash and the European debt crisis). Moreover, we demarcate our study with the use of daily frequency data both for CDS indices and the macro-financial and news correlation drivers. Most macro-financial studies apply lower than daily frequency macro fundamentals (monthly or quarterly) to explain high frequency financial variables using mixed-frequency techniques. We prefer daily macro variables explaining corporate credit risk metrics given that the higher the frequency of macro information flow in the model, the more accurately the significant macro influence will be identified to update the daily correlation trajectory. The choice of the high frequency macro domain in correlation models is critical in crisis times mainly when the macro conditions change very rapidly. Most importantly, we show how our findings are directly implemented in operational research applications for risk analytics and portfolio optimisation. The high frequency counter-cyclical behaviour of credit risk correlations passes through or partly determines the time-varying optimal hedge ratio (hedging costs) dynamics among various risk and portfolio metrics (e.g., optimal portfolio weights, minimum correlation portfolio performance).

The paper is structured as follows. Section 2 develops the theoretical hypotheses underlying the economic fundamentals behind the credit risk correlation evolution. In Section 3, we detail our methodological approach and the data used. Section 4 analyses the estimation results of the correlation models. In Section 5, we present the sensitivity analysis of the correlation determinants (uncertainty channel and crisis shocks). Section 6 discusses our findings operational research and policy implications. The last Section concludes the study.

2. Theoretical background and hypothesis development

In this Section, we first outline the theoretical background of our study, our motivation and contribution. Further, we develop our theoretical hypotheses to be tested in the identification of credit risk correlation drivers. Based on the empirical evidence of credit risk determinants and dependences and motivated by the importance of financial interconnectedness (Bonaccolto, Caporin, & Maillet, 2022; Ellington, 2022), we fill a notable gap in credit risk literature. Although the connection between default risk measures (CDS spreads included) and macro proxies, such as uncertainty, is well-demonstrated, there is no evidence connecting cross-country and cross-sector co-movement of credit risk metrics with economic fundamentals. Finance scholars mostly focus on sovereign and bank CDS connectedness, ignoring significant corporate sectors in the economy. Hence, we hereby complement the sectoral (corporate) credit risk correlations research in the following ways: i) by using daily sectoral CDS index series as corporate credit risk proxies covering almost all industries and two different regions, and ii) by attributing their counter-cyclical correlation dynamics to high frequency macro fundamentals and news effects.

Return and volatility spillovers in tranquil times and contagion effects during crises are ubiquitous among typically distinct markets for most assets traded publicly or privately, in an organised market or over-the-counter. Understanding such spillovers is of great interest for operational research practitioners in business analytics, mainly in portfolio and risk management applications (Al Janabi, Hernandez, Berger, & Nguyen, 2017; Bae, Kim, & Mulvey, 2014; Carroll, Conlon, Cotter, & Salvador, 2017; Engle, 2016). Significantly increased in-crisis or due-to-crisis interdependence is characterised as financial contagion (Forbes & Rigobon, 2002), which jeopardises the stability of the financial system. This elevated and persistent synchronicity of multiple markets with concurrent asset price falls and volatility jumps is to a great extent exacerbated in turbulent times of economic slowdowns and financial turmoil. Financial crashes spread from one country to the rest of the developing and emerging world, or from one asset market to multiple assets internationally. Such co-movements lie at the core of systemic risk considerations, with stress episodes directly transmitted over sectors, economies, and different financial instrument types, often through tightly interrelated counterparties' distress conditions. Similarly, credit derivative markets are subject to spillovers and contagion effects. CDS are deeply traded. Their price, the CDS spread or premium, is associated with the default risk of the bond-issuer entity and represents the cost of protection against default. Given that sovereign and corporate credit risk, proxied by CDS spreads, is disseminated across different counterparties, we observe credit event dominos conveyed in multiple directions through complex financial networks. The research spotlight on CDS market dynamics has unveiled, first, the determinants of CDS spreads and, second, the link between sovereign and bank CDS spreads, which demonstrates the co-movement and risk spillovers of government and bank financial stress.

Credit markets literature has explored the relationship between credit risk metrics and economic aggregates. Numerous studies have provided evidence on the way macro-financial proxies contribute to the time series trajectory of different default risk measures, such as non-performing loans, credit spreads, and CDS spreads (see, for example, Chortareas et al., 2020; Clark & Baccar, 2018; Takada & Sumita, 2011). In the CDS case, more specifically, the focus of attention is on the impact of macroeconomic conditions, crisis episodes, policy actions, and firm- or sector-level factors on the sovereign or corporate CDS premium dynamics (Alexander & Kaeck, 2008; Chan & Marsden, 2014; Dodd, Kalimipalli, & Chan, 2021; Irresberger, Weiß, Gabrysch, & Gabrysch, 2018; Tang & Yan, 2010). The common takeaway of CDS market analyses is that poor macro fundamentals or crisis periods are strongly associated with elevated CDS spreads. To the best of our knowledge, although the relationship between CDS spreads and several macro-aggregates has been well-identified and investigated, there is no literature connecting co-movements of corporate credit risk metrics with economic fundamentals. Moreover, a significant amount of studies focuses on the uncertainty injected into credit markets (Chabot, Bertrand, & Thorez, 2019; Wang, Xu, & Zhong, 2019). The uncertainty literature demonstrates the magnifying impact of the loss of economic confidence on CDS spreads growth, leaving the uncertainty-CDS correlations link an under-researched area. The Economic Policy Uncertainty (EPU) influence on CDS or any credit risk measure interconnectedness has not been addressed for any country/sector combination or any frequency. Hence, in the present study, we reveal the EPU impact on CDS correlations, among other macro-financial effects. Such CDS correlations or, more generally, default risk interdependence can result in credit contagion and systemic risk alarms. Therefore, it constitutes a major threat to the resilience of the financial system and is often a major part of early warning system frameworks (Barro & Basso, 2010; Calabrese & Crook, 2020; Calabrese & Osmetti, 2019; Gupta, Wang, & Lu, 2021; Simaan, Gupta, & Kar, 2020; Torri, Giacometti, & Paterlini, 2018). In this vein, another CDS literature branch on credit risk interconnectedness studies the linkages between CDS mostly of sovereigns and financial institutions in the same or across different countries (Acharya, Drechsler, & Schnabl, 2014; Bratis, Laopodis, & Kouretas, 2020; Chen, Ho, & Yang, 2020). Grundke & Polle (2012) and Apergis, Christou, & Kynigakis (2019) are among the few studies on corporate sectoral CDS indices co-movement (with other asset classes, as well) but without raising the question about the high-frequency driving forces of such a phenomenon. Grundke & Polle (2012) estimate the in-crisis multivariate stochastic dependence between the European iTraxx CDS indices (the total CDS index and six sectoral subindices), equities, bonds, currencies, commodities, and real estate. Apergis et al. (2019) show significant contagion effects between European and US banking and insurance CDS indices, alongside sovereign bond, equity, and implied volatility indices during the 2008 financial turmoil.

Markets' integration and co-movement have been investigated through the multivariate GARCH (MGARCH) econometric framework extended with the computation of time-varying (dynamic) correlations (see, for example, the Correlated ARCH (CorrARCH) of Christodoulakis & Satchell (2002) and the Dynamic Conditional Correlations (DCC) of Engle (2002). Literature on financial markets' time-varying dependence measured by dynamic correlations has shown the cross-border connectedness of a single asset class and the cross-asset linkages inside a single market or globally (see, among others, Al Janabi et al., 2017; Carroll et al., 2017; Christodoulakis, 2007; Engle & Figlewski, 2015; Karanasos, Menla Ali, Margaronis, & Nath, 2018). Common empirical findings from studies on asset co-movement postulate that financial markets are highly integrated in the current era of globalisation, financial liberalisation, and deregulation, with risk spillovers that generally become more intense during crisis periods (see, for example, Bae et al., 2014; Bekiros, Nguyen, Sandoval Junior, & Uddin, 2017; Conlon, Cotter, & Gencay, 2018; Jayech, 2016; Supper, Irresberger, & Weiß, 2020; Yang & Bessler, 2008). The vast majority of studies applying the time-varying correlations approach focus on the correlations calculated in crisis periods compared to times of tranquil market conditions. Among the few attempts to relate the asset correlation evolution with macro fundamentals are the ones making use of the DCC-MIDAS model of Colacito, Engle, & Ghysels (2011) but they explain only the long-run component of daily correlation time series with lower frequency (monthly or quarterly) macro-financial proxies. Considering the superiority of the high frequency macro and news domain in macro-financial linkages research, particularly in turbulent times, and motivated by the recent study of Karanasos & Yfanti (2021) on the daily determinants of cross-asset correlation evolution, we hereby proceed with the credit risk dependence structure. Thus, we first develop the hypotheses underpinning our choice of correlation determinants and their expected impact. Next, we test the hypotheses in order to identify the high frequency driving forces of corporate sectoral CDS co-movements, using daily news and fundamentals which capture the real-time economic stance.

Hypothesis 1 (H1): Economic slowdown drives CDS correlations higher.

Economic slowdown means weak economic fundamentals. Weak fundamentals are expected to exacerbate correlations while economic growth forces should alleviate correlation jumps. Therefore, under *H1*, we identify the macro-financial indices which best describe the macroeconomic environment where the CDS markets operate and are among the key determinants of credit risk metrics already identified by numerous studies (see, for example, Chan & Marsden, 2014). We expect that when such macro proxies show a deterioration (improvement) of the economic outlook, the CDS correlations increase (decrease). Our first hypothesis is mainly based on the well-established evidence of financial contagion with elevated markets' interconnectedness in turbulent times of weak economic conditions. The extant literature demonstrates that markets' synchronisation becomes more intense during business cycle downturns (Bekaert, Harvey, & Ng, 2005). Therefore, we can deduce that CDS markets' cross-sector dependence also becomes tighter. From a credit risk perspective, corporate bankruptcy concentrations or clustering and default risk transmission or contagion constitute a common stylised fact of bear markets and recession periods. Widespread high levels of counterparty credit risk follow poor macroeconomic performance (Das, Duffie, Kapadia, & Saita, 2007; Giesecke & Weber, 2004; Nickerson & Griffin, 2017). Hence, we scrutinise all available daily indicators proxying EU, US, or global macro-financial conditions to be incorporated as CDS correlation macro determinants.

The cyclical variation of credit risk contagion is first traced in a critical economic force driving the business cycle, that is uncertainty. The devastating impact of uncertainty on activity, investment, employment, and financial markets is well-documented in empirical economics and finance research (Bernanke, 1983; Bloom, 2009; Pastor & Veronesi, 2013). Significant economic disruptions are attributed to elevated uncertainty feelings among economic agents. Therefore, our first correlation determinant is the news-based Economic Policy Uncertainty index (Baker, Bloom, & Davis, 2016), the sole economic uncertainty index measured with a daily frequency (for UK and US) and considered the most inclusive metric containing both economic and policy-related ingredients (see also Karanasos et al., 2021, for a thorough discussion on the relative merits of the EPU index and the EPU effect on financial correlations). A further uncertainty variable explaining correlation dynamics is the financial uncertainty proxied by stock market implied volatility. Financial uncertainty is widely used in empirical literature to capture the recessionary and destabilising uncertainty effects (Bloom, 2009). For our EU-US CDS study, we choose the Euro Stoxx 50 and S&P 500 implied volatility indices, VSTOXX and VIX, as the financial uncertainty variables. The Infectious Disease Equity Market Volatility Tracker of Baker et al. (2020) is our third uncertainty proxy, identified as a significant explanatory variable of sectoral credit risk interdependence. This newspaper-based index quantifies the impact of news related to disease outbreaks on US equity volatility. Given the current pandemic times, where we observe the catalytic role of a virus worldwide spread across economies and financial markets, it is highly topical to explore the disease-induced uncertainty effect alongside pure economic and financial uncertainty influence. Since economic slowdown is associated with higher uncertainty, we expect a positive relationship between each of the three uncertainty variables and CDS connectedness.

The next correlation determinant is the credit channel, an important constituent of economic cycles. We consider proxies of both sovereign and corporate credit conditions. Although our study focuses on corporate credit risk, sovereign risk is also crucial for firms' financing given its immediate pass-through to corporations' funding costs. Hence, we use the MOVE index of US government bonds implied volatility to capture the sovereign credit stance. Higher MOVE means sovereign credit market turbulence, with an inflammatory impact on corporate CDS co-movements. The corporate credit conditions are proxied by the global corporate bond default spread calculated as the difference between BAA and AAA bond yields by Moody's. Elevated default risk pricing denotes rising borrowing costs, which increase firms' bankruptcy probability. Thus, we expect a positive effect of corporate default spread on CDS correlations, similar to the sovereign credit case.

Another major driver of business cycle dynamics is the economic activity level. Weaker activity lies at the core of economic downturns with a detrimental impact on business conditions. Corporations will be less productive and profitable during periods of lower output and the probability of default is significantly heightened in multiple economic sectors. Therefore, we should expect a negative relationship between activity and credit risk interdependence. In this context, we test two alternative daily activity proxies: i) the term spread or yield curve slope calculated as the yield difference between 10-year minus 3-month EU treasury bonds and ii) the Aruoba-Diebold-Scotti (ADS) US business conditions index (Aruoba, Diebold, & Scotti, 2009). The term spread is found to be a powerful predictor of activity prospects (Estrella & Hardouvelis, 1991). Higher treasury term structure slope means economic expansion associated with lower credit risk while slope decrease predicts activity contraction (see, for example, Dodd et al., 2021; Gilchrist & Zakrajšek, 2012). The ADS index tracks real-time business conditions indicative of US economic activity nowcasting. Both variables should exert a significant negative effect on correlations. The preferred activity proxy for either the EU or the US case is incorporated in our models based on statistical criteria (information criteria and R-squared).

Overall, according to *H1*, sectoral CDS correlations are expected to rise during weak economic periods. Increased uncertainty and tighter credit conditions drive credit risk interdependence up (positive uncertainty and credit effect) whereas stronger activity reduces this interconnectedness (negative activity effect).

Hypothesis 2 (H2): Bad news drives CDS correlations higher.

Under our second hypothesis, we expect that CDS correlations grow with the arrival of bad news related to the economy and agents' economic decisions and sentiments. Good news or no news should keep correlations low. The news impact on markets' co-movement has been considered by Kaminsky & Schmukler (1999) among others, who attribute contagion to investors' herding behaviour and over-reaction to bad news during crises. Thus, the seventh correlation determinant is the news impact as measured by the daily US News Sentiment Index (NSI). Shapiro, Sudhof, & Wilson (2020) and Buckman, Shapiro, Sudhof, & Wilson (2020) apply a sentiment scoring model to distinguish between positive and negative economic news in sixteen US newspapers. Through news lexical analysis they construct the NSI. Its high/low level means more positive/negative economic news, implying positive/negative sentiment of market participants (e.g., confidence/uncertainty, optimism/pessimism). NSI is the antipode of the uncertainty indicators, whose higher values mean a stronger negative feeling of uncertainty in the macro environment. The central role of news in the economy is notably highlighted nowadays with fake news and infodemics dominating all aspects of the socioeconomic evolution. The negative news is tightly linked with an economic slowdown and is expected to drive credit risk contagion. Thus, under *H2*, we anticipate a negative signed news effect on CDS correlations. Bad or good news often appears far in advance of the downturn or upturn of a macro proxy, acting as a media signal (real or fake) of an imminent market slowdown or expansion. Therefore, although NSI could belong to the overall economic outlook drivers discussed under *H1*, we classify news in our second hypothesis separately from the pure macro fundamentals of *H1*.

Hypothesis 3 (H3): Economic policy uncertainty magnifies the macro and news effects on CDS correlations.

According to our third hypothesis, a rising EPU level is expected to magnify the macro and news impact on correlations. We expect that the positive financial uncertainty, infectious disease, credit turbulence, and the negative activity and news sentiment effects on default risk contagion are partly driven by the uncertainty channel. After identifying the macro-financial and news drivers of corporate credit risk co-movements, we conduct a sensitivity analysis on the uncertainty channel that affects the correlation evolution. Economic uncertainty is well-documented for its recessionary impact on all economic fundamentals, its destabilising influence on financial markets, and its considerable repercussions on news sentiment. We construct our third testable hypothesis motivated by Pastor & Veronesi (2013), who are the first to show that the EPU effect on stock correlations is intensified during economic downturns or the activity negative impact is partially attributed to elevated EPU levels.

Hypothesis 4 (H4): The macro and news effects on CDS correlations are intensified during crisis periods.

According to *H3*, higher EPU should magnify the macro and news influence. Given that a higher EPU level is one of the most crisis-relevant characteristics, under *H4*, we expect that the macro and news positive and negative effects on CDS correlations will become more acute in moving correlations to higher levels during crisis periods. Similarly, the EPU impact on correlation drivers (*H3*) is also expected to be more intense during crises. Thus, we complement our sensitivity analysis by investigating the crisis ramifications on correlation evolution. The contagion literature analyses the direct crisis effect on correlations and provides clear evidence of the upward shift in the correlation pattern during financial turmoil episodes. The common approach in crisis analysis is the detection of mean shifts in the correlation trajectory, which compares the average correlation of pre- and post-crisis periods (see, for example, Bratis et al., 2020; Chiang, Jeon, & Li, 2007; Karanasos, Yfanti, & Karoglou, 2016). Our empirical investigation contributes to this commonplace in crisis analysis by exploring whether the correlation determinants are more drastic in increasing credit risk interdependence during crisis periods.

3. Econometric methodology and data

The present study's aim and contribution are to reveal the determinants of sectoral credit risk correlations and to focus on the crucial role of uncertainty and crisis events on the correlation trajectory. We first estimate the dynamic correlations among sectoral CDS indices through the DECO model and then regress the correlation series on the various macro-financial and news regressors. Our multivariate specification consists of i) a full VAR allowing for cross effects and macro impact in the mean (VARX), ii) an asymmetric (based on the univariate GJR model of Glosten, Jagannathan, & Runkle (1993)) time-varying (TV) MGARCH process for the conditional variances augmented with the crisis influence, shock and leverage spillovers, and iii) the Dynamic Equicorrelations of Engle & Kelly (2012), which calculate the pairwise correlations/equicorrelations among CDS index returns. TV volatility specifications have recently (in the last decade; see, for example, Karanasos, Paraskevopoulos, Ali, Karoglou, & Yfanti, 2014, and the references therein) gained popularity for modelling time variation (i.e., crisis impact, structural breaks) in the volatility process. Conrad & Karanasos (2010) and Karanasos et al. (2014, 2021) introduce a set of theoretical considerations for these types of models. We apply the constrained quasi maximum likelihood (QML) estimation recently introduced by Karanasos et al. (2021). They generalise the non-negativity conditions results of the MGARCH (with spillovers) specification in Conrad & Karanasos (2010) by deriving tractable constraints, expressed as simple matrix inequalities, which can be easily imposed on the estimation (they also applied their technique to N -dimensional asymmetric multiplicative error models, MEM). The enrichment of the MGARCH model with the leverage term, mean and shock cross effects, the crisis impact, and the computational superiority of the DECO estimation (see, for example, Pan, Wang, & Liu, 2016) are the key characteristics of our advanced econometric methodology. This Section proceeds as follows. We present the VARX-GJR-DECO specification (the errors and the conditional correlations parts) estimated for the cross-border and cross-sector combinations of corporate CDS indices (see also the Appendix for the conditional mean and variance parts of the econometric specification). Next, we detail the regression analysis of the correlation time series on the independent variables of uncertainty, credit, activity, and news sentiment and describe our dataset.

3.1. The econometric specification

3.1.1. The VARX-GJR-DECO model

The Errors

MGARCH models have seen a surge in interest not only for financial econometrics research (Engle, 2002; 2016; Engle, Ledoit, & Wolf, 2019; Karanasos et al., 2014) but most importantly for operational research problems (see, for example, Al Janabi et al., 2017; Carroll et al., 2017; Christodoulakis, 2007; Supper et al., 2020). The cDCC (corrected DCC) MGARCH model can be thought of as a *double* MGARCH type of model. To see this explicitly, we will consider two sets of errors, that is the two vector errors: $\varepsilon_{\mathbf{t}}$ in Eq. (A.1) and $\mathbf{e}_t = [e_{it}]$.

Regarding ε_t, we assume that it is conditionally normally distributed with mean vector $\mathbf{0}_{N\times 1}$, and conditional covariance matrix $\mathbf{\Sigma}_t = [\sigma_{ij,t}] = \mathbb{E}(\varepsilon_t \varepsilon_t' | \mathcal{F}_{t-1})$ where $\mathcal{F}_{t-1}$ denotes the information available at time $t-1$. That is, $\sigma_{ij,t} = \mathbb{E}(\varepsilon_{it}\varepsilon_{jt}|\mathcal{F}_{t-1})$. Let $\widetilde{\mathbf{e}}_t = [\widetilde{e}_{it}]$ be the vector of the standardised errors, which follow the conditional standard normal distribution. Let us also denote by $\widetilde{\mathbf{\Sigma}}_t$ the conditional covariance matrix $\mathbf{\Sigma}_t$ with its off-diagonal elements equal to zero. Then ε_t can be expressed as: $\varepsilon_t = \widetilde{\mathbf{\Sigma}}_t^{1/2}\widetilde{\mathbf{e}}_t$, that is $\varepsilon_{it} = \widetilde{e}_{it}\sqrt{\sigma_{ii,t}}$.

It follows from the above analysis that $\mathbf{R}_t = [\rho_{ij,t}]$ where

$$\mathbf{R}_t = \widetilde{\mathbf{\Sigma}}_t^{-1/2}\mathbf{\Sigma}_t\widetilde{\mathbf{\Sigma}}_t^{-1/2}, \tag{1}$$

that is, $\rho_{ij,t} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}}\sqrt{\sigma_{jj,t}}}$, is the conditional correlation matrix of ε_t.

We will assume that the vector of the conditional variances, $\boldsymbol{\sigma_t} = [\sigma_{ii,t}]$, follows an asymmetric TV-MGARCH(1,1) model (see the analysis in the Appendix). In the first step of the VARX-GJR MGARCH model, we will estimate ε_t and $\boldsymbol{\sigma_t}$ (or, equivalently $\widetilde{\mathbf{\Sigma}}_t$), and thus, $\widetilde{\mathbf{e}}_t$.

Similarly, regarding $\mathbf{e}_t$, we assume that it is conditionally normally distributed with mean vector $\mathbf{0}_{N\times 1}$, and conditional covariance matrix $\mathbf{Q}_t = [q_{ij,t}] = \mathbb{E}(\mathbf{e}_t\mathbf{e}_t'|\mathcal{F}_{t-1})$. Let us denote by $\widetilde{\mathbf{Q}}_t$ the conditional covariance matrix $\mathbf{Q}_t$ with its off-diagonal elements equal to zero. In this second step, we assume that $\mathbf{Q}_t$ follows the cDCC model, which is itself a MGARCH type of process (see the analysis below).

It follows from the above analysis that $\mathbf{R}_t$ in Eq. (1) is also the conditional correlation matrix of the vector $\mathbf{e}_t$:

$$\mathbf{R}_t = \widetilde{\mathbf{Q}}_t^{-1/2}\mathbf{Q}_t\widetilde{\mathbf{Q}}_t^{-1/2}, \tag{2}$$

that is $\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}}$. In other words,

$$\rho_{ij,t} = \frac{q_{ij,t}}{\sqrt{q_{ii,t}}\sqrt{q_{jj,t}}} = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}}\sqrt{\sigma_{jj,t}}}. \tag{3}$$

To summarise, the model in the first step estimates the vector ε_t and the vector of the conditional variances $\boldsymbol{\sigma_t}$, using the VARX-GJR MGARCH(1,1) process, and in the second step it estimates the matrix of the conditional covariances of the errors $\mathbf{e}_t$, that is $\mathbf{Q}_t$, using a cDDC process. Once $\boldsymbol{\sigma_t}$ and $\mathbf{Q}_t$ are estimated then the estimated elements of $\mathbf{R}_t$ are obtained using the first equality in Eq. (3), and then the estimated off-diagonal elements of $\mathbf{\Sigma}_t$ are obtained using the second equality in Eq. (3).These are the necessary inputs in a wide variety of operational research applications for risk analytics (see Section 6).

Conditional Correlations

Moreover, the structure of the conditional covariance matrix, $\mathbf{Q}_t$, according to the corrected DCC(1,1) model of Engle (2002) - that is, the cDCC of Aielli (2013) - is expressed as a function of the past (standardised as well) errors:

$$\mathbf{Q}_t = (1-a-b)\mathbf{Q} + a\mathbf{e}_{t-1}\mathbf{e}_{t-1}^{'} + b\mathbf{Q}_{t-1}, \tag{4}$$

where a and b are scalars, $\mathbf{Q} = [q_{ij}]$ is a location correlation parameter matrix and it is commonly assumed to be unit diagonal. For $\mathbf{R}_t$ to be positive-definite it suffices that $\mathbf{Q}_t$ is positive definite, which is the case if a and b are satisfying: $a > 0, b \geq 0$, and $a + b < 1$, and $\mathbf{Q}$ is positive definite (see Aielli, 2013; Engle, 2009).

Notice that we employ the cDCC model, since in Eq. (4) we make use of the vector of $\mathbf{e}_t$ and not just the vector of the standardised errors, $\widetilde{\mathbf{e}}_t$, as in Engle (2002). This correction is necessary because in order for the model to be a MGARCH type of process we need the conditional expectation of the stochastic regressor in Eq. (4) to be equal to the dependent variable, $\mathbf{Q}_t$, and as we have seen from the above analysis: $\mathbb{E}(\mathbf{e}_t\mathbf{e}_t'|\mathcal{F}_{t-1}) = \mathbf{Q}_t$, whereas $\mathbb{E}(\widetilde{\mathbf{e}}_t\widetilde{\mathbf{e}}_t'|\mathcal{F}_{t-1}) \neq \mathbf{Q}_t$. Notice also that Eq. (4) implies that $\mathbf{Q} = \mathbb{E}(\mathbf{Q}_t)$.

It is clear that Engle (2002) and Aielli (2013) specify the conditional correlations as a weighted sum of past correlations since the $\mathbf{Q}_t$ is written as a (correct in the case of Aielli) MGARCH type of process and then transformed to a correlation matrix (see also Karanasos et al., 2016).

Furthermore, the DECO model is built upon the cDCC specification as follows: For computational ease, Engle & Kelly (2012) impose a critical assumption on the calculation of $\mathbf{R}_t$ model in order to estimate dynamic equicorrelation matrices ($\mathbf{R}_t^{DECO}$). Each returns pair should have the same correlation, that is ρ_t^{DECO}. In general, for $N > 2$, the DECO(1,1) correlation matrix is defined as follows:

$$\mathbf{R}_t^{DECO} = (1 - \rho_t^{DECO})\mathbf{I} + \rho_t^{DECO}\mathbf{J},$$

$$\rho_t^{DECO} = \frac{2}{N(N-1)}\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\rho_{ij,t},$$

where $\mathbf{J}$ is the $N \times N$ matrix of ones.

Finally, in the special case of a bivariate specification with assets $N = 2$, the dynamic equicorrelation, ρ_t^{DECO}, equals the cDCC-computed dynamic correlations.

3.1.2. Correlation regression analysis

Next, we attribute the daily time-varying sectoral CDS equicorrelation evolution, computed from the DECO model, to macro and news determinants (*H1* and *H2*). The Fisher transformation of correlations is first applied so that the dependent variable is not restricted to the $[-1, 1]$ interval. The resulting daily time series ρ_t is calculated as follows: $\rho_t = \log(\frac{1+\rho_t^{DECO}}{1-\rho_t^{DECO}})$. Apart from the fifteen bivariate cross-border (EU-US) specifications for each CDS sector, we run two multivariate models with all fifteen indices for each region, where the DECO specification calculates the dynamic equicorrelations series considering all pairwise sectoral correlations in the EU and the US, separately. Each correlation series, ρ_t, is regressed on daily indices of economic policy uncertainty (EPU_t), financial uncertainty (FU_t), infectious disease equity market volatility tracker (ID_t), sovereign (SCR_t) and corporate (CCR_t) credit conditions, economic activity (EC_t), and news sentiment (NS_t), the same macro regressors used in the VARX mean equation (Eq. (A.1)). The regressors selected are tested for their immediate lag effect (first lag) on correlations. While for ID, SCR, CCR, and NS we use a single US or global proxy, for the uncertainty and activity effects we test European and US proxies alternatively. Our stepwise regression procedure incorporates each of the two proxies for each macro effect (EPU, FU, EC) at a time and selects the best model with either the European or the US index for each regressor according to the coefficients' significance, the adjusted R^2 ($\overline{R}^2$) and the information criteria (IC: AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively). Moreover, the first correlation autoregressive lag, ρ_{t-1}, is embodied to eliminate any serial correlation from the regression.

To recap, we estimate the following equation for each cross-border and cross-sector CDS correlation series in order to explain the sectoral credit risk correlation evolution with macro and news drivers and test our first two hypotheses (*H1* and *H2*):

$$\begin{aligned}\rho_t =\ & c_0 + c_1\rho_{t-1} + c_2EPU_{t-1} + c_3FU_{t-1} + c_4ID_{t-1} + c_5SCR_{t-1}\\ & + c_6CCR_{t-1} + c_7EC_{t-1} + c_8NS_{t-1} + u_t,\end{aligned} \quad (5)$$

where c_0 is the constant term and u_t the standard stochastic error term.

3.1.3. Correlation sensitivity analysis

After exploring the drivers of the time-varying sectoral CDS connectedness, we investigate the uncertainty (*H3*) and crisis impact (*H4*) on the determinants of sectoral credit risk correlation dynamics. The sensitivity of the macro-financial and news regressors to EPU levels is measured by adding the EPU interaction terms (multiplying the EPU variable with each macro regressor other than the policy uncertainty) in the correlation regression model (Eq. (5)). Following the commonly applied interaction effects methodology in economic analysis (see, among others, Pastor & Veronesi, 2013), the addition of the EPU interaction terms is used to isolate the macro effects' intensity during periods of high EPU levels. Our third hypothesis (*H3*) is tested through the EPU sensitivity in the following regression, Eq. (6), where the coefficients of the EPU interaction terms are denoted with the superscript ^{EPU}:

$$\begin{aligned}\rho_t =\ & c_0 + c_1\rho_{t-1} + c_2EPU_{t-1} + (c_3 + c_3^{EPU}EPU_{t-1})FU_{t-1} + (c_4\\ & + c_4^{EPU}EPU_{t-1})ID_{t-1} + (c_5 + c_5^{EPU}EPU_{t-1})SCR_{t-1}\\ & + (c_6 + c_6^{EPU}EPU_{t-1})CCR_{t-1} + (c_7 + c_7^{EPU}EPU_{t-1})EC_{t-1}\\ & + (c_8 + c_8^{EPU}EPU_{t-1})NS_{t-1} + u_t.\end{aligned} \quad (6)$$

Then, we focus on the financial and health crisis impact on CDS interdependence. We distinguish between three crisis periods: the Global Financial crisis (GFC), the European Sovereign Debt crisis (ESDC), and the Covid-19 pandemic (COVID) and enrich Eq. (5) with the macro variables' slope dummies corresponding to each crisis period. Following the GFC, ESDC, and COVID timelines, we first construct the respective crisis dummies $d_{CR,t}$, where $CR = GFC, ESDC, COVID$, as follows:

i) $d_{GFC,t} = 1$, if t is in the GFC period else $d_{GFC,t} = 0$,
ii) $d_{ESDC,t} = 1$, if t is in the ESDC period else $d_{ESDC,t} = 0$, and
iii) $d_{COVID,t} = 1$, if t is in the COVID period else $d_{COVID,t} = 0$.

Second, we multiply the crisis dummies with the macro variables to construct the slope dummies for the respective macro effect to include them in Eq. (5). Slope dummies signify the in-crisis macro effects on correlation dynamics. The fourth theoretical hypothesis (*H4*) is investigated through the crisis impact incorporated in the correlation regression analysis as follows:

$$\begin{aligned}\rho_t =\ & c_0 + c_1\rho_{t-1} + (c_2 + c_2^{CR}d_{CR,t-1})EPU_{t-1} + (c_3 + c_3^{CR}d_{CR,t-1})FU_{t-1}\\ & + (c_4 + c_4^{CR}d_{CR,t-1})ID_{t-1} + (c_5 + c_5^{CR}d_{CR,t-1})SCR_{t-1}\\ & + (c_6 + c_6^{CR}d_{CR,t-1})CCR_{t-1}\\ & + (c_7 + c_7^{CR}d_{CR,t-1})EC_{t-1} + (c_8 + c_8^{CR}d_{CR,t-1})NS_{t-1} + u_t,\end{aligned} \quad (7)$$

where $CR = GFC, ESDC, COVID$ and the superscript ^{CR} denotes the coefficients of the crisis slope dummies.

3.2. Data

Next, we present the CDS index data and the macro-financial and news variables driving the sectoral credit risk correlations (see also Table A.1 in the Supplementary Appendix for definitions of the variables). Sectoral CDS indices are used as proxies of credit risk characterising each industry (see also Allen, Powell, & Singh, 2016) and are widely applied as overall benchmarks for investing in the protection against default risk. We choose CDS as the most reliable corporate default risk proxies for our correlation analysis. Various studies argue for the superiority of CDS as a pure credit risk metric and leader in price discovery compared to bond yield indices and credit spreads. Bond pricing data measure several bond features, such as liquidity and tax factors, beyond default risk, which is the focus of the present sectoral empirical analysis (see, for example, Jorion & Zhang, 2007; Tolikas & Topaloglou, 2017, and the literature therein, for thorough discussions on the choice of CDS rather than bond proxies for pure credit risk investigations).

We use daily sectoral five-year CDS index prices for the European Union (EU) and the United States (US). The CDS data, sourced from Refinitiv Eikon Datastream (Credit Market Analysis-CMA Datavision), cover fifteen sectors: Automotive (AUT), Banks

(BNK), Basic Resources (BRS), Chemicals (CHM), Construction Materials (CM), Food & Beverage (FB), Industrial Goods & Services (IND), Insurance (INS), Media (MED), Oil & Gas (OG), Retail (RET), Technology (TEC), Telecommunications (TEL), Travel & Leisure (TL), and Utilities (UTL). Our sectoral coverage includes almost all economic sectors except for two industries with data not available for the EU: Health Care and Personal & Household Goods. The CDS indices are not traded but established to gauge the overall corporate credit risk profile of each industry. They are mostly applied as benchmarks of the CDS sector's systematic risk measurement as opposed to single-name CDS idiosyncratic risk in performance evaluation for investment decisions. They are constructed by averaging the most liquid five-year CDS mid-spreads of the constituent companies, classified under each sector. The CMA CDS indices are equally weighted and frequently rebalanced to better capture market liquidity.

The sample spans from 01/01/2004 to 24/12/2020, giving a total of 4,431 daily observations, apart from the EU IND time series, which starts from 01/08/2004. For each index, the continuously compounded return is computed as: $r_{it} = [\ln(P^C_{i,t}) - \ln(P^C_{i,t-1})] \times 100$, with $P^C_{i,t}$ the daily closing price on day t. CDS index returns are preferred to levels due to unit root considerations. Therefore, our basic credit risk metric is included in its growth form as input for time-varying correlations estimation. Our empirical analysis of sectoral corporate credit risk growth co-movements is in line with studies using CDS index data (Apergis et al., 2019; Grundke & Polle, 2012) and apply the index returns rather than levels. The Augmented Dickey-Fuller (ADF) test rejects the unit root hypothesis (further unit root tests such as the Phillips-Perron (PP) test and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test produce the same conclusions - the results are available upon request). Thus, our dependent variables are suitable for the VARX-GJR-DECO model applied in this study. For robustness purposes, we further test selected CDS spreads of large firms, EU and US leaders in each sector. We use the single-name CDS spreads (returns and log-levels when allowed by unit root tests) as inputs in the DECO specification and observe correlation patterns similar to the sectoral index returns correlations (the results are available upon request). The US CDS indices are on average more volatile than the EU indices. The heterogeneity between EU and US is remarkable in the standard deviation figures of the various sectors. For the EU, the Media and Oil & Gas industries exhibit the lower and higher volatility, respectively. For the US, Industrials are the most stable index returns and Basic Resources the most volatile ones. The pairwise correlation coefficients of all bivariate EU-US combinations of returns are all positive, indicating a strong co-movement of the EU-US sectoral CDS markets. The highest correlation value (0.53) is calculated for the Industrial Goods & Services and the lowest (0.10) for the Retail sector (see Table A.2 in the Supplementary Appendix for the descriptive statistics and unit root tests of the return series). The DECO model will reveal the time-varying features of the conditional correlations and the macro influence on the correlation dynamics.

The daily macro and news factors used as regressors in the mean equation (Eq. (A.1)) and the correlation regressions (Eqs. (5), (6), and (7)) provide evidence of the macro-financial and news sentiment effects on the sectoral CDS mean and correlation evolution (see the theoretical underpinnings of our hypothesis development for the macro and news effects on CDS correlation in Section 2 and the expected signs of correlation determinants in Table A.1). Based on our theoretical hypotheses (*H1* and *H2*), we incorporate seven regressors, as follows:

1. Economic policy uncertainty (EPU_t) is proxied by the daily EPU index in its log-level form, constructed by Baker, Bloom, and Davis (Baker et al., 2016, policyuncertainty.com). We use alternatively the two indices available for the UK ($EPU_{UK,t}$) and the US ($EPU_{US,t}$), as the macro uncertainty factors of the EU region and the US, respectively.
2. Financial uncertainty (FU_t) is proxied by the EU and US stock market implied volatility (IV) indices in their log-level form. We test alternatively the Euro Stoxx 50 IV index VSTOXX ($VSTOXX_{EU,t}$) and the S&P 500 IV ($VIX_{US,t}$).
3. The infectious disease (ID_t) effect on stock markets is captured by the Infectious Disease Equity Market Volatility Tracker (ID_EMV_t) of Baker et al. (2020). ID_EMV is the newspaper-based index (available at policyuncertainty.com) that tracks the effect of news about infectious diseases (e.g. epidemics/pandemics, MERS, SARS, H1N1, Covid-19, etc.) on US stock market volatility.
4. Sovereign credit conditions (SCR_t) are proxied by the log-level of the Merrill Lynch MOVE 1-month index ($MOVE_t$).
5. Corporate credit conditions (CCR_t) are proxied by the global default spread, calculated as the difference between Moody's BAA minus AAA global corporate bond yields (BA_t).
6. Economic activity (EC_t) is proxied by two EU and US proxies alternatively. For the EU, we test the daily change of the European Yield Curve slope (or term spread), as calculated by the difference of 10-year minus 3-month European benchmark government bond yields ($\Delta YCsl_{EU,t}$). For the US, we use the Aruoba-Diebold-Scotti ($ADS_{US,t}$) US business conditions index Aruoba et al. (2009), which tracks daily real business conditions based on economic data releases.
7. News sentiment (NS_t) is proxied by the newly-introduced daily News Sentiment Index (NSI_t) of Shapiro et al. (2020) and Buckman et al. (2020) downloaded from the Federal Reserve Bank of San Francisco dataset (https://www.frbsf.org/economic-research/indicators-data/daily-news-sentiment-index/).

The regressors used cover all major aspects of the macro-financial environment in which the CDS market operates: uncertainty, credit, aggregate activity, and news sentiment[1] For the EPU, IV, and activity effects, we distinguish between the EU and US variables available and test them alternatively as covariates driving the cross-border (EU-US) sectoral connectedness. Given that ID_EMV, MOVE, and NSI are indicators of the US market only, not available for the EU, we consider them as global infectious disease, sovereign credit, and sentiment proxies in our CDS correlation analysis, similar to the global default spread (BA_t). The macro-financial variables data (except for EPU_t, ID_t, and NS_t) are retrieved from Refinitiv Eikon Datastream and FRED economic database (by St. Louis Federal Reserve Bank), for the same sample as the CDS dependent variables. The exogenous macro variables are included in their level ($ID\_EMV_t, BA_t, ADS_{US,t}, NSI_t$), log-level ($EPU_{UK,t}, EPU_{US,t}, VSTOXX_{EU,t}, VIX_{US,t}, MOVE_t$), and daily change of levels ($\Delta YCsl_{EU,t}$) as indicated above in order to ensure, first and foremost, that there is no unit root or multicollinearity[2] in the regressors and, secondly, to select the form with the most significant

[1] We also tested many more macro-financial proxies available with a daily frequency and which have been proposed in the literature on credit risk macro determinants Chan & Marsden (2014). We hereby present the results with the selected jointly significant macro and news effects of Eqs. (A.1) and (5). For example, the TED spread (the difference between three-month libor and three-month T-bill yield) as a funding liquidity proxy is among the macro regressors which are not preferred. It has been estimated significant in many cases but only when included alone as a correlation driver in Eq. (5). For the US economic activity, the ADS index is significant in most cases whereas the US term spread is estimated mostly insignificant, contrary to the significant EU term spread effect in the EU case.

[2] We performed the Variance Inflation Factors (VIF) test for multicollinearity (the results are available upon request). The VIFs calculated for each independent variable are not high enough to distort the regression estimation (VIFs show none, low or moderate correlations among regressors, rejecting the multicollinearity bias).

Table 1
Sectoral CDS equicorrelations: Crisis mean difference tests.

	GFC				ESDC				COVID			
	pre-crisis	in-crisis	mean diff.	*t*-test *F*-test	pre-crisis	in-crisis	mean diff.	*t*-test *F*-test	pre-crisis	in-crisis	mean diff.	*t*-test *F*-test
EU-US_AUT	0.281	0.586	+***	−33.47 1120.0	0.445	0.698	+***	−28.22 796.21	0.639	0.760	+***	−18.94 358.85
EU-US_BNK	0.230	0.286	+***	−7.92 62.79	0.320	0.489	+***	−26.81 718.72	0.448	0.601	+***	−25.37 643.65
EU-US_BRS	0.337	0.426	+***	−5.97 35.62	0.371	0.615	+***	−22.36 499.99	0.606	0.666	+***	−5.40 29.14
EU-US_CHM	0.340	0.389	+***	−4.78 22.83	0.430	0.570	+***	−14.10 198.89	0.646	0.691	+***	−5.86 34.37
EU-US_CM	0.385	0.530	+***	−15.61 243.62	0.489	0.586	+***	−14.62 213.72	0.422	0.570	+***	−9.54 100.00
EU-US_FB	0.393	0.497	+***	−15.74 247.72	0.483	0.482	−	0.24 0.06	0.346	0.487	+***	−12.83 164.67
EU-US_IND	0.438	0.611	+***	−14.18 201.06	0.611	0.670	+***	−7.68 58.98	0.620	0.656	+***	−3.47 12.02
EU-US_INS	0.293	0.410	+***	−30.44 926.56	0.352	0.299	−***	9.55 91.25	0.414	0.500	+***	−19.66 386.55
EU-US_MED	0.476	0.483	+	−0.40 0.16	0.396	0.567	+***	−15.22 231.57	0.406	0.532	+***	−7.07 49.92
EU-US_OG	0.446	0.623	+***	−25.97 674.47	0.542	0.636	+***	−12.69 160.99	0.434	0.386	−***	2.52 6.33
EU-US_RET	0.414	0.583	+***	−10.67 113.86	0.522	0.574	+***	−4.42 19.50	0.215	0.382	+***	−7.38 54.41
EU-US_TEC	0.431	0.530	+***	−7.80 60.88	0.473	0.502	+***	−3.03 9.16	0.492	0.556	+***	−5.08 25.77
EU-US_TEL	0.353	0.511	+***	−18.05 325.92	0.459	0.527	+***	−12.66 160.33	0.091	0.346	+***	−21.43 459.09
EU-US_TL	0.358	0.416	+***	−4.18 17.48	0.336	0.519	+***	−22.12 489.31	0.577	0.592	+	−1.37 1.88
EU-US_UTL	0.386	0.553	+***	−24.08 579.91	0.502	0.433	−***	10.23 104.67	0.499	0.542	+***	−4.03 16.25
EU_ALL	0.351	0.673	+***	−55.92 3127.5	0.626	0.666	+***	−9.23 85.10	0.533	0.695	+***	−20.88 435.80
US_ALL	0.373	0.533	+***	−13.92 193.62	0.489	0.680	+***	−26.35 694.26	0.423	0.529	+***	−8.33 69.31

Notes: The table reports the mean difference tests of the sectoral CDS equicorrelations across the three crisis periods (GFC, ESDC, COVID). 'Pre-crisis' and 'in-crisis' columns report the CDS correlation mean values in the pre-crisis and in-crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the correlations during the crisis subsample. ***, **, * denote the significance of the mean difference test at the 0.01, 0.05, 0.10 levels, respectively. '*t*-test' and '*F*-test' are the two mean difference test statistics, that is the Satterthwaite-Welch *t*-test and Welch *F*-test statistics, respectively. The equicorrelations are computed for each bivariate cross-country EU-US (EU-US_) sectoral CDS combination (denoted by the sector's notation: AUT, BNK, BRS, CHM, CM, FB, IND, INS, MED, OG, RET, TEC, TEL, TL & UTL) and the two 15-variate cross-sector combinations for the EU (EU_ALL) and the US (US_ALL).

effect on equicorrelations (see Table A.3 in the Supplementary Appendix for the summary statistics of the independent variables in the mean and DECO-X equations, with the ADF test rejecting the unit root hypothesis for all regressors).

Finally, in the crisis sensitivity analysis of the sectoral CDS correlations (*H4*), we use the GFC, ESDC, and COVID crisis timelines as defined by the Bank for International Settlements and the Federal Reserve Bank of St. Louis, for GFC, the European Central Bank, for ESDC, and the World Health Organisation, for COVID. The crisis periods are as follows:

- GFC: 09/08/2007 - 31/03/2009. The GFC period starts with the announcement that three major BNP Paribas investment funds have been suspended and ends in the first quarter of 2009 with gradual restoration of markets' 'tranquillity'.
- ESDC: 09/05/2010 - 31/12/2012. The ESDC period starts with the Greek state default and bailout package in May 2010 by the International Monetary Fund, the European Commission, and the European Central Bank. For most Eurozone countries the ESDC ends at the end of 2012.
- COVID: 09/01/2020 - 24/12/2020. The COVID period starts with the first death reported by China in January 2020, while the pandemic crisis is still in place until the end of our sample.

During crisis times, the whole macro environment weakens, with uncertainty increasing, credit conditions tightening, economic activity and agents' confidence contracting, or even slumping sharply. In the special case of a health crisis, we also observe the sound effect of infectious disease news on financial markets' turbulence (see Table A.3, for the time variation of the mean value for each macro and news variable across the crisis subsamples, and Figures A.1–A.10 of the Supplementary Appendix). Both economic and financial uncertainty, captured by EPU and IV indices, are higher on average during all crises, while ID_EMV shows a sharp jump, mostly in the recent pandemic. Credit conditions tightening is mostly observed during the two financial crises (GFC and ESDC), with higher treasury volatility and corporate default spread on average. During the COVID period, the MOVE index increased but its average value in the pandemic subsample is not higher than the overall average of the whole sample, whereas the COVID period average of the default spread exceeds the overall time series mean value. Regarding the activity variables, the daily change of the EU term spread ($\Delta YCsl_{EU,t}$) is more negative during the European debt crisis and the pandemic, denoting an economic slowdown. In the GFC period, the average is calculated with a positive value, while the level of the yield curve slope reaches its minimum during the 2008 financial crash. The US activity indicator ($ADS_{US,t}$) average is significantly lower in the GFC and COVID crisis. Finally, news sentiment decreases across all crisis subsamples, signifying agents' lack of 'positive' feelings, e.g. business/consumer confidence/optimism, during economic turmoil. Intriguingly, four out of six US macro proxies and the global default spread show their vulnerability not only in the two global crises (GFC and COVID) but during the ESDC, as well. The European debt crisis obviously conveys considerable spillovers to the US fundamentals. ID_EMV in-crisis mean values increase beyond the overall mean only in the pandemic while ADS does not fall further from the total average during the ESDC. Thus, only the US activity proxy is resilient to European spillovers. Our CDS analysis will provide sound evidence that sectoral credit risk correlations are higher during crises and the macro and news drivers' effect becomes more intense partly driven by crisis shocks (*H4*) and the uncertainty channel (*H3*).

4. Empirical analysis

4.1. DECO Model estimation

In this section, within the TV-MGARCH framework with shock spillovers, we analyse the dynamic CDS correlations for the European and US CDS sectoral indices. Overall, we estimate fifteen pairwise (bivariate) cross-border EU-US correlations for each CDS sector and two cross-sectoral (same-country) equicorrelations of all fifteen sectors for each region (EU and US). Moreover, we regress the correlations computed by the DECO model on daily macro and news factors.

The first step of the VARX-GJR-DECO model estimates mean (Eq. (A.1)) and variance (Eq. (A.2)) and the second step the equicorrelation equation for each CDS returns combination (the results are available upon request). Next, we extract the time-varying equicorrelations computed by the VARX-GJR-DECO process (graphs in Figures B.1–B.17 and summary statistics in Table B.1 of the Supplementary Appendix). Credit risk correlations are on average positive and remarkably high, around 0.5. The maximum mean value of the cross-border (EU-US_) correlations is observed in the Industrial Goods & Services sector (EU-US_IND) and the minimum is calculated for the Insurance industry (EU-US_INS). In the two cross-sector (same-country) correlation series, European industries (EU_ALL) are on average more correlated than the US case (US_ALL). Interestingly, looking at the top and bottom five mean values of the EU-US pairs, the lowest correlations on average are observed in the two financial services sectors, Retail, Utilities, and Telecommunications while the most connected industries are the 'heavier' manufacturers (Industrials, Oil & Gas, Automotive, Technology, Chemicals).

Focusing on the crisis sensitivity of the CDS correlation pattern, we can further diagnose credit risk contagion and higher or lower interdependence phenomena across the cross-border and cross-sector dimensions. We proceed with mean difference significance tests (Satterthwaite-Welch t-test and Welch F-test) to compare the pre-crisis and in-crisis CDS correlation time series averages. In Table 1, we present our credit risk dependence analysis around the three crisis periods for each correlation time series. The pre-crisis subsamples are of the same length as the corresponding in-crisis period.[3] Following Forbes & Rigobon (2002), contagion can be diagnosed by the significant increase in correlations in response to the crisis shock given a positive in-crisis correlation level. If the increase is insignificant, we can infer higher interdependence. In the case of a significant or insignificant decrease, there is lower CDS interdependence. Since all in-crisis correlations are positive, we should rule out flight-to-quality incidents even with decreasing correlations (see also Baur & Lucey, 2009). The mean difference tests demonstrate a significant increase of the correlation trajectory from the pre-crisis to the crisis level for most CDS combinations, signifying strong contagion phenomena across all crisis episodes. In the cross-sector (same country) case, both EU_ALL and US_ALL equicorrelations show a contagion pattern for all crises. In the cross-border case, only four cases indicate lower interdependence, that is FB, INS, and UTL in ESDC, and OG in COVID. The correlations decrease is mostly small while, for FB, it is insignificant. Moreover, there are two CDS combinations, MED and TL, where the correlations increase is insignificant (during GFC and COVID, respectively), meaning higher interdependence.

We notice significantly elevated interdependence during the global turmoil of 2008, the European debt crisis, and the Coronavirus crisis, in line with previous studies such as Chen et al. (2020), who find cross-border contagion of sovereign credit risk during crises. Although for most correlations the graphical displays (Figures B.1–B.17) show similar fluctuations across time, there are some distinct features of sectoral differentiation. The evolution of certain cross-border correlations does not exhibit wide in-crisis fluctuations away from the overall average (see, for example, EU-US_FB, IND, TEC in Figures B.6, B.7, B.12). Moreover, the first crisis timing is closer to the initial establishment of the CDS markets and could justify a lower degree of global integration in a relatively shallow or illiquid market stance. The European debt crisis shock is not confined inside the European borders but propagated across all US economic sectors. In the recent pandemic era, for many sectors, we observe higher COVID-average correlations than the respective GFC and ESDC mean values. As expected, higher correlations are also computed in the Brexit referendum turbulence (June 2016) for many cases. Overall, post-crisis dynamic correlations return to higher than the pre-crisis levels of the early 2000s for most sectors, confirming the accelerated degree of sectoral integration and more intense systemic threats to financial stability. In what follows, we explain this integration process with common economic factors. Macro and news forces drive dynamic credit risk correlations and show a similar fluctuation pattern during crises, with uncertainties soaring, credit squeezes, activity contracting, and positive sentiment dropping (Figures A.1–A.10). Since higher CDS correlations are mainly attributed to poor fundamentals as a result of a crisis shock and subsequent recessionary consequences, we can conjecture cross-border and cross-sector credit contagion effects.

4.2. CDS correlation regressions

We further regress the dynamic CDS equicorrelations computed by the multivariate DECO specification on global and local macro-financial and news variables in order to identify the drivers of the sectoral credit risk co-movement. The unit root tests (i.e. ADF tests) ensure that correlation levels can be used as dependent variables since there is no unit root in the time series. Table 2 presents the estimation results of the correlation regressions (Eq. (5)), revealing the macro determinants of correlation dynamics. For the three regressors (EPU, FU, EC) with two alternative proxies available, we choose the preferred model based on significance and model selection statistical criteria (AIC, BIC, $\overline{R}^2$). Both EU and US uncertainty and activity proxies are significant but in most cases, we prefer the EU/UK indices (details about the indices choice are omitted due to space considerations but they are available upon request). Equation (5) estimation further shows a high persistence in correlation time series.[4]

Our first regression results provide sound evidence on the macro and news drivers of cross-border and cross-sector CDS correlation evolution, confirming our first two hypotheses (*H1* and*H2*). We do not observe any sectoral variation but a remarkable uniformity in the common forces driving all the correlations examined. The macro coefficients' signs are estimated as expected by our theoretical underpinnings (positive effect from uncertainty, disease, credit and negative from activity, news sentiment). Their significance is high in most cases except for the infectious disease proxy. The ID_t exacerbating impact on correlations is significant in seven out of seventeen equicorrelation series in the whole sample. However, we will show that it becomes significant in all cases when we consider the COVID period separately (Section 5.2). Increased sectoral credit risk correlations are associated with elevated economic and financial uncertainty, infectious disease influence on stock markets, and tighter credit conditions (*H1*), while decreased correlations are related to elevated economic activity (*H1*) and agents' positive sentiment on economic news (*H2*). Thus, we demonstrate the counter-cyclicality of CDS correlations. Fundamentals associated with weak economic conditions (uncertainty, disease, and tighter credit) exacerbate CDS correlations, while activity growth and confidence indicators lower sectoral CDS interdependence.

Overall, our initial regression analysis of CDS correlation evolution gives homogeneous findings for all sectoral dependences

[3] For robustness purposes, we also consider alternative pre-crisis subsamples (one or two years before the start of each crisis) and result in similar conclusions.

[4] Therefore, for robustness checking purposes, we additionally regress the correlation series growth ($\Delta\rho_t = \frac{\rho_t}{\rho_{t-1}} - 1$) on the same macro factors. The conclusions are similar to the empirical analysis of the correlation levels (the results are available upon request).

Table 2
Sectoral CDS dynamic equicorrelations regressions on macro and news factors, Eq. (5).

	c_0	ρ_{t-1}	EPU_{t-1}	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}	AIC BIC	DW $\overline{R}^2$
AUT	0.3815*** (5.41)	0.9541*** (70.90)	0.0020* (1.84)	0.0427** (2.14)	0.0005 (1.41)	0.0666*** (2.86)	0.0293** (1.98)	−0.0039* (−1.81)	−0.0300* (−1.77)	−4.6587 −4.6457	1.9881 0.9865
BNK	0.2081*** (3.54)	0.9644*** (66.78)	0.0013** (2.05)	0.0145* (1.69)	0.0009 (1.34)	0.0694*** (2.90)	0.0261*** (2.47)	−0.0046* (−1.85)	−0.0209* (−1.89)	−5.2306 −5.2162	1.9520 0.9910
BRS	0.4579*** (11.08)	0.9416*** (40.48)	0.0041*** (2.53)	0.0836* (1.80)	0.0058** (2.23)	0.0724*** (2.45)	0.0342** (2.13)	−0.0097** (−2.33)	−0.0718** (−2.23)	−3.1665 −3.1535	1.9925 0.9654
CHM	0.2899*** (4.05)	0.9432*** (75.49)	0.0018** (2.27)	0.0513** (2.01)	0.0004 (0.15)	0.0622*** (2.49)	0.0112 (0.90)	−0.0086** (−2.05)	−0.0224*** (−2.49)	−4.6052 −4.5922	1.9936 0.9862
CM	0.0828 (0.86)	0.9445*** (22.70)	0.0037** (2.13)	0.1221*** (3.08)	0.0096** (2.17)	0.1356*** (2.76)	0.0559** (2.25)	−0.0099* (−1.84)	−0.1437*** (−4.32)	−3.9601 −3.9427	2.0075 0.9824
FB	0.1322*** (6.49)	0.9417*** (66.36)	0.0071** (1.99)	0.1338*** (2.73)	0.0009 (0.26)	0.0692* (1.66)	0.0221* (1.64)	−0.0148** (−2.36)	−0.0582** (−2.37)	−3.0020 −2.9890	1.9885 0.9648
IND	0.1943* (1.68)	0.9355*** (93.29)	0.0075*** (2.46)	0.1543*** (3.50)	0.0040* (1.71)	0.1191** (2.00)	0.0384* (1.69)	−0.0052* (−1.63)	−0.0659** (−1.98)	−3.1087 −3.0909	1.9976 0.9651
INS	0.2515*** (6.67)	0.9645*** (62.03)	0.0098*** (2.55)	0.0266** (1.97)	0.0010 (1.21)	0.0355*** (2.82)	0.0144** (2.05)	−0.0026* (−1.74)	−0.0179** (−2.34)	−6.3031 −6.2901	1.9503 0.9934
MED	0.1740* (1.64)	0.9578*** (78.37)	0.0079* (1.85)	0.1330** (2.08)	0.0035 (1.05)	0.0804* (1.66)	0.0460* (1.69)	−0.0190* (−1.69)	−0.1331*** (−3.02)	−4.5411 −4.5281	1.9876 0.9854
OG	0.1765** (2.28)	0.9256*** (44.58)	0.0039** (2.33)	0.0599* (1.67)	0.0061 (1.16)	0.1595** (2.32)	0.0110** (2.30)	−0.0156*** (−2.51)	−0.0701*** (−2.43)	−4.8332 −4.8159	2.0277 0.9872
RET	0.0765*** (3.57)	0.9372*** (80.36)	0.0242*** (2.99)	0.1373*** (4.80)	0.0105 (1.17)	0.1615*** (3.25)	0.1160*** (2.57)	−0.0354*** (−2.57)	−0.0480*** (−2.70)	−3.2102 −3.1928	2.0033 0.9715
TEC	−0.1395 (0.87)	0.9210*** (134.23)	0.0118** (2.41)	0.2035*** (3.35)	0.0161** (2.28)	0.1552*** (3.30)	0.1132*** (3.50)	−0.0138** (−1.95)	−0.0547** (−2.09)	−3.2568 −3.2438	1.9737 0.9721
TEL	0.2768*** (3.90)	0.9854*** (81.96)	0.0126*** (2.44)	0.0400*** (3.12)	0.0025* (1.71)	0.0428** (2.17)	0.0101** (2.08)	−0.0346** (−2.05)	−0.0360*** (−2.61)	−5.0650 −5.0477	1.9382 0.9885
TL	0.1422*** (2.47)	0.9775*** (40.34)	0.0049*** (2.96)	0.1082*** (3.24)	0.0058* (1.87)	0.0738** (2.28)	0.0148* (1.67)	−0.0121*** (−2.49)	−0.0539* (−1.78)	−3.3043 −3.2870	2.0372 0.9766
UTL	0.0510* (1.71)	0.9679*** (32.19)	0.0058*** (2.45)	0.0449* (1.80)	0.0017 (0.61)	0.1376*** (3.02)	0.0268* (1.64)	−0.0209** (−2.27)	−0.0343** (−2.24)	−3.7834 −3.7660	1.9830 0.9810
EU_ALL	0.3310*** (5.06)	0.9724*** (65.40)	0.0024** (2.19)	0.0475*** (2.53)	0.0029** (2.23)	0.0902*** (3.29)	0.0181* (1.77)	−0.0043** (−2.12)	−0.0375*** (−2.56)	−5.0128 −4.9950	1.9812 0.9874
US_ALL	−0.1459** (−2.12)	0.9782*** (39.25)	0.0051* (1.85)	0.1860*** (4.81)	0.0028 (1.31)	0.1819*** (3.06)	0.0416* (1.76)	−0.0156** (−2.28)	−0.0808*** (−2.80)	−3.3538 −3.3360	1.9724 0.9768

Notes: The table reports the estimation results of the CDS dynamic equicorrelations regressions on macro and news factors Eq. (5) for each bivariate cross-country EU-US sectoral CDS combination (denoted by the sector's notation: AUT, BNK, BRS, CHM, CM, FB, IND, INS, MED, OG, RET, TEC, TEL, TL & UTL) and the two 15-variate cross-sector combinations for the EU (EU_ALL) and the US (US_ALL). Each equicorrelation series is explained by a constant (c_0), the first autoregressive term (ρ_{t-1}), and the macro and news regressors (EPU_t, FU_t, ID_t, SCR_t, CCR_t, EC_t & NS_t). The numbers in parentheses are t-statistics. ***, **, * denote the significance at the 0.01, 0.05, 0.10 levels, respectively. AIC and BIC are the Akaike and the Schwartz Information Criteria, respectively. DW is the Durbin-Watson statistic. $\overline{R}^2$ is the adjusted R^2.

which are alarming for both market players and policymakers. In economic slowdowns with all correlations heightening, investors lose possible diversification benefits from positions in different sectors and increase their hedging costs (see in Section 6 the discussion on the operational research implications for risk and portfolio managers). Most importantly, regulators should be prudent about facing systemic risk alarms given that most industries' default risk would increase synchronously. Although the results appear to be homogeneous in terms of significance, we detect some differences in the magnitude (the size of the regressors' coefficients estimated) of macro and news effects across the sectoral combinations. This is a first indication that our findings are picking up on what is sector-specific rather than being dominated by a market effect. In the cross-border case, the Retail sector's correlations receive the highest impact, in absolute terms, from agents' uncertainty feelings (EPU), both sovereign and corporate credit conditions variables (SCR and CCR), and economic activity (EC). Equities uncertainty (FU) and infectious disease (ID) proxies affect most the Technology sectoral nexus, while the news sentiment parameter is higher for Construction Materials. In the cross-sector (same-country) case, all regressors' coefficients (except for the ID) are higher in the US correlation analysis compared to the EU one. Therefore, although we diagnose similar macro effects, in terms of significance, across all correlations, the sectoral differences detected show that the Retail cross-border and US cross-sector linkages are more vulnerable to fundamentals than the other industry combinations. In this vein, according to the magnitude of the macro effects estimated, regulatory authorities and market practitioners should focus more on the most macro-sensitive cases (Retail and US sectoral co-movements). Operational research approaches in credit contagion, asset allocation, and risk mitigation (Calabrese & Crook, 2020; Carroll et al., 2017; Jayech, 2016; Supper et al., 2020) need to directly incorporate such macro-considerations in estimating sectoral credit co-movements.

5. Sensitivity analysis

After the identification of the economic factors driving sectoral credit risk co-movements, we proceed with the sensitivity analysis of the drivers' impact across the business cycle. We first elaborate on our third hypothesis (*H3*) and investigate the uncertainty channel for the transmission of the macro and news effects, since uncertainty surges are associated with recessionary cycles. Next, we explore crisis shocks to quantify the macro effects under economic downturn conditions and come to a conclusion on our last hypothesis (*H4*).

5.1. The uncertainty channel

The crucial EPU role in CDS correlation dynamics is further investigated with the indirect EPU impact on sectoral credit risk interdependence through the macro and news factors that explain this interdependence. Hence, we answer the question of whether EPU affects correlation evolution not only directly but also indirectly through the economic forces that explain dynamic CDS equicorrelations. Our conclusions have significant implications for operational research solutions implemented by macro-informed investors in the CDS market and policymakers' financial stability considerations and systemic risk supervision. The cross-border and cross-sector corporate credit risk correlation trajectories merit the attention of both investors in portfolio and risk management and regulatory authorities in their proactive risk assessment of the financial system. Although empirical evidence on the link between CDS spreads and uncertainty shows that higher uncertainty increases CDS spreads (Wang et al., 2019), researchers have overlooked the EPU impact (direct and indirect) on CDS correlations, among other macro-financial effects. Against this backdrop, in Section 4.2 we demonstrated the direct EPU impact on CDS correlations, which is positive and significant in all cases. In this

Table 3
The EPU effect on the macro and news drivers of CDS correlations, Eq. (6).

$EPU_{t-1}\times$	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}
AUT	0.0182*** (2.58)	0.0001* (1.82)	0.0206** (2.36)	0.0021*** (2.73)	−0.0015*** (−2.93)	−0.0059*** (−2.56)
BNK	0.0090* (1.81)	0.0003* (1.76)	0.0210*** (2.85)	0.0056*** (2.75)	−0.0019* (−1.90)	−0.0008* (−1.66)
BRS	0.0248* (1.68)	0.0017*** (2.87)	0.0379** (2.37)	0.0036*** (2.55)	−0.0033** (−2.14)	−0.0162* (−1.91)
CHM	0.0014** (2.24)	0.0002 (0.52)	0.0036* (1.66)	0.0010 (0.80)	−0.0019** (−2.38)	−0.0091*** (−2.99)
CM	0.0174* (1.65)	0.0030* (1.92)	0.0256*** (2.64)	0.0059* (1.90)	−0.0040** (−2.04)	−0.0329*** (−3.31)
FB	0.0514*** (2.82)	0.0006 (0.46)	0.0257*** (2.59)	0.0030** (1.97)	−0.0054** (−2.36)	−0.0221*** (−2.55)
IND	0.0563*** (3.53)	0.0014* (1.82)	0.0474*** (2.49)	0.0018* (1.70)	−0.0020* (−1.83)	−0.0193** (−1.96)
INS	0.0109** (2.06)	0.0003 (1.14)	0.0103*** (2.65)	0.0021* (1.69)	−0.0010* (−1.71)	−0.0052** (−2.27)
MED	0.0604** (1.96)	0.0012 (0.98)	0.0210** (2.02)	0.0038** (1.99)	−0.0077* (−1.70)	−0.0375*** (−3.13)
OG	0.0118* (1.66)	0.0021 (1.09)	0.0405** (2.28)	0.0052* (1.80)	−0.0047*** (−2.46)	−0.0221** (−2.05)
RET	0.0272*** (3.55)	0.0026 (0.79)	0.0121*** (2.61)	0.0126** (2.15)	−0.0134*** (−2.48)	−0.0461** (−2.17)
TEC	0.0924** (2.08)	0.0054** (2.14)	0.0329** (2.31)	0.0210*** (2.48)	−0.0057** (−1.94)	−0.0096*** (−2.64)
TEL	0.0162*** (3.34)	0.0010* (1.80)	0.0181*** (2.73)	0.0050*** (2.45)	−0.0107** (−1.95)	−0.0171*** (−3.62)
TL	0.0373*** (3.05)	0.0020** (1.99)	0.0372*** (2.61)	0.0058* (1.65)	−0.0050*** (−2.56)	−0.0166* (−1.70)
UTL	0.0314* (1.67)	0.0007 (0.70)	0.0148** (2.31)	0.0030* (1.65)	−0.0081** (−2.17)	−0.0170** (−2.13)
EU_ALL	0.0189*** (2.80)	0.0009** (2.12)	0.0290*** (3.30)	0.0050** (2.06)	−0.0015** (−1.97)	−0.0151*** (−3.44)
US_ALL	0.0663*** (4.72)	0.0005 (1.28)	0.0567*** (3.22)	0.0105** (1.93)	−0.0058** (−2.18)	−0.0284*** (−3.17)

Notes: The table reports the EPU effect on the macro and news factors' impact on CDS dynamic equicorrelations (Eq. (6)) for each bivariate cross-country EU-US sectoral CDS combination (denoted by the sector's notation: AUT, BNK, BRS, CHM, CM, FB, IND, INS, MED, OG, RET, TEC, TEL, TL & UTL) and the two 15-variate cross-sector combinations for the EU (EU_ALL) and the US (US_ALL). The coefficients of each EPU interaction term, estimated separately, are displayed. The EPU interaction terms are calculated by the multiplication of EPU ($EPU_t\times$) with each macro regressor (FU_t, ID_t, SCR_t, CCR_t, EC_t & NS_t). The numbers in parentheses are t-statistics. ***, **, * denote the significance at the 0.01, 0.05, 0.10 levels, respectively.

Section, we measure the indirect EPU effect on equicorrelations through their macro and news drivers to explore the validity of *H3*. Table 3 presents the estimates of the interaction term coefficients of Eq. (6). We report the uncertainty effect on each correlation determinant estimated from restricted forms of Eq. (6). Every restricted Eq. (6) form includes each EPU effect separately (each coefficient with the superscript ^{EPU} is incorporated separately).

The results show that all EPU interaction terms have the same sign, with the respective macro regressor adding an increment to the respective macro effect. Therefore, we deduce that higher levels of policy uncertainty lead to a more profound impact from financial uncertainty, infectious disease, credit, economic activity, and news sentiment on sectoral CDS correlations, confirming *H3*. Contributing to existing evidence that widespread uncertainty is a common recessionary feature, we demonstrate here that EPU drives or explains the credit risk co-movement determinants by magnifying their effect. Financial uncertainty, disease, and credit EPU interaction terms are always positive and mostly significant, while the activity and sentiment terms are negative. The disease factor associated with the EPU impact is positive and significant in two more sectoral correlations (nine out seventeen) than the direct disease impact (seven out of seventeen) in the baseline regression analysis (Eq. (5), Table 2). All macro and news determinants earn a substantial economic uncertainty impact common for all corporate credit risk dependences. Hence, we conclude that sectoral CDS correlations are consistently intensified by EPU, which also reinforces the influence of the other economic drivers in line with *H3*. Our results should encourage policymakers to assess both the direct and side effects of EPU shocks on the intersectoral CDS contagion. The EPU channel is an economic uncertainty factor closely related to agents' lack of confidence about policy interventions.

5.2. The crisis impact

In this Section, we extend the regression analysis of credit risk correlation evolution in the total sample, by investigating the crisis impact on correlations and their macro regressors, making use of crisis subperiods. In particular, the focus here is on the GFC, ESDC, and COVID repercussions. We demonstrate that the explanatory variables' parameters estimated are not constant but exhibit a time-varying behaviour around a crisis shock, signifying the crisis impact on the cross-border and cross-sector CDS correlation pattern. We include crisis slope dummies in the DECO-X regression (Eq. (5)) and estimate Eq. (7) for each crisis period. The crisis impact on the time-varying macro effects is captured by the slope dummies' coefficients with the ^{CR} superscript. In Table 4 , we sum up the crisis effect on each macro regressor as estimated through alternative restricted forms of Eq. (7) by including each slope dummy separately.

The Three Crises: The crisis analysis confirms our fourth hypothesis (*H4*), with most macro and news factors exerting a more profound influence on dynamic credit risk correlations during crisis periods (always positive crisis increment for uncertainty, disease, and credit, negative for activity and news sentiment). In the GFC subsample (Table 4, Panel A), when CDS markets were closer to their infancy and less connected across borders, we observe most significant crisis effects concentrated on uncertainties and news for EU-US pairs. However, for the cross-sector (same-country) connectedness (EU_ALL and US_ALL), the GFC effect is significant for all macro regressors apart from ID_t in the US case. Moreover, ESDC and COVID effects (Table 4, Panels B & C) are estimated significant in most CDS correlations, indicating that the latter two crises exacerbate the impact of most correlation determinants. The

Table 4
The Crisis effect on the macro and news drivers of CDS correlations, Eq. (7).

Panel A. GFC effect.

$d_{GFC,t-1}\times$	EPU_{t-1}	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}
AUT	0.0032** (2.28)	0.0082*** (2.65)	0.0023 (1.39)	0.0066*** (4.62)	0.0070*** (2.91)	−0.0022* (−1.65)	−0.0168*** (−2.64)
BNK	0.0036** (2.02)	0.0098* (1.69)	0.0015 (1.08)	0.0030 (0.86)	0.0050*** (3.93)	−0.0038 (−0.86)	−0.0084** (−2.41)
BRS	0.0036*** (2.49)	0.0012* (1.84)	0.0003 (1.32)	0.0025 (0.75)	0.0009 (0.58)	−0.0036 (−0.81)	−0.0105** (−2.34)
CHM	0.0041** (2.37)	0.0044* (1.85)	0.0023 (1.24)	0.0031 (1.01)	0.0021 (0.72)	−0.0035 (−0.86)	−0.0455*** (−2.93)
CM	0.0192*** (2.53)	0.0200** (2.13)	0.0035 (0.71)	0.0065 (0.70)	0.0144 (0.80)	−0.0019 (−0.12)	−0.0156* (−1.78)
FB	0.0085** (2.30)	0.0054* (1.66)	0.0055 (0.87)	0.0077 (0.84)	0.0099 (1.00)	−0.0050 (−0.32)	−0.0847*** (−2.55)
IND	0.0017** (2.26)	0.0049** (2.41)	0.0043 (0.66)	0.0041* (1.74)	0.0090** (1.98)	−0.0086*** (−2.54)	−0.0493*** (−2.63)
INS	0.0058* (1.72)	0.0072*** (2.60)	0.0033 (0.37)	0.0010* (1.64)	0.0022 (1.26)	−0.0017 (−0.69)	−0.0113** (−2.05)
MED	0.0067*** (2.56)	0.0028** (2.16)	0.0047 (0.62)	0.0013 (0.12)	0.0266 (1.16)	−0.0107 (−0.44)	−0.1067** (−2.07)
OG	0.0013** (2.14)	0.0259* (1.81)	0.0021 (1.13)	0.0119*** (2.79)	0.0058*** (2.57)	−0.0139** (−2.20)	−0.0859*** (−2.92)
RET	0.0054** (2.18)	0.0158** (2.41)	0.0015 (0.76)	0.0451*** (2.63)	0.0384** (2.13)	−0.0274*** (−2.46)	−0.0972*** (−2.44)
TEC	0.0140*** (2.43)	0.0199* (1.69)	0.0660*** (3.74)	0.0287* (1.67)	0.0215*** (3.65)	−0.0413* (−1.68)	−0.0553** (−2.37)
TEL	0.0079** (2.29)	0.0020*** (3.52)	0.0020 (1.54)	0.0086*** (2.46)	0.0045** (2.24)	−0.0155*** (−2.67)	−0.0313** (−2.40)
TL	0.0092** (2.33)	0.0101* (1.80)	0.0038 (0.87)	0.0107 (0.90)	0.0063 (0.16)	−0.0271 (−1.09)	−0.0868* (−1.82)
UTL	0.0082*** (2.45)	0.0048* (1.72)	0.0017 (0.39)	0.0126*** (3.30)	0.0185** (1.97)	−0.0041** (−2.04)	−0.0130** (−2.26)
EU_ALL	0.0045** (2.04)	0.0032*** (2.49)	0.0034** (2.12)	0.0026*** (2.62)	0.0066* (1.65)	−0.0042* (−1.85)	−0.0353** (−2.34)
US_ALL	0.0057*** (2.63)	0.0121*** (2.79)	0.0047 (0.78)	0.0117** (2.07)	0.0114** (2.02)	−0.0030*** (−3.25)	−0.0029*** (−2.48)

Panel B. ESDC effect.

$d_{ESDC,t-1}\times$	EPU_{t-1}	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}
AUT	0.0013* (1.80)	0.0041** (2.11)	0.0094 (0.83)	0.0157** (1.96)	0.0248* (1.69)	−0.0126** (−2.02)	−0.0492** (−2.11)
BNK	0.0014* (1.81)	0.0061 (1.51)	0.0021 (1.26)	0.0038** (2.10)	0.0022* (1.69)	−0.0066*** (−3.01)	−0.0038 (−1.31)
BRS	0.0015*** (2.45)	0.0056 (1.43)	0.0235** (2.25)	0.0025 (0.92)	0.0001 (0.30)	−0.0074*** (−2.86)	−0.0070** (−1.97)
CHM	0.0070* (1.75)	0.0270* (1.91)	0.0064 (0.65)	0.0279* (1.79)	0.0497* (1.75)	−0.0275*** (−4.47)	−0.0540*** (−2.87)
CM	0.0018** (2.17)	0.0809*** (2.97)	0.0179* (1.71)	0.0403*** (2.72)	0.0623*** (2.52)	−0.0111*** (−2.49)	−0.1159* (−1.66)
FB	0.0016** (2.34)	0.0010* (1.77)	0.0053* (1.80)	0.0028** (2.30)	0.0053 (0.93)	−0.0504** (−2.10)	−0.0069** (−2.14)
IND	0.0132** (2.16)	0.0291** (2.14)	0.0102** (2.38)	0.0321 (0.61)	0.0161 (0.65)	−0.0265 (−0.48)	−0.0116** (−2.15)
INS	0.0023** (2.19)	0.0302*** (2.62)	0.0010 (0.25)	0.0025 (0.80)	0.0060 (1.12)	−0.0030 (−1.00)	−0.0078** (−2.35)
MED	0.0236** (1.97)	0.0351* (1.82)	0.0027 (0.77)	0.0044* (1.81)	0.0124 (1.00)	−0.0207* (−1.85)	−0.1278** (−2.24)
OG	0.0206** (2.22)	0.0819** (2.00)	0.0065 (0.23)	0.0668** (2.08)	0.0146** (2.42)	−0.0201*** (−2.70)	−0.1591** (−2.00)
RET	0.0286** (2.29)	0.1089*** (4.10)	0.0116 (1.34)	0.0803*** (4.07)	0.1355*** (4.11)	−0.0261*** (−2.62)	−0.0338*** (−2.58)
TEC	0.0277** (2.24)	0.0335* (1.74)	0.0089 (1.13)	0.0190* (1.66)	0.0369*** (2.77)	−0.0209* (−1.81)	−0.0472** (−2.20)
TEL	0.0082*** (3.11)	0.0146* (1.86)	0.0049** (2.40)	0.0110* (1.75)	0.0022** (2.01)	−0.0665** (−2.01)	−0.0481*** (−2.73)
TL	0.0027** (2.32)	0.0306** (1.97)	0.0365* (1.73)	0.0265** (1.94)	0.0082* (1.64)	−0.0094*** (−2.60)	−0.0728** (−1.91)
UTL	0.0084*** (2.46)	0.0155*** (2.50)	0.0033 (0.74)	0.0244** (2.31)	0.0139* (1.90)	−0.0505*** (−2.61)	−0.0191** (−2.16)
EU_ALL	0.0105* (1.82)	0.0286* (1.74)	0.0072* (1.64)	0.0296** (1.95)	0.0481* (1.74)	−0.0209*** (−3.41)	−0.0651** (−2.11)
US_ALL	0.0151** (2.18)	0.0259** (2.07)	0.0253* (1.67)	0.0246* (1.77)	0.0439*** (2.56)	−0.0319* (−1.72)	−0.0445* (−1.69)

Panel C. COVID effect.

$d_{COVID,t-1}\times$	EPU_{t-1}	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}
AUT	0.0019** (2.31)	0.0458* (1.89)	0.0018*** (2.59)	0.0118 (1.09)	0.0111** (1.99)	−0.0224* (−1.78)	−0.0409*** (−2.60)
BNK	0.0070** (2.36)	0.0162*** (2.49)	0.0020*** (3.14)	0.0024 (0.49)	0.0241** (1.97)	−0.0164*** (−3.04)	−0.0700* (−1.73)
BRS	0.0014*** (3.20)	0.0271*** (3.13)	0.0019* (1.91)	0.0043 (0.67)	0.0070* (1.69)	−0.0010 (−0.82)	−0.0608** (−1.99)
CHM	0.0061* (1.72)	0.0755** (1.98)	0.0017*** (2.55)	0.0159 (1.00)	0.0045** (2.40)	−0.0094** (−2.22)	−0.0595 (−0.75)
CM	0.0050** (2.37)	0.0869** (2.35)	0.0112*** (2.02)	0.0212 (0.69)	0.0310* (1.87)	−0.0682*** (−2.45)	−0.1386* (−1.77)
FB	0.0065* (1.65)	0.0559** (2.41)	0.0066*** (2.80)	0.0139* (1.64)	0.0260** (1.99)	−0.0459* (−1.86)	−0.1528*** (−2.61)
IND	0.0052** (2.04)	0.1074* (1.80)	0.0059*** (2.55)	0.0370* (1.71)	0.0221** (2.05)	−0.0223* (−1.91)	−0.1613** (−2.12)
INS	0.0042** (1.99)	0.1229*** (2.57)	0.0012** (2.11)	0.0175*** (3.72)	0.0215*** (2.43)	−0.0037** (−2.29)	−0.0198* (−1.69)
MED	0.0089* (1.67)	0.0878** (2.00)	0.0012*** (2.72)	0.0028 (0.15)	0.0149** (2.37)	−0.0301** (−2.40)	−0.4275** (−2.30)

(continued on next page)

Table 4 (*continued*)

Panel C. COVID effect.

$d_{COVID,t-1}\times$	EPU_{t-1}	FU_{t-1}	ID_{t-1}	SCR_{t-1}	CCR_{t-1}	EC_{t-1}	NS_{t-1}
OG	0.0212* (1.87)	0.0401* (1.85)	0.0109*** (2.77)	0.0041 (1.24)	0.0499 (0.93)	−0.0160 (−1.10)	−0.1544*** (−2.77)
RET	0.0139* (1.66)	0.0175** (2.28)	0.0072*** (2.90)	0.0077 (1.02)	0.0150 (0.71)	−0.0125 (−0.17)	−0.0586** (−2.36)
TEC	0.0062*** (2.68)	0.1115** (2.37)	0.0105*** (3.01)	0.0006*** (3.17)	0.0506*** (3.07)	−0.0535* (−1.79)	−0.1991*** (−2.86)
TEL	0.0022*** (2.53)	0.0267*** (3.87)	0.0036*** (2.64)	0.0077 (0.77)	0.0060 (0.90)	−0.0236 (−0.34)	−0.1360** (−2.13)
TL	0.0108*** (2.61)	0.0858** (2.20)	0.0088*** (2.71)	0.0219 (1.60)	0.0036** (2.21)	−0.0901** (−2.03)	−0.1482** (−2.11)
UTL	0.0091** (2.12)	0.0315** (2.07)	0.0032** (1.99)	0.0174 (0.92)	0.0334* (1.66)	−0.0332** (−2.23)	−0.1739* (−1.71)
EU_ALL	0.0046* (1.73)	0.0638*** (2.52)	0.0038** (2.28)	0.0256** (1.93)	0.0199** (1.93)	−0.0046** (−2.24)	−0.0620* (−1.83)
US_ALL	0.0046*** (3.42)	0.0636** (2.21)	0.0030*** (3.01)	0.0163 (1.37)	0.0442*** (2.51)	−0.0296** (−1.98)	−0.0827*** (−2.68)

Notes: The table reports the crisis effect on the macro and news factors' impact on CDS dynamic equicorrelations (Eq. (7)) for each bivariate cross-country EU-US sectoral CDS combination (denoted by the sector's notation: AUT, BNK, BRS, CHM, CM, FB, IND, INS, MED, OG, RET, TEC, TEL, TL & UTL) and the two 15-variate cross-sector combinations for the EU (EU_ALL) and the US (US_ALL). The coefficients of each crisis slope dummy, estimated separately, are displayed. The crisis slope dummies are calculated by the multiplication of the respective dummy for each crisis period (GFC dummy: $d_{GFC,t}\times$, ESDC dummy: $d_{ESDC,t}\times$, COVID dummy: $d_{COVID,t}\times$) with the macro regressors (EPU_t, FU_t, ID_t, SCR_t, CCR_t, EC_t & NS_t). The numbers in parentheses are t-statistics. ***, **, * denote the significance at the 0.01, 0.05, 0.10 levels, respectively.

disease effect is more pronounced during the current pandemic, confirming the strong detrimental effect of the health crisis on credit risk contagion. Interestingly, ID_EMV slope dummies are also significant in many cases during the European crisis, most probably due to the ESDC subsample coincidence with the period immediately after the 2009 H1N1 outbreak, first detected in the US. Crisis shocks add an important increment (in absolute terms) to the drivers of sectoral default risk interdependence and to correlation levels (see also Table 1), as well. Most correlation trajectories increase during economic slowdowns through the economic fundamentals magnified by the recessionary ramifications of the crisis advent. Interestingly, these significant incremental macro effects are estimated even in the correlation pairs whose in-crisis mean values do not increase beyond the whole period average but increase or slightly decrease (on average) relative to pre-crisis mean values (Table 1). Overall, the main finding is that most macro coefficients of uncertainty, infectious disease news effect on equities (during the COVID crisis mostly), sovereign credit turbulence, corporate default spread, activity, and news sentiment are higher in absolute terms during crisis periods, signifying their additive exacerbating influence on correlations. Cross-sector spillovers are more affected by crisis influences (almost all crisis slope dummies are significant) than the cross-border ones.

Sectoral Differences: The crisis analysis of the fifteen cross-border industry pairs helps us further detect notable sectoral differences in terms of each sector's credit correlations' response to crisis shocks. In other words, our analysis is sector-specific rather than being dominated by the interrelationships between aggregate European and US CDS markets. In particular, AUT, TEC, and UTL, among the key industries of a modern economy, are the three sectors with the most significant macro regressors (at least six out of seven macro coefficients are significant) across all crisis periods, signalling their vulnerability to either financial or health crises, global or European. A group of five non-financial (basic and industrial materials, consumer goods and services) sectoral pairs (CHM, CM, FB, MED, and TL) shows lower sensitivity to the GFC shock, with only three macro factors being significant (infectious disease, credit, and activity mostly insignificant). However, their response to macro shocks becomes highly sensitive (at least five macros are significant) to ESDC and COVID effects. For BRS, BNK, and INS, one basic materials and two financial services industries, we estimate at least three insignificant macros during GFC and ESDC, while the COVID impact becomes significant on most correlation drivers (at least five). For Industrials, GFC and COVID effects are overall significant whereas during ESDC three fundamentals turn out to be insignificant. Interestingly, OG, RET, and TEL are the only cases with lower COVID sensitivity (three insignificant macros) than their macro-sensitivity to GFC and ESDC (six or seven significant macros). Hence, cross-country credit correlations of the energy sector, retail consumer and telecommunication services are less affected by the devastating repercussions of the pandemic. Infectious disease, credit and activity are the in-crisis correlation determinants that are most frequently estimated insignificant for the sectors where we observe lower sensitivity to one or two crisis events. Uncertainty and news are the most powerful correlation drivers across all crisis subsamples. Investors and policymakers should consider such sectoral differences, particularly the most crisis-vulnerable sectoral co-movements and the most contagious crisis shocks for corporate credit risk.

Based on the sensitivity analysis, we confirm *H4* and show that both financial and health crises escalate the magnitude of the macro regressors of credit risk correlations, likewise the EPU amplifying impact (Section 5.1, *H3*). We also conclude that higher in-crisis sectoral CDS markets' connectedness constitutes clear proof of the presence of credit contagion given the crisis analysis with the slope dummies. The crisis slope dummies' coefficients demonstrate that the drivers' impact on correlations increase is partly attributed to the economic crash of the crisis advent. Therefore, besides the common factors driving correlations higher in tranquil economic times, we demonstrate the distinct spillover effect of contagion led by the same economic factors but with a larger impact during crises or higher EPU stance (a characteristic feature of turmoil periods). Our results are in line with empirical evidence on financial uncertainty (e.g. VIX), which has been proved to be a significant contagion driver, in Akay, Senyuz, & Yoldas (2013), among others. Such results on the crisis-vulnerable nature of credit correlations should be incorporated into hedging strategies, investments, and further operational research solutions in business finance analytics where the macro-sensitive variance-covariance matrix is used as the main input (Christodoulakis, 2007; Ellington, 2022; Engle, 2016).

Table 5
Cross-border CDS optimal hedge ratios: Total sample and crisis mean differences.

		GFC			ESDC			COVID		
	total sample	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.
EU-US_AUT	0.607	0.290	0.730	+	0.428	0.831	+	0.662	0.806	+
EU-US_BNK	0.354	0.161	0.201	+	0.212	0.474	+	0.359	0.414	+
EU-US_BRS	0.397	0.326	0.337	+	0.273	0.604	+	0.521	0.537	+
EU-US_CHM	0.515	0.346	0.362	+	0.423	0.665	+	0.700	0.713	+
EU-US_CM	0.527	0.430	0.648	+	0.582	0.680	+	0.481	0.658	+
EU-US_FB	0.537	0.450	0.659	+	0.584	0.576	−	0.304	0.642	+
EU-US_IND	0.612	0.439	0.656	+	0.549	0.726	+	0.637	0.691	+
EU-US_INS	0.491	0.290	0.447	+	0.323	0.301	−	0.720	0.765	+
EU-US_MED	0.394	0.390	0.402	+	0.269	0.449	+	0.277	0.419	+
EU-US_OG	0.717	0.641	0.833	+	0.696	0.854	+	0.622	0.563	−
EU-US_RET	0.475	0.568	0.679	+	0.525	0.685	+	0.095	0.365	+
EU-US_TEC	0.374	0.354	0.493	+	0.350	0.406	+	0.336	0.444	+
EU-US_TEL	0.535	0.340	0.654	+	0.617	0.835	+	0.065	0.308	+
EU-US_TL	0.502	0.382	0.472	+	0.415	0.683	+	0.600	0.634	+
EU-US_UTL	0.513	0.452	0.702	+	0.595	0.543	−	0.587	0.641	+

Notes: The table reports the mean values and mean differences of the cross-border sectoral CDS optimal hedge ratios for the total sample and across the three crisis periods (GFC, ESDC, COVID). 'Total sample', 'pre-crisis', and 'in-crisis' columns report the CDS correlation mean values in the total sample, the pre-crisis, and in-crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (−) of the hedge ratios during the crisis subsample. The optimal hedge ratios are computed for each bivariate cross-country EU-US (EU-US_) sectoral CDS combination (denoted by the sector's notation: AUT, BNK, BRS, CHM, CM, FB, IND, INS, MED, OG, RET, TEC, TEL, TL & UTL).

Results Discussion

The empirical investigation of sectoral corporate credit interdependences reveals their macro drivers and crisis vulnerability.[5] In the whole sample period, the macro drivers of CDS correlations are significant, with the expected signs (according to *H1* and *H2*) for the majority of index combinations apart from the infectious disease news impact (only seven out of seventeen significant cases). The indirect EPU impact is significant for almost all macro effects and sectoral CDS combinations, except for the infectious disease proxy (eight out of seventeen insignificant). Moreover, the crisis and EPU under crisis inflating impact on the macro determinants is significant for more CDS index correlation cases during ESDC and the pandemic-induced turbulence compared to GFC. The activity (EC) proxy is insignificant in many cases during the GFC only (eight out of seventeen insignificant cases). The sovereign credit conditions (SCR) proxy is the least important macro driver during COVID. At the same period, the ID effect is always significant for all macros and EPU indirect effects but it becomes less potent in the two financial crises. Given the unprecedented current Covid-19 economic repercussions, the profound corporate credit risk contagion effects following the virus outbreak should be considered by policymakers and market practitioners trying to navigate the uncharted waters of the pandemic.

6. Results implications

From an operational research perspective, our novel findings on the macro-relevance of sectoral credit risk contagion have important implications for risk and portfolio management (e.g., risk diversification and hedging, asset allocation, portfolio analysis and optimisation). Risk-averse investors and portfolio managers seek to mitigate portfolio risk through diversification in multiple assets and cover risks with effective hedging strategies. The increase in most sectoral CDS correlations during crisis periods significantly reduces the diversification benefits of holding positions in multiple sectors and regions. Our superior econometric approach provides the necessary tools (i.e., robust time-varying variance-covariance and correlation matrices) for portfolio analysis in the procedure of constructing minimum correlation portfolios (Christoffersen, Errunza, Jacobs, & Jin, 2014) and optimal hedges (Kroner & Sultan, 1993), among others. Based on the sound evidence that economic fundamentals drive CDS co-movements, the dynamic asset allocation in the CDS market is expected to heavily depend on macro and news factors of interdependences' evolution since the dynamic correlations and covariances lie at the core of portfolio risk calculations.

Against this backdrop, we show how the estimation of our enriched MGARCH specification (allowing for time-varying variances, covariances, and correlations) directly applies to major operational research issues in risk analytics (Engle, 2016; Engle & Figlewski, 2015; Engle et al., 2019; Pakel, Shephard, Sheppard, & Engle, 2021). For example, the reliable computation of optimal hedge ratios to cover the risk of an investment position is crucial. The optimal hedge ratios represent the hedging costs that are not constant since asset dependences cannot remain stable. Hence, we conduct an empirical hedging exercise to illustrate the risk implications of our econometric methodology and results on sectoral CDS contagion. By using the variance-covariance time series of the VARX-GJR-DECO model in the optimal hedge ratios estimation, we investigate how the hedging costs vary over time and the hedge positions are crisis-vulnerable and, therefore, macro-sensitive.

In line with Kroner & Sultan (1993), we construct a portfolio with a long position in one sectoral CDS index (i) hedged by a short position in a second index (j), either in the same sector of a different country (cross-border) or a different sector of the same country (cross-sector). The hedge portfolio payoff ($r_{h,t}$) is calculated as follows: $r_{h,t} = r_{i,t} - \beta_t r_{j,t}$, where $r_{i,t}$ and $r_{j,t}$ are the returns of the CDS indices i and j. β_t is the dynamic optimal (in the sense of risk-minimising) hedge ratio (or the so-called time-varying beta) such that the hedge portfolio contains the one-dollar long position in index i covered by a β_t-dollar short position in index j (see also Engle, 2016). The β_t amount of dollars in the short position is time-varying, following the variance-covariance dynamics of the two indices, and determines the hedging cost of this strategy. Solving the first derivative of the portfolio's variance with respect to β_t

[5] Our conclusions on the crisis vulnerability of credit risk correlations are further confirmed, when we combine the EPU with the crisis impact to estimate the uncertainty effect on each macro regressor during crisis periods (the in-crisis EPU impact), separately (the results are available upon request).

Table 6
Cross-sector EU and US Banks CDS correlations and optimal hedge ratios.

Panel A. EU Banks CDS

	Dynamic Correlations										Optimal Hedge Ratios									
		GFC			ESDC			COVID				GFC			ESDC			COVID		
	total sample	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	total sample	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.
AUT	0.500	0.284	0.589	+	0.572	0.663	+	0.441	0.621	+	0.524	0.268	0.596	+	0.557	0.741	+	0.390	0.430	+
BRS	0.475	0.265	0.474	+	0.456	0.626	+	0.445	0.582	+	0.465	0.267	0.584	+	0.514	0.710	+	0.308	0.395	+
CHM	0.434	0.221	0.583	+	0.512	0.561	+	0.394	0.531	+	0.495	0.227	0.695	+	0.656	0.718	+	0.347	0.392	+
CM	0.479	0.224	0.562	+	0.501	0.625	+	0.476	0.580	+	0.490	0.255	0.597	+	0.543	0.713	+	0.334	0.401	+
FB	0.448	0.239	0.558	+	0.544	0.508	+	0.398	0.535	+	0.591	0.289	0.764	+	0.728	0.909	+	0.388	0.490	+
IND	0.497	0.266	0.598	+	0.597	0.625	+	0.454	0.585	+	0.620	0.324	0.785	+	0.778	0.830	+	0.462	0.515	+
INS	0.624	0.501	0.700	+	0.671	0.717	+	0.597	0.722	+	0.472	0.387	0.662	+	0.511	0.595	+	0.335	0.413	+
MED	0.438	0.234	0.561	+	0.494	0.553	+	0.414	0.520	+	0.618	0.265	0.823	+	0.756	0.880	+	0.446	0.529	+
OG	0.352	0.180	0.449	+	0.449	0.501	+	0.121	0.456	+	0.301	0.155	0.404	+	0.426	0.487	+	0.073	0.313	+
RET	0.436	0.236	0.595	+	0.544	0.605	+	0.174	0.467	+	0.483	0.256	0.741	+	0.651	0.747	+	0.144	0.361	+
TEC	0.402	0.203	0.545	+	0.461	0.501	+	0.342	0.489	+	0.445	0.206	0.730	+	0.594	0.622	+	0.299	0.404	+
TEL	0.470	0.238	0.575	+	0.520	0.584	+	0.500	0.610	+	0.409	0.217	0.548	+	0.386	0.541	+	0.368	0.407	+
TL	0.410	0.227	0.493	+	0.481	0.544	+	0.362	0.442	+	0.426	0.254	0.540	+	0.490	0.666	+	0.383	0.486	+
UTL	0.526	0.284	0.635	+	0.605	0.662	+	0.488	0.594	+	0.607	0.347	0.659	+	0.611	0.728	+	0.546	0.617	+

Panel B. US Banks CDS

		GFC			ESDC			COVID				GFC			ESDC			COVID		
	total sample	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	total sample	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.	pre-crisis	in-crisis	mean diff.
AUT	0.554	0.284	0.506	+	0.454	0.724	+	0.666	0.731	+	0.686	0.376	0.909	+	0.511	0.924	+	0.749	0.817	+
BRS	0.347	0.234	0.288	+	0.319	0.479	+	0.484	0.578	+	0.374	0.277	0.453	+	0.096	0.570	+	0.409	0.530	+
CHM	0.442	0.264	0.295	+	0.344	0.630	+	0.566	0.699	+	0.633	0.396	0.496	+	0.600	0.804	+	0.738	0.817	+
CM	0.450	0.292	0.548	+	0.547	0.588	+	0.487	0.620	+	0.624	0.385	0.438	+	0.492	0.719	+	0.531	0.807	+
FB	0.436	0.305	0.498	+	0.518	0.603	+	0.263	0.546	+	0.652	0.479	0.666	+	0.428	0.779	+	0.308	0.901	+
IND	0.541	0.314	0.465	+	0.577	0.739	+	0.687	0.738	+	0.669	0.473	0.605	+	0.369	0.675	+	0.521	0.856	+
INS	0.407	0.394	0.481	+	0.408	0.511	+	0.542	0.553	+	0.485	0.520	0.534	+	0.470	0.504	+	0.672	0.735	+
MED	0.393	0.234	0.391	+	0.348	0.591	+	0.397	0.471	+	0.535	0.343	0.738	+	0.457	0.799	+	0.485	0.583	+
OG	0.384	0.258	0.426	+	0.441	0.545	+	0.238	0.312	+	0.504	0.389	0.763	+	0.588	0.769	+	0.147	0.192	+
RET	0.425	0.299	0.518	+	0.530	0.637	+	0.420	0.523	+	0.622	0.469	0.605	+	0.582	0.783	+	0.452	0.495	+
TEC	0.507	0.292	0.481	+	0.538	0.669	+	0.642	0.645	+	0.814	0.476	0.852	+	0.662	0.909	+	0.695	0.923	+
TEL	0.424	0.209	0.596	+	0.502	0.599	+	0.285	0.389	+	0.515	0.233	0.632	+	0.680	0.765	+	0.182	0.358	+
TL	0.428	0.125	0.394	+	0.310	0.548	+	0.565	0.631	+	0.628	0.249	0.837	+	0.548	0.943	+	0.426	0.620	+
UTL	0.350	0.242	0.487	+	0.472	0.494	+	0.470	0.538	+	0.602	0.414	0.721	+	0.557	0.890	+	0.614	0.779	+

Notes: The table reports the mean values and mean differences of the cross-sector CDS dynamic correlations and optimal hedge ratios for the total sample and across the three crisis periods (GFC, ESDC, COVID). 'Total sample', 'pre-crisis', and 'in-crisis' columns report the CDS correlation and hedge ratio mean values in the total sample, the pre-crisis, and in-crisis subsamples, respectively. 'Mean diff.' denotes the increase (+) or decrease (-) of the correlations and hedge ratios during the crisis subsample. Correlations and hedge ratios are computed for each bivariate cross-sector Banks CDS combination with the other sectors (denoted by the sector's notation) in the same country, separately for EU (Panel A) and US (Panel B).

will give as the optimal hedge ratio formula: $\beta_t = \frac{\sigma_{ij,t}}{\sigma_{jj,t}}$ (see Kroner & Sultan, 1993, for the derivation of β_t). Both dynamic covariances ($\sigma_{ij,t}$) and variances ($\sigma_{jj,t}$) are extracted from our VARX-GJR-DECO estimation on sectoral CDS indices (see Eq. (3)). Accordingly, we first compute the dynamic betas of cross-border CDS hedge portfolios (a long position in an EU sectoral CDS index hedged by a short position in the respective US sector) using the bivariate models of the EU-US combinations for each sector (Section 4.2). In the cross-sector case, we present a simple indicative illustration with bivariate sectoral combinations rather than a fifteen-variate portfolio with all sectors included. Therefore, we take the pairs of Banks with the other sectors (BNK with each of the other fourteen sectors) for each country (EU and US) separately. Next, we analyse the time-varying behaviour of the hedge ratios and focus on their response to crisis shocks.

The time series pattern of the cross-border dynamic betas is similar to the respective correlation pattern. Table 5 reports the mean values of the optimal hedge ratios in the whole sample, the pre-crisis and in-crisis subsamples, similarly to Table 1 for the first fifteen EU-US sectoral CDS pairwise correlations across crises. In all CDS contagion or higher interdependence cases, the hedging costs increase during crises. The only decreases are calculated for FB, INS, and UTL in ESDC, and for OG in COVID, in line with the respective lower interdependence phenomena in correlations' crisis sensitivity. Consequently, the hedge ratios are countercyclical in most cases, the same as the credit risk correlations. When the beta time series are further regressed on the macro and news factors of correlations' evolution with crisis effects, we obtain similar results with correlations macro and crisis analyses (Tables 2, 3, and 4) and confirm the betas' countercyclical behaviour (the results are available upon request). Moreover, in the cross-sector dimension (Table 6), we present our crisis analysis of EU (Table 6, Panel A) and US (Table 6, Panel B) banks correlations with the other sectors in the same country and the corresponding hedging costs. All dynamic correlations and betas exhibit contagious effects in crises. Time-varying betas follow the correlation pattern in line with the cross-border case. Overall, we demonstrate that hedging costs are highly sensitive to crises and poor fundamentals while their change (mostly increase) during turbulent times is more profound than the correlations' response to such shocks. That is, the optimal hedge ratio mean changes from the pre-crisis to the post-crisis levels are relatively higher than the correlation changes. In the same way as with the dynamic betas exercise, our methodology and empirical findings can be directly implemented in further operational research applications for optimal portfolio weights, minimum variance or minimum correlation portfolio selection and optimisation and any risk or business analytics involving estimates of asset correlations and credit risk transmission (Engle & Figlewski, 2015; Engle et al., 2019).

All in all, our sectoral credit risk analysis provides new evidence on credit markets' connectedness driven by daily macro-financial factors, a policy-relevant and topical issue in current times of widespread pandemic-induced fear, uncertainty, and economic slowdown. Although financial integration and globalisation have been beneficial for real activity (De Nicolò & Juvenal, 2014), the negative externalities lie at the core of contagion and systemic risk literature debates (Allen & Gale, 2000). The concentration of defaults and the transmission of financial stress conditions both in the cross-sector and the cross-border dimensions can be explained by lagged economic fundamentals and news sentiment, which, in turn, should be considered in Early Warning Systems (EWS) as leading indicators or early warning signs of an imminent crisis or an extensive financial stress episode (Geng, Bose, & Chen, 2015; Huang, Kou, & Peng, 2017; Savona, 2014). Our findings on sectoral corporate credit interdependence further complement the conclusions on credit contagion among sovereigns or financial institutions (Acharya et al., 2014; Apergis et al., 2019; Bratis et al., 2020; Chen et al., 2020; Grundke & Polle, 2012). It is also crucial to incorporate considerations about sectoral credit contagion dynamics in crisis-induced insolvency predictions, credit risk or CDS pricing models (Jorion & Zhang, 2007; Ketelbuters & Hainaut, 2022), and resources or credit reallocation models as a result of sectoral supply and demand shocks (Arellano, Bai, & Mihalache, 2018; Herrera, Kolar, & Minetti, 2011).

Moreover, policymakers should proactively act to mitigate the destabilising impact of credit contagion and systemic risk for the financial system in order to prevent subsequent instability or turmoil periods. The macro- or micro-prudential policy responses (Acharya, 2009) can use the leading economic indicators of sectoral CDS co-movement, we reveal, in macro scenarios of bank stress-testing exercises and capital requirement frameworks (micro-prudential tools, e.g. sectoral capital requirements to discourage systemic risk-taking), as well as in macro-based regulatory interventions to the whole financial system in response to weakening economic conditions (macro-prudential tools). Individual banks or the whole banking sector's risk-taking profile should not be assessed separately from other economic sectors but inside the complex network of sectoral interdependence. For example, credit risk transfer actions taken by bankers during crises may amplify credit risk contagion through highly interconnected sectors. Lastly, our contribution is important due to the use of daily frequency economic fundamentals and news effects in explaining credit risk correlation evolution. Recently, the research community and central banks have focused on nowcasting to monitor real-time economic conditions far in advance of the monthly or quarterly releases published with a significant time lag (Berger, Morley, & Wong, 2020; Carriero, Clark, & Marcellino, 2020). During the Covid health crisis, we diagnose the urgent need for policies responding to the day-to-day deterioration of the economic outlook. Such a slowdown is partly determined by the pandemic progress, and often heavily affected by the information contagion (Ahnert & Georg, 2018) or the so-called 'infodemics'[6], jeopardising the management of both the financial system and the pandemic itself.

7. Conclusions

Our study has investigated cross-border and cross-sector corporate credit risk interlinkages by estimating the dynamic equicorrelations among EU and US sectoral CDS indices through the VARX-GJR-DECO model. We reveal the common macro and news determinants of the CDS correlation evolution and demonstrate the presence of contagion effects across sectors during crisis periods. Higher economic policy and financial uncertainty, infectious disease impact on equity volatility, sovereign credit turbulence, tighter credit conditions, lower economic activity, and negative news sentiment are the factors identified to increase CDS interconnectedness. Poor economic fundamentals during business cycle downturns increase the sectoral nexus. Therefore, we conclude that default risk correlation dynamics are counter-cyclical. We further conduct a sensitivity analysis of these cyclical variation characteristics and show the EPU and crisis magnifying impact on the economic drivers of the correlation pattern. Higher EPU levels, and financial and health crises inflate the macro and news influence on CDS co-movement, manifesting the contagious credit risk transmission during economic slowdowns. Hence, uncertainty, credit, activ-

[6] World Health Organization (WHO), 2020. Managing the COVID-19 infodemic: Promoting healthy behaviours and mitigating the harm from misinformation and disinformation. Statement 23/9/2020 (https://www.who.int/news/item/23-09-2020-managing-the-covid-19-infodemic-promoting-healthy-behaviours-and-mitigating-the-harm-from-misinformation-and-disinformation).

ity, and news are the contagion transmitters of corporate default risk in turmoil periods. Our results further indicate the differences in the credit risk time-varying nexus across sectors and countries. European sectors are more tightly connected than the US ones, while certain sectoral correlations are more affected by fundamentals and crises than others. Finally, the recent pandemic constitutes the most contagious shock on corporate credit risk interlinkages for the majority of sectoral combinations.

Our novel results on the driving forces of credit contagion should urge both policymakers and market practitioners. We demonstrate that the counter-cyclical behaviour of CDS correlations is reflected in the similar dynamics of time-varying hedging costs among other risk and portfolio performance metrics. Regulators', investors', and managers' risk assessments must consider the macro perspective of default risk correlation dynamics in policy interventions to prevent or mitigate systemic risk and financial stability threats and in diversifying or hedging out credit risk in loan and bond portfolios. They should be particularly alert to the sectoral credit correlations which are higher (e.g. European vs. US, Industrials vs. Retailers) and which have been detected as more sensitive to macros (e.g. Retailers and US) and crises than others (e.g. cross-country vs. cross-sector). Credit contagion constitutes an alarming early warning signal for financial crashes. Therefore, as part of future research, we suggest a thorough investigation of cross-sector and cross-border corporate CDS correlation dynamics in further economies, beyond the EU and US, in association with the macro environment of each country as well as global or regional macro-financial factors, the catalytic role of global or local news sentiment, and the widely spread infodemics. Lastly, another interesting line of future research would be the application of our CDS correlation framework to single-name CDS contracts. We consequently intend to further explore whether CDS spreads and their co-movements can be decomposed into heterogeneous factors related to bond-, issuer-, or contract-specific features, in line with the bond credit spreads decomposition Gilchrist & Zakrajšek (2012).

Declaration of Competing Interest

None.

Appendix A

VARX-GJR-DECO

Conditional Mean

We first estimate the dynamic correlations of EU and US sectoral CDS index returns with the VARX-GJR-DECO specification. Let us define the N -dimensional column vector of the returns $\mathbf{r}_t$ as $\mathbf{r}_t = [r_{it}]_{i=1,\dots,N}$ and the corresponding residual vector ε_t as $\varepsilon_t = [\varepsilon_{it}]$ (hereafter, for notational simplicity we will drop the subscript when the order is N). The structure of the VAR(1)-X (VARX, hereafter) mean equation is given by

$$\mathbf{r}_t = \mu_{\mathbf{t-1}} + \varepsilon_{\mathbf{t}}, \tag{A.1}$$

with

$$\mu_{t-1} = \phi + \mathbf{\Phi}\mathbf{r}_{t-1} + \mathbf{Z}\mathbf{x}_{t-1},$$

where $\phi = [\phi_i]$ is an $N \times 1$ vector of constants and $\mathbf{\Phi} = [\phi_{ij}]$ is the $N \times N$ coefficient matrix with the first-order autoregressive coefficients in the diagonal elements, ϕ_{ii}, and the mean cross effects in the off-diagonal elements, $\phi_{ij}, i \neq j$. $\mathbf{Z} = [\mathbf{z}_{ij}]_{\substack{i=1,\dots,N \\ j=1,\dots,K}}$ is the $N \times K$ exogenous coefficient matrix and $\mathbf{x}_t = [x_{it}]_{i=1,\dots,K}$ is the $K \times 1$ vector with the various macro factors included as exogenous variables (to address any possible endogeneity issues, the macro regressors used in the mean equation are the same as the ones used in the correlation analysis, see Eq. (5)).

Conditional Variance

Next, the structure of the conditional variance vector, σ_t, is specified as an asymmetric (in the spirit of Glosten et al., 1993 - GJR) TV-MGARCH(1,1) model, with arch and leverage spillovers. This specification is further augmented with the time-variation across crisis periods, as in Karanasos et al. (2014), by allowing the drift and the shock parameters to be time-varying as follows:

$$(\mathbf{I} - \mathbf{B}L)\sigma_t = \omega + L\mathbf{A}_t\varepsilon_t + \sum_{l=1}^{n} LD^{(CR)}\left(\omega^{(CR)} + \mathbf{A}_t^{(CR)}\varepsilon_t\right), \tag{A.2}$$

where L is the lag operator, $\mathbf{B}$ is a diagonal matrix with entries the garch coefficients, β_i, and $\omega = [\omega_i], \omega_i \in (0, \infty)$; $\mathbf{A}_t = \mathbf{A} + \mathbf{\Gamma} diag(\mathbf{s}_t)$, with $\mathbf{A} = [\alpha_{ij}]$, $\mathbf{\Gamma} = [\gamma_{ij}]$, and $\mathbf{s}_t = 0.5[\mathbf{j} - sign(\varepsilon_t)] = [s_{jt}]$ ($\mathbf{j}$ denotes the $N \times 1$ vector with unit entries), that is $s_{jt} = 1$ if $\varepsilon_{jt} <$ 0 and 0 otherwise. In other words, $\mathbf{A}$ and $\mathbf{\Gamma}$ are full matrices with entries the arch and leverage coefficients, respectively. Positive γ_{ij} denotes a larger contribution of negative shocks to the volatility process by exacerbating the conditional variance estimated (common for risky asset returns, e.g. equities, bonds) whereas negative γ_{ij} means that negative shocks exert a lower influence on raising volatility.

We further allow the drift (ω) and the shock ($\mathbf{A}_t$: own and cross, arch and leverage) parameters to shift across crisis periods. $D^{(CR)}$ are crisis (CR) dummy variables defined as 0 in the period out of each crisis and one during each crisis interval, and $\omega^{(CR)} = [\omega_i^{(CR)}]$, $\mathbf{A}_t^{(CR)} = \mathbf{A}^{(CR)} + \mathbf{\Gamma}^{(CR)}\mathbf{s}_t$ with $\mathbf{A}^{(CR)} = [\alpha_{ij}^{(CR)}]$, $\mathbf{\Gamma}^{(CR)} = [\gamma_{ij}^{(CR)}]$. We consider three crisis periods ($CR = GFC, ESDC, COVID$) as described in the correlation sensitivity analysis (see Eq. (7)).

Following Karanasos, Xu, Yfanti, Zopounidis, & Christopoulos (2021), we also impose the conditions which are necessary and sufficient for $\sigma_t > \mathbf{0}$ for all t:

$$\mathbf{B} \geq \mathbf{0}, \omega > \mathbf{0}, \mathbf{A} > \mathbf{0}, (\mathbf{A} + \mathbf{\Gamma}) > \mathbf{0},$$
$$(\omega + \omega^{(CR)}) > \mathbf{0}, (\mathbf{A} + \mathbf{A}^{(CR)}) > \mathbf{0},$$
$$(\mathbf{A} + \mathbf{\Gamma} + \mathbf{A}^{(CR)} + \mathbf{\Gamma}^{(CR)}) > \mathbf{0}$$

(non-negativity constraints). The stability condition for the MGARCH model is that the maximum eigenvalue of the matrix: $\mathbf{C} = \mathbf{B} + \mathbf{A} + \frac{1}{2}\mathbf{\Gamma}$ must be less than one. The relative merits of our asymmetric TV-MGARCH specification are important since our extension allows for shock spillovers in the conditional variance system of equations and isolates the crisis impact on the model's parameters.[7] For robustness purposes, we also estimate a second alternative TV-MGARCH specification, namely the DCC-GARCH-MIDAS model, with correlation analysis results similar to the DECO model (the results are available upon request).

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ejor.2022.04.017.

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[7] The particular asymmetric MGARCH specification enhanced with crisis and spillover effects is the most appropriate for the CDS index returns. Asymmetries, crisis dummies, and spillovers are significant and improve the model's fit relative to simpler or more sophisticated long-memory GARCH specifications we have tested. The model chosen is the best according to the *logL* scores, information criteria and a battery of misspecification tests (tests for model selection, asymmetries, arch spillovers, leverage spillovers, and dummies, by Engle & Ng, 1993; Nakatani & Teräsvirta, 2009; Pedersen, 2017, among others) compared with several nested or non-nested GARCH specifications (the results are available upon request).

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