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

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We delve into default risk interlinkages quantified by conditional correlations and explain the time-varying behaviour of the credit correlation pattern with economic 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.
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 and Mars den, 2014, JIFMIM).
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.
UNCERTAINTY

- The cyclical variation of credit risk contagion is first traced in a critical economic force driving the business cycle, that is uncertainty.

- EPU

- Therefore, our first correlation determinant is the news-based Economic Policy Uncertainty index (Baker et al., 2016, QJE), the sole economic uncertainty index measured with a daily frequency (for UK and US) and considered as the most inclusive metric containing both economic and policy-related ingredients

- (see, also, Karanasos and Yfanti, 2021, JIFMIM, 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. 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.
Figure A.1. UK Economic Policy Uncertainty index (log-level)

Figure A.2. US Economic Policy Uncertainty index (log-level)

Figure A.3. Euro Stoxx 50 Implied Volatility index, VSTOXX (log-level)

Figure A.4. S&P 500 Implied Volatility index, VIX (log-level)
The **Infectious Disease Equity Market Volatility** Tracker of Baker et al. (2020, QJE) 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.

Since economic slowdown is associated with higher uncertainty, we expect a **positive** relationship between each of the three uncertainty variables and CDS connectedness.
Figure A.5. Infectious Disease Equity Market Volatility Tracker (level)
CREDIT CHANNEL

The next correlation determinant is the credit channel, an important constituent of economic cycles. We consider proxies of both corporate and sovereign credit conditions.

CORPORATE

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.
**SOVEREIGN**

- 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.
Figure A.6. Merrill Lynch MOVE 1-month index (log-level)

Figure A.7. Moody’s corporate default spread, BAA minus AAA global corporate bond yields (level)
**ECONOMIC ACTIVITY**

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.

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 et al., 2009, JBES).
The term spread is found to be a powerful predictor of activity prospects (Estrella and Hardouvelis, 1991, JF).

Higher treasury term structure slope means economic expansion associated with lower credit risk while slope decrease predicts activity contraction (see, for example, Gilchrist and Zakrajöek, 2012, AER, Dodd et al., 2021, IRFA).
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).

Figure A.8. European Yield Curve slope, 10-year minus 3-month European government bond yields (level)

Figure A.9. Aruoba-Diebold-Scotti (ADS) US business conditions index (level)

Overall, according to H1, sectoral CDS correlations are expected to rise during weak economic periods.
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.

Thus, the seventh correlation determinant is the news impact as measured by the daily US News Sentiment Index (NSI).

Shapiro et al. (2020, FRB-SF) and Buckman et al. (2020, FRB-SF) 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.
Figure A.10. News Sentiment index (level)
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.

We construct our third testable hypothesis motivated by Pastor and Veronesi (2013, JFE), 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 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, Chiang et al., 2007, JIMF, Karanasos et al., 2016, IRFA, Bratis et al., 2020, JFS).

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.
Model
A multivariate cDCC-GARCH process

The errors
We have three set of errors:
1. $\tilde{e}_{it}$ are the standardised errors, which follow the conditional standard normal distribution.
2a. $\varepsilon_{it} = \tilde{e}_{it} \sqrt{\sigma_{ii,t}}$, that is $\mathbb{E}(\varepsilon_{it}^2 | F_{t-1}) = \sigma_{ii,t}$
2b. $\mathbb{E}(\varepsilon_{it}\varepsilon_{jt} | F_{t-1}) = \sigma_{ij,t}$ is the conditional covariance
Conditional Correlations

Notice that

\[ \mathbb{E}(\varepsilon_{it}\varepsilon_{jt} | \mathcal{F}_{t-1}) = \sigma_{ij,t} = \mathbb{E}(\tilde{e}_{it}\tilde{e}_{jt} | \mathcal{F}_{t-1}) \sqrt{\sigma_{ii,t}} \sqrt{\sigma_{jj,t}}, \]

Which implies that

\[ \mathbb{E}(\tilde{e}_{it}\tilde{e}_{jt} | \mathcal{F}_{t-1}) = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}} \sqrt{\sigma_{jj,t}}} = \rho_{ij,t}. \]

So \( \rho_{ij,t} \) are the dynamic (time-varying) conditional correlations of both \( \tilde{e}_{it} \) and \( \varepsilon_{it} \).
How are they estimated?

Two step procedure

In the first step we estimate the conditional variances \( \sigma_{ii,t} \) and the errors \( \varepsilon_{it} \), using a GARCH-type of model.

Thus we get an estimate of the standardized errors: 
\[
\hat{e}_{it} = \frac{\varepsilon_{it}}{\sqrt{\sigma_{ii,t}}}.
\]
The third error

3a. \( e_{it} = \tilde{e}_{it} \sqrt{q_{ii,t}} \), that is \( \mathbb{E}(e_{it}^2 | \mathcal{F}_{t-1}) = q_{ii,t} \), is the conditional variance

3b. \( \mathbb{E}(e_{it}e_{jt} | \mathcal{F}_{t-1}) = q_{ij,t} \) is the conditional covariance
Notice that

$$\mathbb{E}(e_{it} e_{jt} \mid \mathcal{F}_{t-1}) = q_{ij,t} = \mathbb{E}(\tilde{e}_{it} \tilde{e}_{jt} \mid \mathcal{F}_{t-1}) \sqrt{q_{ii,t}} \sqrt{q_{ij,t}},$$

Which since

$$\mathbb{E}(\tilde{e}_{it} \tilde{e}_{jt} \mid \mathcal{F}_{t-1}) = \frac{\sigma_{ij,t}}{\sqrt{\sigma_{ii,t}} \sqrt{\sigma_{ij,t}}} = \rho_{ij,t},$$

it implies that

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

That is, $\rho_{ij,t}$ are the dynamic correlations of $e_{it}$ as well.
The second step

We estimate a corrected DCC (dynamic conditional correlation, see Engle, 2002, JBES):

\[ q_{ij,t} = (1 - a - b)q_{ij} + ae_{i,t-1}e_{j,t-1} + bq_{ij,t-1}, \]

where recall that: \( e_{it} = \sqrt{q_{it}}\tilde{e}_{it} \), and we have the estimated \( \tilde{e}_{it} \) from the first step.

Notice also that \( q_{ij} = \mathbb{E}(q_{ij,t}) \), (see, Aielli, 2013, JBES).
The **DECO** (Dynamic Equicorrelations)

For computational ease, Engle and Kelly (2012, JBES) impose a critical assumption to the calculation of $R_t$ model in order to estimate dynamic **equicorrelation** matrices ($R_{t}^{DECO}$).

Each returns pair should have the same correlation, that is $\rho_{t}^{DECO}$.

In general, for $N > 2$, the DECO(1, 1) correlation matrix is defined as follows:

$$R_{t}^{DECO} = (1 - \rho_{t}^{DECO})I + \rho_{t}^{DECO}J,$$

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

where $J$ is the $N \times N$ matrix of ones.
- 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 \(\rho_t\) is calculated as follows:
  \[
  \rho_t = \log\left(\frac{1+\rho_{t}^{DECO}}{1-\rho_{t}^{DECO}}\right).
  \]

- 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.
Correlation Regression Analysis

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 $H2$):

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

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

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.
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 (results available upon request).

The sample spans from 01/01/2004 to 24/12/2020, giving a total of 4,431 daily observations.
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.
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.
Following Forbes and Rigobon (2002, JF), 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 and Lucey, 2009, JFS).
<table>
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<td>in-crisis</td>
<td>mean</td>
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<td>0.385</td>
<td>0.530</td>
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<td>EU-US_FB</td>
<td>0.393</td>
<td>0.497</td>
<td>+***</td>
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<td>EU-US_IND</td>
<td>0.438</td>
<td>0.611</td>
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<td>EU-US_INS</td>
<td>0.293</td>
<td>0.410</td>
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<td>0.476</td>
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<td>EU-US_OG</td>
<td>0.446</td>
<td>0.623</td>
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<td>0.414</td>
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<td>0.373</td>
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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.

- 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)
Figure B.6. Cross-country EU-US Food & Beverage sectoral CDS correlation (EU-US_FB)
Figure B.7. Cross-country EU-US Industrial Goods & Services sectoral CDS correlation (EU-US_IND)
Figure B.12. Cross-country EU-US Technology sectoral CDS correlation (EU-US_TEC)
Figure B.8. Cross-country EU-US Insurance sectoral CDS correlation (EU_US_INS)
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.

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.
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<td>0.1160***</td>
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<td>(4.80)</td>
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<td>(3.20)</td>
<td>(3.50)</td>
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<td>0.0025*</td>
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<td>0.0058*</td>
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<td>(2.96)</td>
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<td>0.0017</td>
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<td>-0.0343**</td>
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<td></td>
<td>(2.45)</td>
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<td>(2.19)</td>
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<td>(2.53)</td>
<td>(2.23)</td>
<td>(3.29)</td>
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<td>(-2.12)</td>
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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 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 operations 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.

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.
EPU Interaction Terms

- 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.

- Following the commonly applied interaction effects methodology in economic analysis (see, among others, Pastor and Veronesi, 2013), the addition of the EPU interaction terms is used to isolate the macro effects’ intensity during periods of high EPU levels.

\[
\rho_t = c_0 + c_{1}\rho_{t-1} + c_{2}EPU_{t-1} + (c_{3} + c_{3}^{EPU}EPU_{t-1})FU_{t-1} + (c_{4} + c_{4}^{EPU}EPU_{t-1})ID_{t-1} \\
+ (c_{5} + c_{5}^{EPU}EPU_{t-1})SCR_{t-1} + (c_{6} + c_{6}^{EPU}EPU_{t-1})CCR_{t-1} + (c_{7} + c_{7}^{EPU}EPU_{t-1})EC_{t-1} \\
+ (c_{8} + c_{8}^{EPU}EPU_{t-1})NS_{t-1} + u_t.
\]
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.

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.
Crisis Impact

- 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:

\[
\rho_t = c_0 + c_1 \rho_{t-1} + (c_2 + c_2^{CR} d_{CR,t-1}) EPU_{t-1} + (c_3 + c_3^{CR} d_{CR,t-1}) FU_{t-1} \\
+ (c_4 + c_4^{CR} d_{CR,t-1}) ID_{t-1} + (c_5 + c_5^{CR} d_{CR,t-1}) SCR_{t-1} + (c_6 + c_6^{CR} d_{CR,t-1}) \\
+ (c_7 + c_7^{CR} d_{CR,t-1}) EC_{t-1} + (c_8 + c_8^{CR} d_{CR,t-1}) NS_{t-1} + \epsilon_t,
\]
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 5, 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.

Moreover, ESDC and COVID effects (Table 5, Panels B & C) are estimated significant in most CDS correlations, indicating that the latter two crises exacerbate the impact of most correlation determinants.
The 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.
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.
HEDGING STRATEGIES

- From an operational research perspective, our findings on the macro-relevance of sectoral credit risk contagion have important implications in 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 from 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 (Christofersen et al., 2014, IJF) and optimal hedges (Kroner and Sultan, 1993, JFQA), among others.
In line with Kroner and 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 \( j \).

\( \beta_t \) 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 \( \beta_t \)-dollar short position in index \( j \).
The $\beta_t$ 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 $\beta_t$ will give as the optimal hedge ratio formula: $\beta_t = \frac{\sigma_{ij,t}}{\sigma_{jj,t}}$ (see Kroner and Sultan, 1993, for the derivation of $\beta_t$).
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.

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 3, 4, and 5) and confirm the betas’ countercyclical behaviour (results available upon request).

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.
The same way as with the dynamic betas exercise, our methodology and empirical findings can be directly implemented on further operational research applications for optimal portfolio weights, minimum variance or correlation portfolio selection and optimisation and any risk or business analytics involving estimates of asset correlations and credit risk transmission.
CONCLUSIONS

- 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, Kashyap et al., 2020) 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 (Carriero et al., 2020, FRB-CL, Berger et al., 2020, JE).

• 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 and Georg, 2018, JFS) or the so-called ‘infodemics’, jeopardising the management of both the financial system and the pandemic itself.