The Core, the Periphery, and the Disaster: Corporate-Sovereign Nexus in COVID-19 Times

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ABSTRACT

We show that the COVID-19 pandemic triggered a surge in the elasticity of non-financial corporate to sovereign credit default swaps in core EU countries, characterized by strong fiscal capacity. For peripheral countries with lower budgetary slackness, the pandemic had essentially no impact on such elasticity. This evidence is consistent with the disaster-induced repricing of government support, which we model through a rare-disaster asset pricing framework with public guarantees and defaultable sovereign debt. The model implies that risk-adjusted guarantees in the core were 2.6 times those in the periphery, suggesting that fiscal capacity buffers provide relief to firms' financing costs.

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1 Introduction

How do sovereign and domestic corporate credit risk interact with each other? Given the soaring level of outstanding corporate and sovereign debt in developed economies, a deep understanding of the channels at work in such relation is of paramount importance from both an academic and a policy perspective. For financial firms, and most notably banks, a fundamental characterization of the channels at work has been formalized through the so-called "doom loop," which derives from the combination of bank exposures and bailout (see, e.g., Acharya et al., 2014; Brunnermeier et al., 2016; Farhi and Tirole, 2018). There is also some empirical evidence that credit risk spillovers take place between the sovereign and the domestic non-financial sectors (see, e.g., Lee et al., 2016; Almeida et al., 2017). The sobering message from this literature is that a rise in sovereign risk generates negative externalities on the ability of corporations to service their debt, and hence on their creditworthiness. These externalities are generally deemed to be exacerbated in governments with already low fiscal space and high credit spreads, for which a further deterioration in credit conditions would raise concerns of future increases in corporate taxes and more generally a disruption in the legal, political, and economic framework (Corsetti et al., 2013; Augustin et al., 2018).

In this paper, we study the behavior of credit risk markets at the onset of the COVID-19 pandemic, when investors swiftly repriced the cost of default insurance. In the cross section of countries in the European Union (EU), the first Western countries hit by the pandemic, five-year credit default swap (CDS) spreads on both sovereign and corporate entities experienced a massive surge. This pattern characterizes both core EU countries with strong public finances and peripheral EU member states, where the volume of outstanding public debt and its financing costs are more concerning. While it is well known that credit markets often experience sudden run-ups in spreads (Pan and Singleton, 2008), the pandemic stands out as a unique environment for testing the drivers of the corporate-sovereign credit risk loop and the role of fiscal space for at least two reasons. First, the shock was unanticipated and exogenous to pre-existing levels of credit risk and public finances, an argument also made by Augustin et al. (2021). Second, EU governments initially responded to the pandemic by imposing widespread halts to economic activity, thereby threatening firms' profitability and even survival. The unprecedented breadth of these interventions and the discussions around foreseeable support measures to businesses that followed have ignited a debate on the asset pricing implications of government support towards non-financial corporations, as the pricing of public support was largely confined to claims issued by financial firms ahead of the pandemic.

We offer the following three contributions to advance our understanding of credit markets. First, we document a strengthening of the corporate-sovereign credit risk relation at the COVID-19 outbreak only in countries that have strong fiscal capacity. This evidence is robust to the inclusion of a wide array of firm and country characteristics. Direct econometric tests point toward a pivotal role of public finances through the pricing of expected government support as factored in forward-looking market prices. Our second contribution is to develop an asset pricing model featuring the stochastic occurrence of a rare disaster. In the model, government support acts by putting a ceiling to the severity of the disaster for companies' default risk. The model enables us to formalize the transmission of fiscal capacity to the pricing of corporate claims. Third, we use a synthetic control approach to estimate the model-implied ratio of government support for core and peripheral countries during the pandemic. We are thus able to quantify how the strength of public finances affects firms' credit risk pricing, and ultimately their cost of capital.

In detail, we find that the sensitivity of CDS spreads referencing non-financial corporations to those on the corresponding governments, which we term the "corporate-sovereign nexus," increased in the period following the first Italian lockdown (February 24, 2020) only in the core of the EU; namely, in countries with *strong* fiscal capacity. For this group of countries – Belgium, Finland, France, Germany, and the Netherlands – the pandemic had an economically large and statistically significant positive impact on the nexus. By contrast, in peripheral EU countries (e.g., Greece, Italy, Portugal, and Spain) the effect of the pandemic on the nexus was, albeit positive, small and not statistically significant. Overall, by September 2020, we observe a complete alignment in the sensitivity of corporate CDS spreads to their sovereigns between the two groups of countries to a value of about 0.25; namely, a 10% increase in sovereign spreads is accompanied by an expected 2.5% increase in corporate credit spreads. Considering that our sample covers non-financial firms with an overall market cap of Eur 3.25 trillions – about 56% of the EU market – the economic magnitude of this effect cannot be understated.

We obtain these results in a panel regression setup, where we control for a number of factors, including the firm's equity return, aggregate volatility and fixed effects. The equity return in particular should absorb the effect of aggregate shocks on both firm assets and sovereign creditworthiness that could bias our inference (Acharya et al., 2014). Moreover, the focus on EU countries provides us with an ideal setting, as monetary policy, exchange rates, and pandemic intensity are homogeneous. Within this setup, we drill down into economic channels that could explain the differential reaction of core and peripheral countries.

We begin by augmenting the setting with firm-level characteristics – firm profitability, liquidity, and financing structure – that have been shown to trigger a differential response to the shock in the cross section of firms. In a similar vein, we incorporate in the regression country-level proxies for the resilience to COVID-19 and the severity of the shock, such as the importance of the tourism sector and the strength of the healthcare system. The aforementioned difference persists in all these augmented models, as well as for the subset of firms whose bonds were not targeted by the ECB's Pandemic Emergency Purchase Programme (a "monetary policy channel"), for firms whose CDS spread was above that of their sovereign counterparts at the inception of the pandemic (an "exodus from sovereign ceiling" channel, as in Lee et al., 2016), for companies with below-average government ownership (a "direct ownership channel"), and if we restrict the COVID-19 sample to the month following the Italian lockdown, when discussions about the European Recovery Fund were yet to reach the market (a "demand channel"). Econometrically, we account for imbalances between core and periphery in the distribution of covariates and in sample size and industrial structure, and assess robustness to a number of specification tests. Similar estimates ensue when replacing CDS spreads with corporate bond credit spreads, which are available for a larger cross section of firms.

Conversely, we find evidence that the corporate-sovereign credit risk relation in the face of COVID-19 is directly tied up to a country's fiscal capacity and to firms' likelihood to benefit from it, for instance business size. With regard to the former, prior to the pandemic the nexus is decreasing in measures of fiscal health of a country government (such as, debt-to-GDP ratio, interest expenditures on debt, and government quality indicators), with a stark reversal of the relation in the second half of the sample. The surge in the nexus is pervasive across all core countries and muted across all peripherals. Thus, the core/periphery grouping is well representative of the disaggregated cross section of countries, but our findings extend more broadly to several metrics of fiscal space. Within the cross section of firms, we detect differential effects as a function of company size (i.e., market capitalization), which is often regarded to as a proxy for the probability to benefit from government support. Our baseline regression estimates of the nexus in the core strengthen when we value-weight observation based on size. After the Italian lockdown we unmask systematic departures between observed spreads and those implied by a standard structural model of default that are a decreasing function of firm size (in the spirit of Kelly et al., 2016), but only for companies headquartered in core countries. By contrast, size does not explain deviations from fundamentals in the periphery.

To gain an historical perspective, we expand the times series dimension of the data and estimate the corporate-sovereign relation on a rolling fashion throughout the period following the Global Financial Crisis. The nexus has been historically larger and more volatile in the periphery than in the core, until the pandemic hit and triggered the core coefficient to unprecedented high levels, almost at par with those of peripheral countries. In other words, as soon as governments started to impose economic lockdowns posing a threat to companies survival, credit markets sparked higher credit risk spillovers in European countries with strong fiscal capacity.

Altogether, our analysis points toward market participants factoring the strength of government support into the valuation of corporate claims. Resting on ample budget maneuverability space, a state backstop option ties corporate credit spreads and government default risk to share a common destiny. Firms' debtholders become concerned in rising sovereign risk when corporations count on fiscal support to service their obligations, and conversely the likelihood and breadth of public intervention increase in the distress of the private sector once the economy derails. We formalize this argument in an asset pricing model that integrates sovereign risk and the pricing of corporate claims. In doing so, we offer a parsimonious model to capture government support in the pricing of credit risk.

The model features the following three ingredients. We resort to the standard intensity-based approach to credit risk (see, among others, Longstaff et al., 2005), as it provides us with a common framework for the pricing of corporate and sovereign claims. To capture the gist of the reaction to the COVID-19 pandemic we rely on a rare-event model with time-varying probability of a disaster, whose magnitude is stochastic as in Gabaix (2012). In our setup, a disaster consists of a negative jump in consumption and a positive jump in default intensity. The probability of a rare event follows a persistent Markov process. This implies that the one-time occurrence of a disaster has long-lasting consequences on the pricing of credit risk.

Finally, we allow fiscal capacity buffers to affect market prices via the ability of the government to grant collective guarantees to the domestic sector. More specifically, market participants expect the government to activate those guarantees when it deems the size of the jump in corporate intensity of default too large. We model such guarantees as a ceiling on the size of the jump, as in Kelly et al. (2016) and Gandhi et al. (2020). We enrich their framework by accounting for risk-bearing government debt, meaning that the activation of the guarantee determines an increase in the default risk of public debt equal to the portion of the shock that the government absorbed. This extension allows us to study the structural drivers of the relation between corporate and sovereign credit spreads.

The model delivers closed-form expressions for the covariance between changes in default intensities of government and domestic corporations and, to an approximation, changes in their CDS spreads. Conditionally on the disaster taking place, the covariance increases with the strength of the government guarantee. This implies that, all else constant, countries with broader fiscal space should experience a stronger increase in the nexus, consistent with our empirical findings. The covariance also increases with the sensitivity of a firm's credit risk to the economic contraction and hence to government intervention. To tease out how these two components – the bredth of public guarantees and the sensitivity of firms the latter – compare between core and periphery, we rely on the synthetic control method of Abadie et al. (2010), which is also used by Almeida et al. (2017) to study sovereign risk spillovers. We construct "synthetic spreads" for companies in a region (say, core) by matching them during the pre-COVID sample with firms in the other region (periphery) on standard balance sheet and market-based variables capturing credit risk. The method allows us to evaluate the difference between actual (i.e., treated) spreads and a portfolio of spreads (control group) that are subject to the same level of guarantees but have different sensitivity to government support.

This analysis delivers a number of insights. The treated and control CDS series are very similar in the pre-COVID sample but diverge thereafter, with spreads on synthetic core firms being on average higher than those of peripheral firms. This implies that, as the disaster unfolds, credit risk in the two groups of firms is priced differently. It also reveals that corporate credit risk is more sensitive to sovereign support in the core than in the periphery. In other words, when the disaster looms, corporate credit risk responds strongly to the pricing of public intervention in countries whose governments are regarded to be better positioned to provide a solid backstop option. Finally, based on our modelling framework, comparing synthetic and actual spreads delivers an estimate of the pricing impact of fiscal capacity as measured by the ratio of CDS-implied public guarantees in the two regions. We find that, in risk-adjusted terms, expected guarantees are 2.6 times larger in the core than in the periphery, which indicates that firms in core EU countries benefitted from a milder increase in their spreads compared to those in the periphery thanks to the perception of a more effective support.

Our findings have broad implications in light of the debate around the benefits of fiscal capacity. Recently, Blanchard (2019) argues that in a low interest rate environment, high public debt may not imply large fiscal costs. However, provided markets are informationally efficient, our analysis uncovers a positive effect originating from sovereign fiscal space, as spending capacity buffers directly spill over to corporate credit risk following disaster-induced repricing. Ultimately, as our model calibration via synthetic control method shows, this effect lowers corporate credit spreads – and hence the cost of capital – for companies headquartered in fiscally sound countries, thereby increasing their resiliency. In a similar vein, Romer and Romer (2018) claim that the size of the fiscal stimulus depends on fiscal space. By contrast, we focus on a broad notion of expected government support over the medium term (which includes, e.g., solvency measures, liquidity provisions, and tax exemptions) as factored in credit markets.

Related Literature: Our work builds on the literature that studies the pass-through of risk between sovereigns and firms. A large body of literature has focused on the "doom loop" between the sovereign and the banking sector. Acharya et al. (2014), Bocola (2016), Brunnermeier et al. (2016), Mäkinen et al. (2020), and Crosignani (2021) provide theoretical and empirical frameworks to understand this relation. By contrast, the nexus between the public and non-financial corporate sector has received comparably less attention. Credit risk spillovers to domestic non-financial firms are discussed in, among others, Almeida et al. (2017), who exploit variation in credit ratings and investigate the real effects of rating agencies' sovereign ceiling policies, and Bevilaqua et al. (2020), who use bond yields and suggest that the relation might be state dependent and driven by an information channel. Our interest in a crisis period motiates the focus on CDS spreads, because flight-to-safety and flight-to-liquidity affect the price of treasury bonds (He et al., 2022). Notable contributions in this area that rely on CDS spreads as a measure of credit risk include Bedendo and Colla (2015), Lee et al. (2016), and Augustin et al. (2018). Unlike their work, our focus is on how the corporate-sovereign nexus changes in the face of a rare disaster. Corsetti et al. (2013) modify the standard neo-Keynesian framework by allowing sovereign default risk to impact funding costs in the private sector over concern for tax hikes and disruptive strikes and calibrate the model on CDS data. What differentiates our modelling approach from theirs is the analysis of the pricing of government guarantees within an intensity-based asset pricing framework.

We naturally connect to the growing number of studies on the effects of the pandemic on financial markets. Among others, Augustin et al. (2021) document that sovereign credit risk in countries with more fiscal space is relatively less sensitive to the COVID-19 pandemic. We provide complementary evidence by investigating the relation between sovereign and corporate debt credit risk, on top of the response of equity returns, and offer a theoretical framework to interpret it. Unlike their study, we do not rely on observable metrics of fiscal space. Rather, we look directly at the market recognition of the expected effectiveness of government guarantees (which reflect fiscal slackness and the sustainability of debt) as priced into credit derivatives. Our study dovetails with Benmelech and Tzur-Ilan (2020), who argue that country credit risk is a strong determinant of countercyclical policies during the COVID-19 crisis, and Gerding et al. (2020), who find that a country's debt-to-GDP ratio is a strong determinant of domestic stock market reaction to the outbreak.[1] By studying credit markets through the lenses of a rare-disaster model, we are able to quantify the benefits of fiscal space for the cost of capital, as measured by the value of government guarantees implicit in credit spreads.

Elenev et al. (2020) carry a quantitative comparison of the impact of direct debt purchases, guarantees on credit provision, and a combination thereof in mitigating US corporate credit risk during the pandemic through a macroeconomic model with financial frictions. By contrast, we provide an international perspective on guarantees in a group of countries with a common currency but differently perceived government space of maneuver.

Finally, we relate to the literature on disaster models (see Rietz, 1988; Barro, 2006; Gabaix, 2012). Pagano et al. (2020) test the predictions of disaster models on equity prices during the COVID-19 pandemic. By contrast, we extend the bailout-augmented disaster model of Kelly et al. (2016) and Gandhi et al. (2020) by considering the implications of the pricing of government support on the relation between corporate and sovereign debt.

[1] Along similar lines, Greppmair et al. (2020) suggest that short sellers made profits on companies located in financially weak countries, anticipating the importance of a country's fiscal space for the resiliency of its domestic firms.

2 Data and summary statistics

We focus on how credit default swap (CDS) spreads of major European corporate (i.e., non-financial) firms relate to spreads referencing their sovereigns. CDS are standardized contracts providing insurance against default of a reference entity in exchange for a premium in basis points (bps) per year as a fraction of the underlying notional (Duffie, 1999). If default takes place, the insurance buyer is entitled to sell the underlying at face value to the insurance seller.[2]

Our source for the CDS data is Markit. The working sample consists of daily mid-quotes from January 1, 2019 to September 10, 2020 (443 trading days) and covering the following nine European countries: Belgium, Finland, France, Germany, and the Netherlands, which we label as core of the EU, and Greece, Italy, Portugal, and Spain, which we refer to as periphery of the EU, following the classification in Ehrmann and Fratzscher (2017). The sample selection follows Ang and Longstaff (2013), conditional on data availability for corporate CDS.[3] The focus on European Monetary Union countries anchored to a common currency but unable to take independent re- or de-valuation decisions minimizes concerns about the effect of strategic devaluation on credit risk. The inclusion of other countries, on the other hand, could bias our estimates.[4]

We work on spreads on CDS contracts with five-year tenor (the most liquid) that reference senior unsecured debt and denominated in Euros. For sovereigns, we rely on cum-restructuring (CR 2014 protocol) instruments, which is the standard reference for Western European sovereign CDS contracts. Corporate CDS data availability leads to the selection of the modified-modified restructuring clause (MMR), but our results are robust to the choice of the clause.[5] To include a company in the analysis, we require availability of equity data on Refinitiv, from which we also gather credit ratings and balance sheet data (such as market capitalization, leverage, return on equity, and dividend per share) as of the end of 2018 and 2019. The final sample for our baseline analysis consists of a panel of 123 non-financial European firms, of which 99 are in the core and 24 in the periphery, and their sovereigns. The top-100 firms by market capitalization are listed in Appendix Table A.1. We also collect data on 43 financial firms, which we use for benchmark purposes in section 3.2.

Summary statistics of the spreads over the period are reported in Panel A of Table 1, with countries grouped into core and periphery. For the former, France and Germany have the highest

[2] Hull (2003) and Duffie and Singleton (2012) are standard textbook references in the literature on credit risk. Determinants and decomposition of sovereign and corporate CDS are discussed, respectively, in Longstaff et al. (2011) and Berndt and Obreja (2010). For an appraisal of the literature, see Augustin et al. (2014).

[3] We only consider firms with at least 300 valid (i.e., not stale) CDS quotes. Two European countries, Ireland and Austria, are omitted as they have only one non-financial firm on Markit with valid CDS data.

[4] This aspect is confirmed by the results in Table 5 of Augustin et al. (2021), where the effect on sovereign CDS of the interaction between COVID-19 and fiscal space is largely attenuated when including the foreign exchange rate returns for a sample of 13 countries outside the Eurozone.

[5] Berndt et al. (2007) point out that the cheapest to deliver option is less of a concern in contracts issued under the MMR clause compared to the full restructuring clause. Using corporate MMR spreads as dependent variable, the effect of full restructuring sovereign CDS, whose cheapest to deliver option is relatively less expensive, is likely to be *underestimated*, as our Table 4 shows.

number of firms (40 and 33, respectively), while Italy and Spain are the most represented in the periphery (11 and 9, respectively).[6] As expected, spreads on sovereign debt of core countries have been on average much lower than for peripherals (13 vs. 98 bps, respectively). For both groups, the period has been characterized by substantial fluctuations in the pricing of sovereign credit risk, as testified by the large standard deviations. Interestingly, unlike for sovereigns, the average CDS spreads of corporations in the core over the period is quite closely aligned to that of peripheral corporations (112 vs. 133 bps), and more volatile over time and in the cross section (205 vs. 119 bps).

As is customary in the literature, to alleviate statistical concerns our analysis is on changes (i.e., first differences) in log CDS spreads. Panel B collects the corresponding statistics. We note that this data transformation largely attenuates differences in moments between the two areas. For example, the standard deviation of the sovereign series is 43 bps in the core versus 46 bps in the periphery, and a variance-comparison Levene test cannot reject the null hypothesis of equality between groups (p-value: 0.12). This evidence reassures us that our conclusions are not unduly influenced by the fact that variables in the two areas fluctuate over markedly different ranges, although the results continue to hold if we work on first differences in spreads.

Lastly, Panel C reports means and standard deviations of firm characteristics that capture relevant dimensions of credit risk. Peripheral firms are on average somewhat smaller and more leveraged than core firms. In our empirical analyses, we account for imbalances in the number of firms and their characteristics across regions by using, respectively, a re-sampling procedure and an entropy-balanced estimator.

Figure 1 presents a graphical illustration of the spreads over the study period. For each country, we plot a corporate CDS index computed as the average CDS spread across firms weighted by market capitalization as of the end of 2019. Spreads were mostly flat to slightly decreasing until the end of February, 2020. The onset of the pandemic is marked by a dizzying spike in CDS referencing non-financial companies across all countries, with average spreads exceeding 200 bps for Greek and Italian firms, followed by a reversal. By the end of the sample period, nearly all series are some 20 to 30 bps above their pre-COVID19 levels. Consistent with the summary statistics, we note that corporate credit risk of firms in some core countries has been on average comparable and at times higher than that of peripheral companies (not controlling for characteristics). Figure 2 displays the time series of the CDS spreads on European sovereign debt. There, we again observe a run-up in spreads until June 2020 and a flattening thereafter. Compared to the corporate sector, there is a distinct fragmentation in the sovereign CDS market, with higher credit risk for peripheral countries.

[6]These numbers are comparable to those in Berndt and Obreja (2010) and Bedendo and Colla (2015), considering that we filter out financial companies.

Following Pagano et al. (2020), and spurred by the previous figures, we date the beginning of the COVID-19 subsample as February 24, 2020, which corresponds to the first Italian lockdown.[7]

To complete the picture of core/periphery classification, Figure 3 displays six proxies for the fiscal space of the countries in our sample. Fiscal space can be broadly defined as the ability of a government to fund its fiscal policy and service its financial obligations (Romer and Romer, 2018). Following Augustin et al. (2021), we account for the multifaceted nature of fiscal space through a battery of variables capturing the amount of outstanding debt, the cost of financing, and the overall quality of the government. Specifically, we report data as of December 2019 on gross government debt as a portion of GDP, interest expenditures on debt, and four indicators of institutional quality.[8] All variables clearly confirm the presence of two clusters in the Euro Area, with the five countries in the core being less fiscally constrained than those in the periphery.

3 The corporate-sovereign nexus

In this paper, we aim to investigate the impact of fiscal capacity on credit risk linkages between non-financial corporations and governments, which we refer to as "corporate-sovereign nexus" or simply "nexus." We address the general question whether and under which conditions, on average, fiscal capacity increases or reduces credit risk spillovers between publicly quoted firms and governments.

The main challenge in establishing a direct effect of fiscal capacity on the nexus is that their relation could be influenced by a wealth of confounding factors. As an illustration, credit risk of both governments and corporations responds to macroeconomic conditions such as economic growth and shocks to technology and productivity, and so does their comovement. These fundamentals have also a direct effect on public finances through their impact on revenues and expenditures, albeit at a lower frequency. A cross-sectional approach would therefore suffer from endogeneity concerns. However, a substantial economic contraction that triggers a swift surge in credit risk does not anywise affect fiscal capacity right away. To achieve a good identification, such contraction should in principle be exogenous to both the pre-existing structure of the nexus and the fiscal capacity of countries, and reach simultaneously and homogeneously the entirety of the sample. The COVID-19 pandemic clearly meets such requirements, and offers a fruitful context to study how the nexus varies in a cross section of countries with different fiscal capacities at the outset of the shock, allowing for a clean measurement of the amplifying role, if any, of ex-ante public finances on the transfers of sovereign risk to national financial markets.

Prior to the pandemic, a broad consensus in the profession viewed the transmission of aggregate

[7] Moving our event date to February 20, 2020 – when the first case of COVID-19 was diagnosed in the Italian town of Codogno – does not, however, affect our conclusions.

[8] The sources are the OECD, ECB, and World Bank.

demand shocks to domestic firms to be amplified in countries with already high levels of sovereign credit spreads and limited fiscal space – a "sovereign risk channel." For these countries, a further deterioration in government credit merit could increase credit spreads on the debt of domestic corporations through, for example, the threat of tax hikes and disruptive strikes, as in the model of Corsetti et al. (2013). The hazard of an increase in tax burden or expropriation is usually associated with the concept of "sovereign ceiling," a transfer from sovereign to corporate risk (Almeida et al., 2017). In a similar vein, Lee et al. (2016) view transmissions of sovereign risk to private sector firms as originating in the threat of expropriation and the transfer of country risks, like corruption and political instability. In our context, the argument that sovereign funding strains exacerbate the severity of the shock and private sector creditworthiness thus predicts that credit risk spillovers in the face of the pandemic should be felt more strongly in peripheral EU countries that are closer to their fiscal capacity limits.

Nonetheless, COVID-19 brought about profound changes in economic relations. The widespread nature of the shock along with generalized economic lockdowns imposed by governments posed a threat to the resilience of the productive system. Under these circumstances, it is conceivable that market participants factored into credit markets the likelihood that the government will use (at least part of) its fiscal space to rescue the non-financial corporate sector. A link between sovereign and corporate credit risk might therefore arise from the pricing of government guarantees. Much of the literature on the pricing of guarantees has thus far focused on financial companies. Acharya et al. (2014) show that, during the European sovereign debt crisis, government bailouts increased the comovement between sovereign and domestic banks' CDS. In a similar vein, Kelly et al. (2016) document that a collective government guarantee for the financial sector was priced in crash insurance contracts during the 2007–2009 crisis. For banks, credit risk comovement arises from two channels: (i) banks' holding of domestic sovereign bonds, and (ii) a backstop option offered by the government to domestic firms. In our context, the first channel is not present, since non-financial firms do not retain significant amounts of sovereign bonds. However, if market participants perceive that a backstop option will be extended also to non-financial firms, changes in government risk would impact spreads of non-financial corporations through their effect on the value of guarantees. The "government support channel" thus predicts that COVID-19 should have strengthened the corporate-sovereign nexus in core countries, as they were perceived to better sustain firms through ample and credible budgetary measures.

Both the "sovereign risk channel" and the "government support channel" predict that a firm's credit risk sensitivity to its own sovereign should overall become stronger in the face of COVID-19. However, they differ in their predictions regarding the role of fiscal space as captured by the core/periphery classification, with the former implying that the nexus should increase more in the periphery, while the latter sees the nexus increasing in the core of the Union.

It is therefore largely an empirical question which of the two channels prevails in the face of the COVID-19 shock. In Section 3.1, we empirically assess how the sensitivity of corporate to sovereign credit risk changed at the outbreak of the pandemic for core versus peripheral EU countries. In Section 3.2, we carry sub-sample analysis by estimating the model separately by country and industry. In Section 3.3, we conduct a number of checks to assess the robustness of our findings along several dimensions. We are mindful that several candidate economic channels could explain our findings. For example, it could be the case that credit risk in peripheral countries was more impacted by the pandemic due to their industrial structure or firm financing constraints. In Section 3.4, we investigate competing channels by enriching our specification with country characteristics – measuring, for example, the severity of the pandemic and degree of country openness to international trade – and firm characteristics capturing profitability, liquidity, and reliance on the banking system. Alternatively, we provide more substantive support to the government support channel by interacting sovereign spreads with measures of country fiscal space, and looking at the role of firm size in explaining deviations of observed CDS from theoretical ones. Finally, Section 3.5 puts the evidence into perspective by extending the sample in the time series and in the cross section using bond data.

3.1 Baseline results

As a first step in our analysis, Figure 4 illustrates the relation between government and corporate CDS spreads around the COVID-19 pandemic by means of a binned scatterplot. Observations are grouped into equal-width bins, and points in the diagram correspond to within-bin averages of corporate and sovereign spreads. The top plot is for the pre-COVID19 sample (i.e., from January 1, 2019 until February 23, 2020), while the bottom one refers to the COVID-19 period. By staring at the graphs, two conclusions emerge. First, two distinct data clusters arise within each plot, coherently with the core/periphery classification. Second, it appears that the pandemic was accompanied with a mild steepening of the relation in peripheral countries, and a much more pronounced one in the core. Thus, first-pass evidence indicates that the outbreak strongly affected unconditional credit risk comovement in fiscally-strong countries.

To formally test whether this result holds also conditionally on a variety of factors, we resort to a panel regression model with corporate CDS spreads as the dependent variable. The setting allows us to exploit the granularity of the data and pin down the relation between corporate and government CDS spreads conditional on aggregate and firm-level controls. In addition, and specific to the evolution of the COVID-19 shock, firm credit risk ultimately reacted to a government decision to impose national lockdowns halting, in part or in full, a number of corporate activities, so it is natural to think of the former as the outcome variable. Following Acharya et al. (2014)

and Augustin et al. (2018), we work with daily growth rates in CDS; namely, first differences in log (sovereign and corporate) CDS spreads. This setup enhances the stationarity of the data, given that CDS are highly persistent on a daily basis, and is better suited for a panel of firms and countries with different levels of spreads. Therefore, we measure the nexus with the sensitivity (i.e., elasticity) of a firm's credit risk to that of its sovereign.

In our empirical approach, we seek to capture two dimensions of the corporate-sovereign nexus. First, in the time series, we interact all variables in the model with the dummy E that equals one in the days after February 24, 2020 and zero otherwise. The interaction terms reveal how the COVID-19 shock changed pre-existing relations. Second, we look for differential effects in the cross section of countries by estimating the model separately for core versus periphery, which were characterized by markedly different fiscal capacity at the inception of the crisis (Augustin et al., 2021).

Our panel regression model takes the form

$$\begin{aligned}\Delta log(\text{CDS Corp})_{ijt} &= \alpha_0 + \alpha_1 \times E + \delta_i + \beta_1 \Delta log(\text{CDS Sov})_{jt} + \beta_2 \Delta log(\text{CDS Sov})_{jt} \times E \\ &\quad + \gamma_1 X_{ijt} + \gamma_2 X_{ijt} \times E + \varepsilon_{ijt}, \qquad (1)\end{aligned}$$

where $\Delta log(\text{CDS corp})_{ijt}$ is the first difference (between day t and day $t-1$) in the log CDS spread of company i incorporated in country j, and $\Delta log(\text{CDS Sov})_{jt}$ is the contemporaneous first difference in the log CDS spread on the sovereign debt of country j. The vector X includes the following: a lag term $\Delta log(\text{CDS corp})_{ij\,t-1}$ to further filter residual persistence in the dependent variable; the firm equity return R_{ijt}, which mirrors the pricing of debt under standard Merton (1974)-type contingent-claim models and should be sufficient (absent guarantees) to absorb the effect of aggregate shocks on both firm's assets and sovereign creditworthiness that could bias our inference (Acharya et al., 2014); and the CBOE option implied volatility index VIX_t, which captures aggregate volatility and risk appetite (using VSTOXX as an alternative does not affect our results). All variables enter the equation both in level and interacted with the COVID-19 period dummy E. The firm fixed effects δ_i absorb away any time-invariant attributes such as country and sector, and arguably – given the relatively short time span of our event window – book leverage.[9]

Columns (1) and (2) in Table 2 present the corresponding OLS estimates for core and periphery, respectively, with associated standard errors clustered at the firm level in parentheses.[10] The coefficient β_1 (first row of the table) measures the corporate-sovereign nexus in the sample preceding the Italian lockdown. In this period, a shock to sovereign credit risk was accompanied by a

[9]Market leverage would instead mostly be driven by changes in the value of equity, for which we already control. We also considered additional controls, such as Euroswap rates and the slope of the term structure of sovereign credit risk, and find they do not affect our conclusions. In section 3.3, we show that our findings continue to hold using an alternative pooled model with fully saturated time and sector or country fixed effects.

[10]We resort to OLS estimation because the time dimension far exceeds the number of cross-sectional units, which makes the bias with respect to estimating a dynamic panel fairly negligible. In section 3.3, we show our results are robust to using a GMM dynamic panel data estimator.

statistically significant change in corporate risk in the same direction. The effect is about twice as large for non-financial corporations in the periphery, for which a 10% increase in sovereign CDS translates into a 2.08% increase in their CDS, compared to firms in the core, for which a shock of the same magnitude generates in a more modest 1.27% increase.[11] These estimates are in line with the common wisdom that, in normal times, credit risk comovements are amplified in countries with fiscally-constrained governments.

The second row of the table reveals that the COVID-19 pandemic had a massive impact on the corporate-sovereign nexus for companies in the core, as demonstrated by an economically and statistically significant β_2^{Core} coefficient. The 0.125 estimate implies that the sensitivity of these companies' credit spreads to shocks in their sovereigns effectively doubled during the period, bringing the overall impact ($\beta_1^{Core} + \beta_2^{Core}$) to a level of about 0.25 – thus, a 10% increase in sovereign spreads in the second half of the sample translates into an expected 2.5% increase in spreads for corporate sector debt. Notably, this figure is at par with that of companies in the periphery, for which the additional contribution from the COVID-19 sample β_2^{Peri} is a meager 0.052 (statistically insignificant). The p-value for the F-test of equality between β_2^{Core} (0.125) and β_2^{Peri} (0.052), reported in the last row of the table, confirms that their difference is not only economically but also statistically significant. Overall, these results point toward the government support channel as the dominant force in the repricing of credit risk markets in the face of the shock: countries that were better positioned to extend government support experienced a tightening in the corporate-sovereign relation.

Among the controls, we note some persistence in CDS growth rates, whose extent did not change in the COVID-19 sample. The loading on stock return is strong and negative and becomes larger in absolute terms during the pandemic for both core and periphery, in line with the intuition from the Merton (1974) model. Option-implied market volatility positively relates to spread changes in the first part of the sample for both groups, and even more so during the COVID-19 period in core countries thereby highlighting the importance of partialling out changes in the pricing model of corporate credit risk between the two regions unrelated to sovereign risk.

In columns (3) and (4) of Table 2 we perform a value-weighted least squares estimation, where weights are based on equity market capitalization (as of 2019). Intuitively, the larger the company, the stronger its ties with the government, according to both a government support channel and a coercive taxation motive. This specification strengthens our conclusions, as the difference in the β_2 coefficient between core and periphery widens even further to a full 0.15. This evidence is consistent with market participants perceiving and pricing in generous and effective government transfers mostly targeting larger firms in the core. In peripheral countries, with relatively weaker public fi-

[11] These estimates are comparable to, although generally higher than, those reported in Bedendo and Colla (2015), possibly because of additional risk transfer taking place during the European sovereign debt crisis, which is not in their sample.

nances and less resilient structural economic conditions, the COVID-19 shock was accompanied by a very modest increase in corporate-sovereign sensitivity.

In columns (5) and (6), we repeat our baseline analysis using the entropy-based reweighting algorithm of Hainmueller (2012); see Jacob et al. (2018) for a recent application. Given that sample selection is driven by CDS data availability, our estimates could be biased by structural differences in the characteristics of listed firms headquartered across the two Eurozone regions. To mitigate this concern, we rely on a reweighting scheme that matches the first three moments of credit risk related variables – market capitalization, leverage, market to book ratio, and equity volatility – between core and periphery.[12] The results show that accounting for covariate imbalance raises the difference between β_2^{Core} and β_2^{Peri}, in both magnitude and statistical terms.

3.2 Subsample analysis

Panel A of Table 3 reports the loadings on sovereign CDS when the model in Eq.(1) is separately estimated by country (the controls are included, but their coefficients are omitted for brevity). Despite the substantial cross-country heterogeneity in the number of firms, we find that every country in the core is characterized by an economically large and statistically significant surge in sovereign credit risk transfer during the COVID-19 sample, with values ranging from 0.076 for Finland to 0.156 for Germany. In contrast, none of the peripheral members displays a significant reaction to the pandemic. This result confirms that our core/periphery classification has a strong financial backbone in the repricing of corporate credit risk induced by the shock.

In Panel B of Table 3 we stratify the data by four industrial sectors; namely, energy and utilities, industrial, technology, and goods and services.[13] The effect we document is not concentrated in a single sector but rather pervasive, with β_2 coefficients ranging from 0.055 for tech firms to 0.120 for goods and services. Notably, the sectors for which we find a larger increase in comovement with the sovereign correspond to those classified by Dunn et al. (2020) as COVID-19 sensitive using credit card transaction data, which is in line with a strong reliance on the pricing of government support. The last column of the panel provides estimates for financial firms, which are excluded from our working sample. The increase in the corporate-sovereign nexus for financials is lower than all other sectors and only marginally significant, despite being the highest before the pandemic. This result is consistent with the non-financial nature of the shock and with the pricing of government guarantees extended to the real sector.

[12] Entropy balancing optimally determines weights to achieve exact moment matching while keeping the distribution of observations as close as possible to the data in an entropy sense. Appendix Table A.2 reports the moments of credit risk related variables before and after the reweighting.

[13] The industry classification is based on Refinitiv Eikon.

3.3 Robustness checks

We assess the robustness of our finding to a number of econometric concerns and model design choices. The corresponding estimates are collected in Table 4, which reveals that our results on the reaction of the nexus to the pandemic continue to hold or are even reinforced in all these tests.

Specifically, in columns (1) and (2), we augment the model with firm-level at-the-money option-implied volatility, as a timely and forward-looking market assessment of a firm's total risk.[14]

Next, we worry that our findings might be picking up the effect of the ECB's Pandemic Emergency Purchase Programme (PEPP), the temporary asset purchase program targeting private and public sector securities.[15] To rule out this concern, in columns (3) and (4) we show that our conclusions extend to the subsample of non-eligible PEPP corporate issuers.[16] In a similar vein, in columns (5) and (6) we re-estimate our baseline model while restricting the COVID-19 sample to only one trading month (i.e., through March 24, 2020). By doing so, we minimize concerns that our estimates are capturing the effect of direct government support to local demand and the foreseeable effects of the European Recovery Plan, the implementation of which was not even being discussed.

In columns (7) and (8), we use the Arellano–Bover/Blundell–Bond system GMM dynamic panel data estimator (Arellano and Bover, 1995; Blundell and Bond, 1998) as opposed to OLS. Using a FGLS estimator as an alternative (not reported for brevity) again confirms our findings. In columns (9) and (10), we estimate the model on data aggregated at the weekly frequency. In columns (11) and (12), we select the cum-restructuring clause for corporate CDS. Additionally, Appendix Table A.3 reports the estimates from adding a squared equity term to account for non-linearities in the equity-CDS relation and running the model in first differences.

In columns (13) and (14), we restrict the estimation to firms whose average CDS during the pre-COVID period was higher than that of their government in order to verify that our results are not triggered by asymmetries in the effect of changes in sovereign risk (Almeida et al., 2017). Analogously, in columns (15) and (16) we show that the result we document persists on the sample of firms with below-average government ownership, defined as the fraction of a firm's equity that is owned by the government and sovereign wealth funds (source: Bloomberg). The interaction term between government ownership and sovereign CDS (not shown for brevity) is also largely statistically insignificant. In columns (17) and (18), we control for cross-area spillovers by adding the first principal component of sovereign CDS spreads in the other area (periphery and core, respectively), both in level and interacted with the E dummy. Importantly, the nexus of core

[14] The source is Bloomberg. Data are missing for seven core and four peripheral firms.

[15] The list of eligible PEPP collateral is available at `https://www.ecb.europa.eu/paym/coll/assets/html/index.en.html`. While the program does not directly target CDS contracts, it might still act as a confounding factor by exerting downward pressure on bond yields with an intensity that depends on market size and thus overlap in part with the core/periphery classification.

[16] This result lines up with evidence from Krishnamurthy and Vissing-Jorgensen (2011) that QE has a significant effect on CDS spreads of low-rated securities only, while our sample is composed of high-rated issuers.

companies remains country specific even if we include the credit risk of peripheral sovereigns, which implies that we are not capturing cross-area subsidy effects.

Finally, we carry out the following bootstrap re-sampling experiment to control for imbalances in the number of firms or industrial composition between core and periphery. In every bootstrap run, we match each firm in the periphery with a random core firm in the same industry classification. We then estimate our baseline panel regression on this randomized sample of core firms, whose size and industrial composition match (by design) those in the periphery, store the resulting coefficients and standard errors, and repeat the procedure 1,000 times. Figure 5 plots the distributions of the β_2 coefficient (left panels) and its t-statistic (right panels) for the equally-weighted (top panels) and market cap-weighted (bottom panels) models across the 1,000 randomized core samples. If our results were driven by CDS data in the periphery being available only for fewer firms or firms operating in sectors with low sensitivity to the COVID-19 shock, we should observe no effect in balanced sets of Core firms in the same sectors. By contrast, none of these artificial samples delivers estimates that are lower than those obtained in Table 2 for the actual periphery (which are marked in each panel by a vertical dotted line).

3.4 Economic channels at work

The startling result that, among European countries, the pandemic sparked higher credit risk transfers only in those with strong fiscal capacity indicates government support as a strong candidate explanation. However, while public finances are the hallmark of the distinction between core and periphery, countries differ in a number of dimensions that may be at the root of the reaction to the shock. We take on the task of separating potentially co-existing mechanisms using either firm-level or country-level variables in the next two subsections, and lastly carry a direct test for the public guarantees channel using the approach in Kelly et al. (2016).

3.4.1 Firm-level characteristics

We augment our baseline regression model with firm-level characteristics that capture a company's sensitivity to the COVID-19 shock, and might correlate with the core/periphery grouping. Wenzhi et al. (2021) show that the pandemic-induced drop in stock prices was milder among firms with larger pre-2020 profitability. We thus control for a firm's profit before taxes over employees (PPE).[17] Fahlenbrach et al. (2020) provide evidence that firms with greater financial flexibility exhibited stronger resiliency to COVID-19 thanks to their ability to fund the shock-induced revenue shortfall and, as a consequence, were less in need of policy responses. We control for this feature by adding $Liquidity$, the ratio of current assets minus stocks to current liabilities. Relatedly, a

[17] We obtain analogous results using net asset turnover (not shown for brevity).

firm's funding structure and reliance on the banking sector affect its ability to cope with unexpected shortfalls in profitability by temporarily increasing borrowing. Acharya and Steffen (2020) show that firms' ex-ante funding structure is priced in the cross section of stock returns. We capture this effect through $Loans$, the log of a firm's ratio of short-term financial debt to total debt. We include the three variables in the model both in level and interacted with $\Delta log(\text{CDS sovereign})_{jt}$. The corresponding estimates are collected in Table 5, where Z alternatively denotes the three different characteristics, which are all computed in excess of the year-industry median.

The overall message from the table is that none of profitability, liquidity, or bank dependence explains the different increases in the intensity of the corporate-sovereign nexus in the two regions.

3.4.2 Country-level characteristics

We next consider country-level proxies for the severity of the COVID-19 shock on the country's productive system. To incorporate country-level determinants, we follow the empirical setup of Augustin et al. (2021). To this end, we report in column 1 of Table 6 estimates from a pooled (i.e., difference-in-difference) panel version of Eq.(1), where firm-level data are pooled across all countries while allowing for a differential loading on sovereign risk in core countries. The coefficient on the triple interaction term – $\text{Core}_j \times \Delta log(\text{CDS sovereign})_{jt} \times E$ – in the second row of the table again confirms that the corporate-sovereign nexus in core countries ($\text{Core}_j = 1$) during COVID-19 ($E = 1$) is larger by 0.113 than that in peripheral countries.

Given that national lockdowns caused a severe slowdown or even halt in international trade, we control in column (2) for a country's degree of openness (computed as the ratio of exports plus imports to GDP), which measures its reliance on foreign demand and the international supply chain (Ramelli and Wagner, 2020).[18] In column (3), we consider the country's share of GDP generated by tourism, as this sector was arguably among the most impacted by the shock, and in turn generated a slowdown in satellite activities. In column (4), we control for the strength of a country's healthcare system, which we measure with the number of hospital beds per thousand inhabitants, as better-positioned systems likely attenuated or deferred the social and economic consequences of the pandemic. Finally, while all countries we examine responded to the COVID-19 shock by imposing similar economic freezes during the sample period, in column (5) we explicitly account for the strictness of government-imposed "lockdown-style" policies through the Oxford COVID-19 Government Response Tracker.[19] As an alternative modelling approach, we consider a fully saturated fixed effect model by adding week times sector (in column 6) and week times country (in column 7) fixed effects, in addition to firm fixed effects.

[18] Data on a firm's reliance on international markets – e.g., the ratio of foreign to domestic revenues or sales – are insufficiently populated in Refinitiv Eikon for us to carry out this analysis at the firm level.

[19] This variable is available on a daily basis. The previous three variables, by contrast, are available at an annual frequency, and we use their values as of the most recent year end preceding date t to prevent any look-ahead bias.

From the table, we see that the differential in the nexus between countries classified as core versus periphery remains intact notwithstanding the inclusion of the four country-level variables and the alternative fixed effect models. Out of the four country characteristics, only the Government Response Tracker significantly relates to the reaction of corporate credit spreads to COVID-19, but does not explain away the surge in the corporate-sovereign relation for fiscally-sound countries.

3.4.3 Role of fiscal space

The persistence of our result compels us to explore more directly the role of fiscal slackness in triggering the reaction of credit risk markets to the outbreak. As a step in this direction, we use the six measures of fiscal capacity from Figure 3, which capture different facets of public finances. Specifically, we re-estimate the pooled model by replacing the Core_j dummy with such measures, one at a time. To ease the interpretation of the coefficients, we sign the variables so that higher values reflect healthier governments – i.e., we flip the sign of Gross Government Debt over GDP, Interest Expenditures on Debt, and the Long Term Interest Rate.

The corresponding estimates are reported in Table 7. In the pre-COVID19 sample, the loading on the interaction between log CDS sovereign spreads and each fiscal capacity variable (first row of the table) is consistently negative, confirming the common wisdom that the nexus tends to be stronger in countries with wimpy public finances in "normal times." During the pandemic sample, the relation reverses, as the interaction coefficients with the COVID-19 dummy (second row of the table) are positive and large when compared to the previous ones. The effect is statically strongest for Long Term Interest Rate, and least so for the Fiscal Wealth measure. In addition to the individual series, we also use their first principal component (labeled PC1) as a catch-all variable in the last columns, which further highlights the change of sign around COVID-19. Therefore, our result extends to continuous variables capturing a government's fiscal health, thereby confirming its key role in the repricing of credit risk in the Eurozone at the first sights of the pandemic. In what follows, we privilege the binary core/periphery classification for its simplicity as a grouping criterion.

3.4.4 Deviations from fundamental credit risk

Standard models for credit risk predict that in a frictionless world, any shock to a firm's asset would affect its liabilities, with an intensity that depends on leverage. By contrast, in the face of COVID-19, the cost of default risk protection for non-financial corporate debt became more tightly linked to sovereign credit risk, even after controlling for, among other variables, equity returns. This is consistent with the wedge in the valuation of corporate claims created by the pricing of government guarantees extended to debtholders (Acharya et al., 2014). A complementary test in Kelly et al.

(2016) looks at systematic deviations of actual spreads from those predicted by a standard structural model of default. They document deviations that are a negative function of size for financial firms during the Global Financial Crisis and argue that this fact reflects the pricing of public guarantees. We show that a similar analysis on our sample uncovers wider deviations for large non-financial firms during COVID-19 in core countries only.[20]

We compute the model-implied CDS rate from the Merton (1974) model using Bharath and Shumway (2008)'s measure of distance to default (DD).[21] Similar to Kelly et al. (2016), we then estimate cross-sectional weekly regressions of the form

$$\text{CDS}_{it} = a_t + b_{1t}\text{Merton Spread}_{it} + b_{2t}\text{Size}_{it} + b_{3t}\text{Leverage}_{it} + \varepsilon_{it}, \tag{2}$$

separately for observations in the core and periphery. As in Kelly et al. (2016), we define size as the one-month-lagged log of market value of equity plus book value of debt and leverage as the one-month-lagged log ratio of book value of assets to market value of equity.

Figure 7 plots the four-week trailing average of the resulting slope coefficient on size (b_{2t}), along with standard error bands. Controlling for leverage and volatility, the slope of risk-adjusted corporate spreads to firm size in the pre-COVID sample fluctuates in a rather narrow and similar range in both core and peripheral countries. As the shock hits the markets, we observe markedly different behaviors between the two areas. The slope becomes more negative in core countries, and the discount widens to values as much as five times pre-COVID levels. Despite the similarity in the severity of the shock and the relative increase in credit risk, size does not systematically explain departures from fundamentals for CDS referencing firms in peripheral countries. Therefore, at the outbreak of the COVID-19 shock, actual CDS spreads were priced at a discount with respect to predicted spreads only in the case of large(r) companies located in core EU countries; in other words, countries that were perceived to be far from their fiscal capacity limits and whose governments were deemed ready to extend public support.

3.5 Larger cross section or longer time series

We resort to CDS data to quantify the corporate-sovereign nexus as they offer a clean and timely measurement of credit risk. This design naturally limits our study to the cross section of companies on which CDS contracts are referenced – typically, large and well-established companies. To beef up the representativeness of our sample, while sacrificing some data quality, we repeat our analysis

[20] This type of analysis is compliant with the approach in Bai et al. (2019), who argue that the basket-index put spreads puzzle can be solved by accounting for equity dynamics and the "leverage effect."

[21] As is customary, we take current liabilities plus one half of long term debt to proxy for face value of debt and close price times amount of ordinary shares as market value of equity. We update the stock's volatility using the RiskMetrics variance model to take into account time variation in risk. Using option-implied volatility diminishes sample size due to data availability but conveys the same message.

on corporate bonds. We use Refinitiv data on 1898 plain vanilla bonds issued by non-financial public companies in the considered countries and alive during 2020. We summarize a firm's debt structure by computing daily yield to redemption and modified duration as value-weighted averages across all its available bonds on that day, with weights given by a bond's relative amount issued. After eliminating stale quotes and firms with a high percentage of missing values, the final sample of 255 firms – of which 194 in the core and 61 in the periphery – makes our analysis more representative of the universe of European public firms. On the downside, it is well known that corporate bonds trade infrequently and that their spreads contain a significant nondefault time-varying component, which relates to bond-specific and marketwide liquidity (Longstaff et al., 2005; Houweling et al., 2005; de Jong and Driessen, 2012). Both these issues potentially contaminate our inference.

We re-estimate the model in Eq.(1) by replacing the corporate CDS spreads with bond credit spreads, which we compute by subtracting from the aforementioned yield to maturities the Euro area risk free rate of the nearest modified duration. Columns (1) and (2) of Table 8 use daily data, and show that our main conclusions extend to bond credit spreads. The ex-pandemic loadings on sovereign credit risk in the first row are positive, and much larger in the periphery. During the COVID-19 period, the opposite holds as the 0.172 interaction coefficient in the core far outweighs the 0.048 figure in the periphery (the p-value of the difference being 0.000). We also report in columns (3) and (4) the estimates from weekly data, which ameliorate concerns of low trade frequency (but at the cost of fewer observations). Similar conclusions arise, with the corporate-sovereign soaring in fiscally-healthy countries during the pandemic.

As a complementary exercise, we expand the time series dimension of the CDS data to put our results into a broader historical perspective. Specifically, we estimate the panel regression in Eq.(1) separately for core and peripheral countries throughout the whole post-Global Financial Crisis period from January 1, 2010 to September 10, 2020 – and thus, without interaction terms with an event dummy. To appreciate time variation in the nexus, we run the estimation on one-year windows of data that are rolled forward after one quarter. Figure 6 displays the resulting nexus coefficient relating changes in log corporate CDS spreads to those in log CDS spreads of the corresponding sovereign in the two areas. Each coefficient is plotted in correspondence to the begin date of its estimation window, and the dashed vertical line marks the first sample that includes COVID-19 data.

From the figure, we note that the nexus has been historically stronger in peripheral countries, in line with the common wisdom that sovereign spillovers are normally amplified in fiscally-strained countries (Corsetti et al., 2013; Lee et al., 2016; Augustin et al., 2018). By comparison, the core coefficient varies in a much more narrow range in the pre-COVID19 sample and does not exhibit economically large swings, even during the European sovereign debt crisis. The pandemic changed this picture quite strikingly. It leads to an unprecedented surge in the nexus for core countries, with a coefficient reaching levels above 0.20. In comparison, the increase has been milder and far less exceptional for peripheral countries, to the point that the two coefficients have never been any closer historically. By marking a watershed, the nimble diffusion of the coronavirus pandemic well exemplifies the role of tail event contractionary episodes in altering the pricing elements at work in credit markets.

4 Disaster-risk intensity-based model with public guarantees

To rationalize the evidence in the previous section, we develop an asset pricing model featuring both disaster risk and government intervention to sustain domestic firms. The scope of this analytical framework is twofold. First, it helps us understand how fiscal space (via the pricing of government guarantees) enters the relation between corporate and sovereign credit risk in the face of a disaster. Second, it allows us to develop further relations that we explore in the data.

In the model, a disaster triggers a negative jump in consumption and an increase in corporate credit risk through a jump in the default intensity of non-financial corporations. The government can provide collective guarantees through a ceiling on the size of the jump, thereby limiting the increase in the level of credit spreads. However, when the guarantee is activated, it causes an increase in the default risk of public debt that is commensurate with the portion of the shock that the government has absorbed. This mechanism is responsible for the comovement between corporate and sovereign credit risk conditional on the disaster taking place.

4.1 Model setup

The model builds on the disaster-risk bailout-augmented setup of Kelly et al. (2016) and Gandhi et al. (2020). We assume that a disaster of stochastic intensity hits the economy with probability $p_i \sim \Pi$, a persistent Markov process with $i \in \{1, .., I\}$ states. All stochastic processes are specified under the risk-neutral measure $\mathbb{Q}$. In the face of a rare disaster, the growth rate in log aggregate (i.e., "world") consumption $\Delta\mathcal{C}_{t+1}$ jumps by the Gaussian process J^r_t, with $\mathbb{E}_t[J^r_{t+1}] = \theta_r$. The process for $\Delta\mathcal{C}_{t+1}$ is modelled as the mixed jump-diffusion

$$\Delta\mathcal{C}_{t+1} = \begin{cases} \gamma_i - \sigma_i\eta_{t+1} & \text{No Disaster} \\ \gamma_i - \sigma_i\eta_{t+1} - J^r_{t+1}\,, & \text{Disaster} \end{cases} \tag{3}$$

where γ_i and σ_i denote the state-dependent mean and volatility, respectively, and η_{t+1} is a standard normal innovation.

We are interested in the implications of the disaster for the pricing of default risk. As is customary in the credit risk literature (see, among others, Longstaff et al., 2005), we model the default event as the first jump of a Poisson process with state-dependent intensity. We assume that the disaster triggers a jump J_t^λ in the risk-adjusted intensity of default that is normally distributed and perfectly correlated with the jump in consumption growth J_t^r, with $\mathbb{E}_t[J_{t+1}^\lambda] = \theta_\lambda$ and $\mathbb{V}_t[J_{t+1}^\lambda] = \delta_\lambda^2$. In this way, times of low consumption growth (and higher marginal utility) are associated with higher risk-adjusted spreads. The relation between J_t^λ and the jump in the risk-adjusted default intensity of the average corporation J_t^c depends on government intervention.

Specifically, we assume that the risk-adjusted distribution of firm c's default intensity λ_t^c evolves according to[22]

$$\lambda_t^c = \begin{cases} \nu^c + \phi_c \sigma_i \eta_t + \sigma_c \epsilon_t & \text{No Disaster} \\ \nu^c + \phi_c \sigma_i \eta_t + \sigma_c \epsilon_t + \kappa_c J_t^c \,. & \text{Disaster} \end{cases} \tag{4}$$

In the ex-disaster region, the parameter ν^c captures the unconditional intensity while ϕ_c is the firm-specific sensitivity to aggregate consumption growth innovations. The firm is also exposed to an idiosyncratic innovation ϵ_t in credit risk. In the disaster state, a government stands ready to bail out its corporate sector should the realization of J_t^λ be deemed too large.[23] We capture government intervention through the fiscal policy function

$$J_t^c = \min\{J_t^\lambda, \underline{J}\} \,. \tag{5}$$

This specification implies that the actual jump in corporate credit risk J_t^c is bounded from above by the amount of the (deterministic) guarantee $\underline{J}$. If an excessively severe disaster hits the economy – that is, if J_t^λ is too large – state intervention mitigates the increase in corporate $\mathbb{Q}$-default intensity. Stronger guarantees, for instance liquidity and solvency provisions, map into lower $\underline{J}$. Note that $\underline{J}$ does not correspond to the sheer amount of government support (i.e., a fiscal package or direct transfers) to firms. Rather, it captures how government spending factors into the pricing of credit risk claims. Therefore, it incorporates the market participants' assessment of how credibly the government can sustain its spending through an efficient use of resources and promote a swift recovery.

Finally, the parameter κ_c captures firm c's sensitivity to the actual contraction, so that its λ_t^c is effectively shocked by an amount $\kappa_c J_t^c$. The cross-sectional mean (across all firms in the "world") of κ_c is one. Therefore, government intervention ultimately affects the pricing of firm-level credit risk through two parameters: the country-specific shock $\underline{J}$ and the firm-level multiplier κ_c.[24]

[22] Alternatively, one could view c as the aggregation of the domestic private sector.

[23] The model by Hanson et al. (2020) shows that borrowing frictions and demand externalities from rescuing firms might motivate government intervention toward non-financial corporations, particularly at times in which cash flows are not informative about solvency as in the recent pandemic.

[24] Our framework shares similarities with Mäkinen et al. (2020), where government support is measured by two parameters capturing the strength of the guarantee and its riskiness. Unlike their agency model, we allow one parameter to capture the consequences for asset prices of government intervention, essentially triggered with certainty by a large disaster.

Taking the first difference of Eq. (4) yields a discrete-time Ornstein–Uhlenbeck process, in the spirit of Lando (2009). Defining $\mu_t^c = \nu^c - \lambda_t^c$, the process for changes in default intensity $\Delta\lambda_{t+1}^c$ satisfies

$$\Delta\lambda_{t+1}^c = \begin{cases} \mu_t^c + \phi_c\sigma_i\eta_{t+1} + \sigma_c\varepsilon_{t+1} & \text{No Disaster} \\ \mu_t^c + \phi_c\sigma_i\eta_{t+1} + \sigma_c\varepsilon_{t+1} + \kappa_c J_{t+1}^c. & \text{Disaster} \end{cases} \tag{6}$$

Unlike previous studies, we explicitly model the relation between a government's credit quality and the magnitude of its "put option" (Veronesi and Zingales, 2010). To be precise, we assume that the sovereign debt default intensity λ_t^g is also state-dependent and that its jump in the face of the disaster equals the support it pledges to its corporate sector

$$\Delta\lambda_{t+1}^g = \begin{cases} \mu_t^g + \phi_g\sigma_i\eta_{t+1} & \text{No Disaster} \\ \mu_t^g + \phi_g\sigma_i\eta_{t+1} + \max\{J_{t+1}^\lambda - \underline{J}, 0\}. & \text{Disaster} \end{cases} \tag{7}$$

Changes in default intensity in public debt have drift $\mu_t^g = \nu^g - \lambda_t^g$ and loading ϕ_g on aggregate consumption growth innovations. The portion of the jump that is absorbed by the government generates an increase in default risk of its debt, which is therefore jointly determined by the realized disaster J_{t+1}^λ and the size of the guarantees $\underline{J}$. Appendix Figure A.1 provides a graphical illustration of the government support policy discussed in the model.[25]

4.2 Model-implied corporate-sovereign nexus

Our framework allows us to explicitly express the relation between changes in corporate and sovereign credit risk as a function of the structural parameters. As a first step, since we empirically measure credit risk with CDS spreads, we establish a mapping between spreads and default intensities.

Proposition 1. *Assume constant risk-adjusted recovery rate R. Spread changes are approximately equal to the product of first differences in risk-adjusted default intensities and losses given default.*

$$\Delta\text{CDS}_{t+1} \approx (1-R)\Delta\lambda_{t+1}.$$

Proof. See Appendix A. ■

Next, let Φ be the CDF of a normal random variable evaluated at the point $\frac{\underline{J}-\theta_\lambda}{\delta_\lambda}$ and φ its corresponding pdf. The covariance between changes in government and corporate CDS spreads

[25] For parsimony, we do not allow for an idiosyncratic component to public debt, akin to the expression for corporate credit risk. Introducing such an element, however, would not affect any of the results. On a related matter, our conclusions extend to allowing a sensitivity κ_g of government credit spreads to the cost of fiscal intervention, from which we abstract for simplicity. Moreover, we do not model the direct increase in sovereign credit risk resulting from a disaster, such as reduced tax revenues which may impair government's ability to repay pre-disaster debt. Rather, we assume that all consequences for the public sector are either absorbed by the ex-disaster component or come from guarantees-financing debt.

can be expressed in closed form as follows.

Proposition 2. *Conditionally on the fiscal policy function and up to a factor of* $(1-R)^2$,

$$\mathrm{Cov}(\Delta CDS^{c}_{t+1}, \Delta CDS^{g}_{t+1}) \approx \underbrace{\phi_g \phi_c \sigma_i^2}_{\substack{\textit{Ex-disaster}\\ \textit{Term}}} + \underbrace{p_i \kappa_c \mathbb{E}_t[\max\{J^{\lambda}_{t+1} - \underline{J}, 0\}](\underline{J} - p_i \min\{J^{\lambda}_t, \underline{J}\})}_{\textit{Disaster Risk Term}} . \quad (8)$$

Proof. See Appendix B. ■

Eq. (8) clarifies that the corporate-sovereign covariance can be decomposed into two terms. The first term captures the link between corporate and sovereign credit risk that arises from common exposure to ex-disaster aggregate economic shocks. As long as the probability p_i that a disaster hits the economy and the government needs to intervene to support corporations is low to negligible, this term dominates the covariance. As soon as market participants observe sights of a tail event and start factoring in a higher probability of disaster, the relative contribution of the second term takes up.[26] This "disaster risk term" is increasing in the probability of the occurrence of a disaster p_i, the corporate sensitivities to disaster risk κ_c, and the product of expected jumps in firm and government credit risks.

From Eq. (8), we see that higher corporate sensitivities κ_c always map into higher corporate-sovereign covariances. The effect of an increase in $\underline{J}$, by contrast, is not as obvious, as $\underline{J}$ enters the expression in a nonlinear way. However, taking the derivative of Eq. (8) with respect to $\underline{J}$ yields the following result.

Corollary 1. *Assuming for simplicity* $\delta_\lambda = 1$ *and provided* $\underline{J} > .5(\theta_\lambda + \frac{\phi}{1-\Phi})$*, the corporate-sovereign nexus decreases in the ceiling to the default intensity of domestic corporations* $\underline{J}$

$$\frac{\partial \mathrm{Cov}(\Delta CDS^{c}_{t+1}, \Delta CDS^{g}_{t+1})}{\partial \underline{J}} < 0 ,$$

or, if we define Guarantee as $-\underline{J}$*,*

$$\frac{\partial \mathrm{Cov}(\Delta CDS^{c}_{t+1}, \Delta CDS^{g}_{t+1})}{\partial Guarantee} > 0 .$$

Appendix B proves this result and Figure A.2 presents an illustration from which much intuition derives. Under the parameter restriction requiring the government not to assume a disproportionate

[26] To clarify, let the system begin in the state where the probability of a disaster occurring is the lowest. The system stochastically transits to a state featuring a higher possibility of a catastrophe, which eventually occurs. As long as the process sojourns in a state with relatively high p_i, a disaster is likely to occur, even after a jump – for instance, a lockdown following an outbreak or another pandemic wave. As in Krishnamurthy and Li (2020), a large economic contraction induces market participants to update their inference about the Markov state. This feature allows the one-time occurrence of a disaster to generate long-lasting repricing of tail risk and associated government intervention.

amount of corporate risk, the covariance between sovereign and corporate CDS spreads *increases* with the extent of government support, in the spirit of Acharya et al. (2014). An implication of Corollary 1 is that governments with wider fiscal space, whose public guarantees are considered larger and more effective, should display a stronger increase in the link between private and public sector credit risk as the disaster hits, holding all other parameters fixed.[27]

4.3 Model predictions and empirical analysis

The model-implied relation we establish in the previous section enables us to gain a structural interpretation of the empirical facts we document in Section 3. For the sake of our discussion, let the "world" be divided into two groups of countries $j = \{Core, Peri\}$. The two groups differ in the extent of perceived government support and in the reliance of both their sovereign and (average) corporate debt default intensities on consumption shocks.

The first row of Table 2 reports that the sensitivity of corporate to sovereign risk was positive and higher for firms in the periphery during the pre-COVID sample, when pandemic disaster was by and large unpriced. From Eq. (8), this finding implies that the ex-disaster term is larger in the periphery, possibly because of a more pronounced sensitivity of sovereign credit risk to ex-disaster fluctuations; that is, it points toward ϕ_g^{Peri} being greater than ϕ_g^{Core}.

As soon as the first signs of the pandemic reached the market, the investors revised the likelihood of a disaster and priced in the value of government support to the private non-financial sector. The second row of Table 2 reveals a positive and significant increase in the corporate-sovereign nexus for core countries only in the aftermath of COVID-19. This indicates that a radical repricing of disaster risk reshaped the relation in credit markets. Turning again to Eq.(8), this result must originate from differences between core and periphery in the effectiveness of the government backstop option and in the (average) corporate creditworthiness sensitivity to state provisions. The wider fiscal space of core countries implies that guarantees were likely perceived to be stronger for core firms, or $\underline{J}^{Core} < \underline{J}^{Peri}$. The difference in average corporate sensitivities κ_c^{Core} and κ_c^{Peri} could be either positive or negative and thus either amplify or attenuate differences in the strength of guarantees.

To infer the direction and contribution of the two components – value of public guarantees and firm sensitivity to government intervention – on the corporate-sovereign credit risk comovement, we resort to the synthetic control method of Abadie et al. (2010); see Almeida et al. (2017) for a recent application. In our setup, the rationale for the method is as follows. Let the treatment be the simultaneous occurrence of a jump in consumption growth during COVID-19 *and* the government

[27] The covariance term in Eq. (8) is indeed only the numerator of the β_2 coefficient measuring the corporate-sovereign nexus in our empirical setting. As we point out above, with reference to Panel B of Table 1, we cannot reject the null of differences in variance between core and periphery, so that our results are truly driven by changes in the covariance term.

support in a given EU area j – in other words, the treatment is the event $\left(\mathbb{1}_{[E=1]} \times \mathbb{1}_{[\underline{J}=\underline{J}^j]}\right)$. The outcome variable is corporate CDS spread with five years tenor. The synthetic control method permits us to infer the unobservable counterfactual CDS spread of a company headquartered in region j if the pricing of the shock reflected the firms' exposure to the public support in the other EU area, all else being equal – that is, we want to compute the CDS under $\left(\mathbb{1}_{[E=1]} \times \mathbb{1}_{[\underline{J}=\underline{J}^{-j}]}\right)$.

We collect details on the implementation of the method in Appendix C and provide an example to clarify matters. Consider the German company E.ON SE. We would like to observe its CDS spreads if it were in the periphery and COVID-19 hits, so that the firm would have been deemed to receive less effective government support than it had in the core. We can approximate the potential outcome by choosing, from the convex hull of CDS on peripheral firms, a portfolio of firms with similar values of a set of outcome predictors – for instance, such firms could include Enel S.p.A. and Atlantia S.p.A. In our application, we use as predictors the following variables capturing relevant dimensions of corporate credit risk: five-year credit rating, historical market beta and volatility, quintiles by market capitalization, share price over book value per share, and total debt over total capital.

The procedure provides us with two time series of CDS quotes: a "synthetic core" series, which reproduces the hypothetical CDS of core firms had they been headquartered in the periphery, computed as weighted averages of portfolios of suitable peripheral CDS, and symmetrically, a "synthetic periphery" series that tracks the hypothetical CDS of peripheral firms had they been incorporated in the core and is computed as weighted averages of portfolios of suitable core CDS.

The top panel of Figure 8 displays the time series of the value-weighted average CDS of firms in the periphery (solid line) and in the synthetic core (dotted line). Before the Italian lockdown, the two series overlap with each other, which indicates that in the absence of priced government guarantees, the average cost of credit protection for the two sets of firms coincides. When the COVID-19 shock hits, the portfolios diverge, along with perceptions of government support across EU regions, with CDS spreads in the synthetic core group on average some 16.9 bps higher than those in the actual periphery.

Reading this evidence through the lenses of the model yields the following insight. The periphery series reflects the pricing of credit risk for firms subject to public guarantees $\underline{J}^{Peri}$ and average sensitivity κ_c^{Peri}. By construction, the default intensity of synthetic core series has a loading κ_c^{Core} to jumps in consumption growth but is exposed to $\underline{J}^{Peri}$, as it is a convex combination of spreads on peripheral entities. The difference between the two lines, conditional on the disaster taking place (and given that the pre-COVID differences are null), equals

$$\begin{aligned}\left[CDS^{Synth.\,Core} - CDS^{Peri}|E=1\right] &\approx (1-R)\left(\lambda^{Synth.\,Core} - \lambda^{Peri}\right) \\ &= (1-R)(\kappa_c^{Core} - \kappa_c^{Peri})\underline{J}^{Peri}\,.\end{aligned} \tag{9}$$

The positive difference over the period indicates that, when core firms are artificially exposed to less government support in the face of a rare disaster, their CDS spreads react on average more than those of peripheral ones. This fact points towards a larger sensitivity to disaster risk through their reliance on sovereign emergency provisions; namely, $\kappa_c^{Core} > \kappa_c^{Peri}$. From an economic viewpoint, debtholders of core firms foresee stronger government support when a disaster looms. Therefore, they expect a more aggressive truncation of their credit losses, and the pricing overweights favorable states of the world. Consistently, the disaster would have an even more dramatic effect on core default swaps when such government support is deemed to be lower or missing.[28]

Symmetrically, the bottom plot of Figure 8 displays the time series of the value-weighted average CDS of firms in the core (solid line) and synthetic periphery (dotted line). Again, we find that, in the pre-COVID period, differences are negligible. In the post-COVID subsample, the credit risk of companies in the core was always priced higher than those in the synthetic periphery, with the difference averaging about 6.5 bps.

In model terms, the synthetic periphery quantifies the credit risk of the synthetic portfolio of core firms, which replicates the corporate spreads in the periphery had they been priced according to government support $\underline{J}^{Core}$. Proceeding as above, we can write

$$\begin{aligned}\left[CDS^{Core} - CDS^{Synth.\,Peri}|E=1\right] &\approx (1-R)\left(\lambda^{Core} - \lambda^{Synth.\,Peri}\right) \\ &= (1-R)(\kappa_c^{Core} - \kappa_c^{Peri})\underline{J}^{Core}\,.\end{aligned} \tag{10}$$

The 6.5 bps positive difference again confirms the conclusion from the previous analysis that core companies are more sensitive to support of their sovereigns.

Taking the ratio of the average value of the two differences during the COVID sample, we obtain an estimate the ratio of priced government guarantees in the two regions:

$$\frac{\left[CDS^{Synth.\,Core} - CDS^{Peri}|E=1\right]}{\left[CDS^{Core} - CDS^{Synth.\,Peri}|E=1\right]} = \frac{\underline{J}^{Peri}}{\underline{J}^{Core}} = \frac{0.00169}{0.00065} = 2.60. \tag{11}$$

This figure reveals that, over the medium term, firms in the core are perceived as being insulated from (risk-neutral) default risk shocks that are 2.60 times larger than those on the periphery.

[28] In line with this reasoning is the evidence in Correa et al. (2014) that the negative effect of sovereign credit downgrades on the performance of large banks is stronger in advanced economies, which are better positioned to extend support than emerging markets.

Overall, post-treatment differences between treated and synthetic units from both panels deliver the following two messages. First, core firms' spreads are characterized by a higher sensitivity to disaster risk relative to their peripheral counterparts, or $\kappa_c^{Core} > \kappa_c^{Periphery}$. Second, credit swap spreads signal sizable differences in government floors, with support that is expected to be stronger in the core, or $\underline{J}^{Core} < \underline{J}^{Peri}$. According to Eq. (8), both these relations have the effect of amplifying the disaster-induced nexus in the core of the EU, consistent with the regression-based evidence in Section 3. In these respects, the corporate-sovereign nexus is not necessarily a concerning characteristic of debt (credit risk) markets. Rather, credit risk transfers between corporate and public debt could reflect the pricing of public guarantees, which are reassessed when a tail event materializes and are credible only for countries with sufficient fiscal space and directly impact the level of credit spreads and thus the cost of capital for firms. On the other hand, however, the excess sensitivity of firms that benefit from government support makes them more exposed to fluctuations in sovereign risk.

5 Conclusion

This work investigates the effect of fiscal capacity on credit risk spillovers between governments and domestic non-financial corporations in the Euro Area using the exogenous variation prompted by the COVID-19 pandemic. Such externalities are generally deemed to result from a sovereign risk channel, which views spillovers as originated by the amplification of a negative demand shock caused by fiscal strains and the threat of tax hikes. And indeed, prior to the diffusion of the coronavirus, the data line up with this interpretation.

However, the pandemic triggered a significant increase in the elasticity of firms' credit default swaps to their sovereign only in countries with wide fiscal capacity, and the effect of the outbreak on the corporate-sovereign nexus increases in direct measures of fiscal capacity. This result is strongly robust to a wealth of compelling economic and econometric sensitivity checks and its magnitude dominates the one of alternative channels. In the cross-section of firms, the increased sensitivity to government risk is more pronounced for larger firms and size systematically explains discounts over a standard credit risk model for larger firms at the core of the Euro Area, which are consistent with perceived sovereign fiscal capacity playing a key role when systemic tail risk materializes. These findings suggests that the government support channel is a major determinant of the corporate-sovereign nexus in the wake of the Great Lockdown, which views spillovers as resulting from the pricing of expected government support.

To illustrate the mechanisms at work, we propose an asset pricing model featuring stochastic jumps in consumption growth and government support. The model delivers a closed-form expression for the covariance between corporate and sovereign intensities of default, which depends on the amount of space for fiscal intervention. Through the lenses of the model, the disaster-induced spike in the corporate-sovereign nexus results from market participants' repricing of the expected value of government support to non-financial firms.

The application of a synthetic control method shows that CDS quotes embed the perception that, after the coronavirus outbreak, firms in the periphery of the Euro Area were on average about 2.6 times more exposed to a systemic shock on risk-neutral default intensity relative to firms in the EU core. This figure demonstrates that thoughtful fiscal capacity buffers are beneficial for the level of financing costs of domestic firms.

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Appendix A: Proof of Proposition I

Proof. Using a discrete-time version of Longstaff et al. (2005), the net present value (NPV) of the protection leg of a CDS can be expressed as

$$\text{PR}_t = \mathbb{E}_t\left[(1-R)\sum_{i=t}^{T}\lambda_i \exp\left(-\sum_{s=t}^{i}(r_s+\lambda_s)\right)\right] \tag{A.1}$$

while the NPV of the premium leg is

$$\text{P}_t = \mathbb{E}_t\left[\text{CDS}_t\sum_{i=t}^{T}\exp\left(-\sum_{s=t}^{i}(r_s+\lambda_s)\right)\right] \tag{A.2}$$

In line with the literature and industry practice, we assume a constant recovery rate. Denote the discount factor by $D(t)$. Consider first the NPV of the protection leg

$$\begin{aligned}\text{PR}_t &= (1-R)\mathbb{E}_t\left[\sum_{i=t}^{T}D(i)\lambda_i \exp\left(-\sum_{s=t}^{i}\lambda_s\right)\right] \\ &= (1-R)\left[\lambda_t + \mathbb{E}_t[\lambda_{t+1}e^{-\lambda_{t+1}-r_{t+1}}] + \mathbb{E}_t[\lambda_{t+2}e^{-\lambda_{t+1}-\lambda_{t+2}-r_{t+1}-r_{t+2}}] + \cdots\right]\end{aligned} \tag{A.3}$$

Evaluating the same quantity at $t+1$ yields

$$\begin{aligned}\text{PR}_{t+1} &= (1-R)\mathbb{E}_{t+1}\left[\sum_{i=t+1}^{T}D(i)\lambda_i \exp\left(-\sum_{s=t}^{i}\lambda_s\right)\right] \\ &= (1-R)\left[\lambda_{t+1} + \mathbb{E}_{t+1}[\lambda_{t+2}e^{-\lambda_{t+2}-r_{t+2}}] + \mathbb{E}_{t+1}[\lambda_{t+3}e^{-\lambda_{t+2}-\lambda_{t+3}-r_{t+2}-r_{t+3}}] + \cdots\right]\end{aligned} \tag{A.4}$$

All shocks in the model are transitory. By a rational expectations argument, provided the Markov states are sufficiently persistent (i.e. for $\pi_{ii} \to 1\ \forall i \in I$) successive discounted default intensities tend to the random walk model

$$\lim_{\pi_{ii}\to 1}\sum_{i\in I}\left[\mathbb{E}_t[\lambda_{t+1}e^{-\lambda_{t+1}-r_{t+1}}]\Big|p_t = p_i\right] = \lim_{\pi_{ii}\to 1}\sum_{i\in I}\left[\mathbb{E}_{t+1}[\lambda_{t+2}e^{-\lambda_{t+2}-r_{t+2}}|p_{t+1} = p_i]\right] \tag{A.5}$$

Therefore,

$$\mathbb{E}_t[\lambda_{t+1}e^{-\lambda_{t+1}-r_{t+1}}] = \mathbb{E}_{t+1}[\lambda_{t+2}e^{-\lambda_{t+2}-r_{t+2}}] \qquad a.s. \tag{A.6}$$

Replacing (18) in (15) and (16) and rearranging terms yields

$$\begin{aligned}\Delta\text{PR}_{t+1} &= (1-R)\left[\lambda_{t+1} - \lambda_t - \mathbb{E}_t\left[D(T)\lambda_T \exp\left(-\sum_{s=t}^{T}\lambda_s\right)\right]\right] \\ &\approx (1-R)\Delta\lambda_{t+1}\end{aligned} \tag{A.7}$$

The approximation accuracy increases in time to maturity. Consider now the NPV of the premium leg at time t

$$\begin{aligned}\mathrm{P}_t &= \mathbb{E}_t\Bigg[\mathrm{CDS}_t \sum_{i=t}^{T} \exp\Bigg(-\sum_{s=t}^{i}(r_s+\lambda_s)\Bigg)\Bigg] \\ &= \mathrm{CDS}_t\Bigg[1+\mathbb{E}_t[e^{-\lambda_{t+1}-r_{t+1}}]+\mathbb{E}_t[e^{-\lambda_{t+1}-\lambda_{t+2}-r_{t+1}-r_{t+2}}]+\cdots\Bigg]\end{aligned} \tag{A.8}$$

At time $t+1$, the value of the contract for the protection seller is

$$\begin{aligned}\mathrm{P}_{t+1} &= \mathbb{E}_{t+1}\Bigg[\mathrm{CDS}_{t+1} \sum_{i=t+1}^{T} \exp\Bigg(-\sum_{s=t+1}^{i}(r_s+\lambda_s)\Bigg)\Bigg] \\ &= \mathrm{CDS}_{t+1}\Bigg[1+\mathbb{E}_{t+1}[e^{-\lambda_{t+2}-r_{t+2}}]+\mathbb{E}_{t+1}[e^{-\lambda_{t+2}-\lambda_{t+3}-r_{t+2}-r_{t+3}}]+\cdots\Bigg]\end{aligned} \tag{A.9}$$

Disregarding the term $\mathbb{E}_t\Bigg[\exp\Bigg(-\sum_{s=t+1}^{T}(r_s+\lambda_s)\Bigg)\Bigg]\approx 0$,

$$\Delta\mathrm{P}_{t+1} = \Delta\mathrm{CDS}_{t+1} \tag{A.10}$$

Equating the changes in NPV of buyer's and seller's legs completes the proof

$$\Delta\mathrm{CDS}_{t+1} \approx (1-R)\Delta\lambda_{t+1}.$$

The quality of the approximation increases in time to maturity $T-t$. ■

Appendix B: Proof of Proposition II

Proof. Disaster-induced changes in default intensity are piecewise linear in J^{λ}_{t+1} for both government and corporate debt issuers (see Figure A.1). Remember that $\underline{J}$ is deterministic. Therefore,

$$\mathbb{E}_t[\max\{J^{\lambda}_{t+1}-\underline{J},0\}] = \Bigg(1-\Phi\Bigg)\Bigg(\theta_\lambda+\frac{\delta_\lambda\varphi}{1-\Phi}-\underline{J}\Bigg) = (1-\Phi)(\theta_\lambda-\underline{J})+\delta_\lambda\varphi \tag{B.1}$$

$$\mathbb{E}_t\Bigg[\min\{J^{\lambda}_{t+1},\underline{J}\}\Bigg] = \Bigg[\underline{J}\Bigg(1-\Phi\Bigg)+\Phi\Bigg(\theta_\lambda-\frac{\delta_\lambda\varphi}{\Phi}\Bigg)\Bigg] \tag{B.2}$$

The terms $\frac{\delta_\lambda\varphi}{1-\Phi}$ and $-\frac{\delta_\lambda\varphi}{\Phi}$ come from the truncation of the lower and upper tails of the distribution of the government default intensity jump at $\underline{J}$, respectively. Moreover,

$$
\begin{aligned}
\mathbb{E}_t\Big[\min\{J^\lambda_{t+1},\underline{J}\}\max\{J^\lambda_{t+1}-\underline{J},0\}\Big] &= \Big(1-\Phi\Big)\mathbb{E}\Big[\min\{J^\lambda_{t+1},\underline{J}\}\max\{J^\lambda_{t+1}-\underline{J},0\}\Big| J^\lambda_{t+1}>\underline{J}\Big]+0\\
&= \Big(1-\Phi\Big)\mathbb{E}\Big[\underline{J}(J^\lambda_{t+1}-\underline{J})\Big| J^\lambda_{t+1}>\underline{J}\Big]\\
&= \Big(1-\Phi\Big)\underline{J}\mathbb{E}\Big[(J^\lambda_{t+1}-\underline{J})\Big| J^\lambda_{t+1}>\underline{J}\Big]\\
&= \Big(1-\Phi\Big)\underline{J}\Big(\theta_\lambda+\frac{\delta_\lambda\varphi}{1-\Phi}-\underline{J}\Big)\\
&= \underline{J}\mathbb{E}_t[\max\{J^\lambda_{t+1}-\underline{J},0\}].
\end{aligned}
\tag{B.3}
$$

For clarity of notation, let us use $J^c_{t+1}=\min\{J^\lambda_{t+1},\underline{J}\}$ and denote thorugh λ^{ND}_t and λ^D_t the intensity of a credit event in a non disaster and disaster case, respectively. By definition,

$$
\begin{aligned}
\mathrm{Cov}(\Delta\lambda^g_{t+1},\Delta\lambda^c_{t+1}) &= (1-p_i)\mathbb{E}_t\Big[\Delta\lambda^{g,ND}_{t+1}\Delta\lambda^{c,ND}_{t+1}\Big]+p_i\mathbb{E}_t\Big[\Delta\lambda^{g,D}_{t+1}\Delta\lambda^{c,D}_{t+1}\Big]\\
&-\Big[(1-p_i)\mathbb{E}_t[\Delta\lambda^{g,ND}_{t+1}]+p_i\mathbb{E}_t[\Delta\lambda^{g,D}_{t+1}]\Big]\Big[(1-p_i)\mathbb{E}_t[\Delta\lambda^{c,ND}_{t+1}]+p_i\mathbb{E}_t[\Delta\lambda^{c,D}_{t+1}]\Big]\\
&= (1-p_i)\mathbb{E}_t\Big[(\mu^g_t+\phi_g\sigma_i\eta_{t+1})(\mu^c_t+\phi_c\sigma_i\eta_{t+1}+\sigma_c\varepsilon_{t+1})\Big]\\
&+p_i\mathbb{E}_t\Big[(\mu^g_t+\phi_g\sigma_i\eta_{t+1}+\max\{J^\lambda_{t+1}-\underline{J},0\})(\mu^c_t+\phi_c\sigma_i\eta_{t+1}+\sigma_c\varepsilon_{t+1}+\kappa_cJ^c_{t+1})\Big]\\
&-\Big[(1-p_i)\mathbb{E}_t[\mu^g_t+\phi_g\sigma_i\eta_{t+1}]+p_i\mathbb{E}_t[\mu^g_t+\phi_g\sigma_i\eta_{t+1}+\max\{J^\lambda_{t+1}-\underline{J},0\}]\Big]\\
&\times\Big[(1-p_i)\mathbb{E}_t[\mu^c_t+\phi_c\sigma_i\eta_{t+1}+\sigma_c\varepsilon_{t+1}]+p_i\mathbb{E}_t[\mu^c_t+\phi_c\sigma_i\eta_{t+1}+\sigma_c\varepsilon_{t+1}+\kappa_cJ^c_{t+1}]\Big]\\
&= (1-p_i)\Big[\mu^g_t\mu^c_t+\phi_g\phi_c\sigma^2_i\Big]+p_i\Big[\mu^g_t\mu^c_t+\mu^g_t\kappa_c\mathbb{E}_t[J^c_{t+1}]+\mu^c_t\mathbb{E}_t\max\{J^\lambda_{t+1}-\underline{J},0\}\\
&+\phi_g\phi_b\sigma^2_i+\kappa_c\mathbb{E}_t[J^c_{t+1}\max\{J^\lambda_{t+1}-\underline{J},0\}]\Big]-\mu^g_t\mu^c_t\\
&-p_i\Big[\mu^g_t\kappa_c\mathbb{E}_t[J^c_{t+1}]+\mu^c_t\mathbb{E}_t[\max\{J^\lambda_{t+1}-\underline{J},0\}]\Big]-p^2_i\kappa_c\mathbb{E}_t[\max\{J^\lambda_{t+1}-\underline{J},0\}]\mathbb{E}_t[J^c_{t+1}]\\
&= \phi_g\phi_c\sigma^2_i+p_i\kappa_c\mathbb{E}_t[J^c_{t+1}\max\{J^\lambda_{t+1}-\underline{J},0\}]-p^2_i\kappa_c\mathbb{E}_t[\max\{J^\lambda_{t+1}-\underline{J},0\}]\mathbb{E}_t[J^c_{t+1}].
\end{aligned}
$$

Using Eq. B.3 to simplify the expected value of the product of jumps,

$$\begin{aligned}\mathrm{Cov}(\Delta\lambda^g_{t+1}, \Delta\lambda^c_{t+1}) &= \phi_g\phi_c\sigma_i^2 + p_i\kappa_c\underline{J}\mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}] - p_i^2\kappa_c\mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}]\mathbb{E}_t[J^c_{t+1}] \\ &= \phi_g\phi_c\sigma_i^2 + \underbrace{\phi_g\phi_c\sigma_i^2}_{\text{Ex-disaster Term}} + \underbrace{p_i\kappa_c\mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}](\underline{J} - p_i\min\{J^\lambda_t, \underline{J}\})}_{\text{Disaster Risk Term}}.\end{aligned}$$

Substitute Eq. B.1 and B.2 to obtain

$$\mathrm{Cov}(\Delta\lambda^g_{t+1}, \Delta\lambda^c_{t+1}) = \phi_g\phi_c\sigma_i^2 + p_i\kappa_c\Big((1-\Phi)(\theta_\lambda - \underline{J}) + \delta_\lambda\varphi\Big)\left(\underline{J} - p_i\left[\underline{J}\Big(1-\Phi\Big) + \Phi\left(\theta_\lambda - \frac{\delta_\lambda\varphi}{\Phi}\right)\right]\right).$$

Suppose for simplicity $\delta_\lambda = 1$, so that $\Phi = \int_{-\infty}^{\underline{J}-\theta_\lambda} \frac{e^{-t^2/2}}{\sqrt{2\pi}}dt$. By Leibniz integration rule, $\frac{\partial\Phi}{\partial\underline{J}} = \varphi$. Moreover, as $\varphi = \frac{1}{\sqrt{2\pi}}e^{\frac{-(\underline{J}-\theta_\lambda)^2}{2}}$, $\frac{\partial\varphi}{\partial\underline{J}} = (\theta_\lambda - \underline{J})\varphi$.

$$\begin{aligned}\frac{\partial\text{Disaster Term}}{\partial\underline{J}} &\overset{\text{up to } p_i\kappa_c}{\propto} -\Big(\underline{J} - p_i\mathbb{E}_t[J^c_{t+1}]\Big)\Big[1 - \Phi\Big] + \mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}\Big[1 - p_i(1 - \Phi)\Big] \\ &= -\underline{J}(1-\Phi) + \mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}] \\ &\quad - \underbrace{p_i(1-\Phi)\Big(\mathbb{E}_t[J^c_{t+1}] + \mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}]\Big)}_{>0 \text{ since } \Phi<1 \text{ and } \underline{J} \text{ and } \theta_\lambda \text{ are both } \geq 0} \\ &< -\underline{J}(1-\Phi) + \mathbb{E}_t[\max\{J^\lambda_{t+1} - \underline{J}, 0\}] \\ &< -\underline{J}(1-\Phi) + (1-\Phi)(\theta_\lambda - \underline{J}) + \varphi.\end{aligned}$$

Therefore, provided $\underline{J} > 0.5(\theta_\lambda + \frac{\varphi}{1-\Phi})$, the derivative is negative. In words, the disaster risk term is increasing in the extent of sovereign support as long as the government does not take on too much risk relative to the private sector. The mapping between default intensities and CDS premia established by Proposition I completes the proof. ■

Appendix C: Synthetic Control Method

Formally, consider the following approach. For each firm in a given region of the Euro Area (whether core or periphery), we select a combination of firms in the other region to mimic its performance. Since the procedure is computationally intensive, the estimation in Abadie et al. (2010) is constrained on a subsample of 250 trading days. We use the first 150 days prior to the event date (February 24, 2020) as a training sample, where the optimal replicating portfolio is constructed to minimize the distance between treatment and synthetic control over a set of predictor variables. For every treated unit, the weight given to each variable is a function of its explanatory power for the outcome variable, the five-year tenor CDS spread. In the out-of-sample period (i.e., the 100 days following the event date), the synthetic performance of a quote is evaluated from the evolution of the quotes among the constituents of the approximating portfolio. In sum, akin to event-study approaches, we identify the replicating portfolio using the pre-COVID-19 period and evaluate its performance afterwards.

We repeat this procedure for all firms in the sample. For each region, the quotes of the replicating portfolios are then averaged with weights corresponding to the market capitalization of the treated unit. In line with the literature, we drop units with large pre-treatment root mean square prediction error (RMSPE). This procedure results in a portfolio of CDS that reference firms in either of the two regions replicating the performance of the value-weighted average CDS spread in the other region.

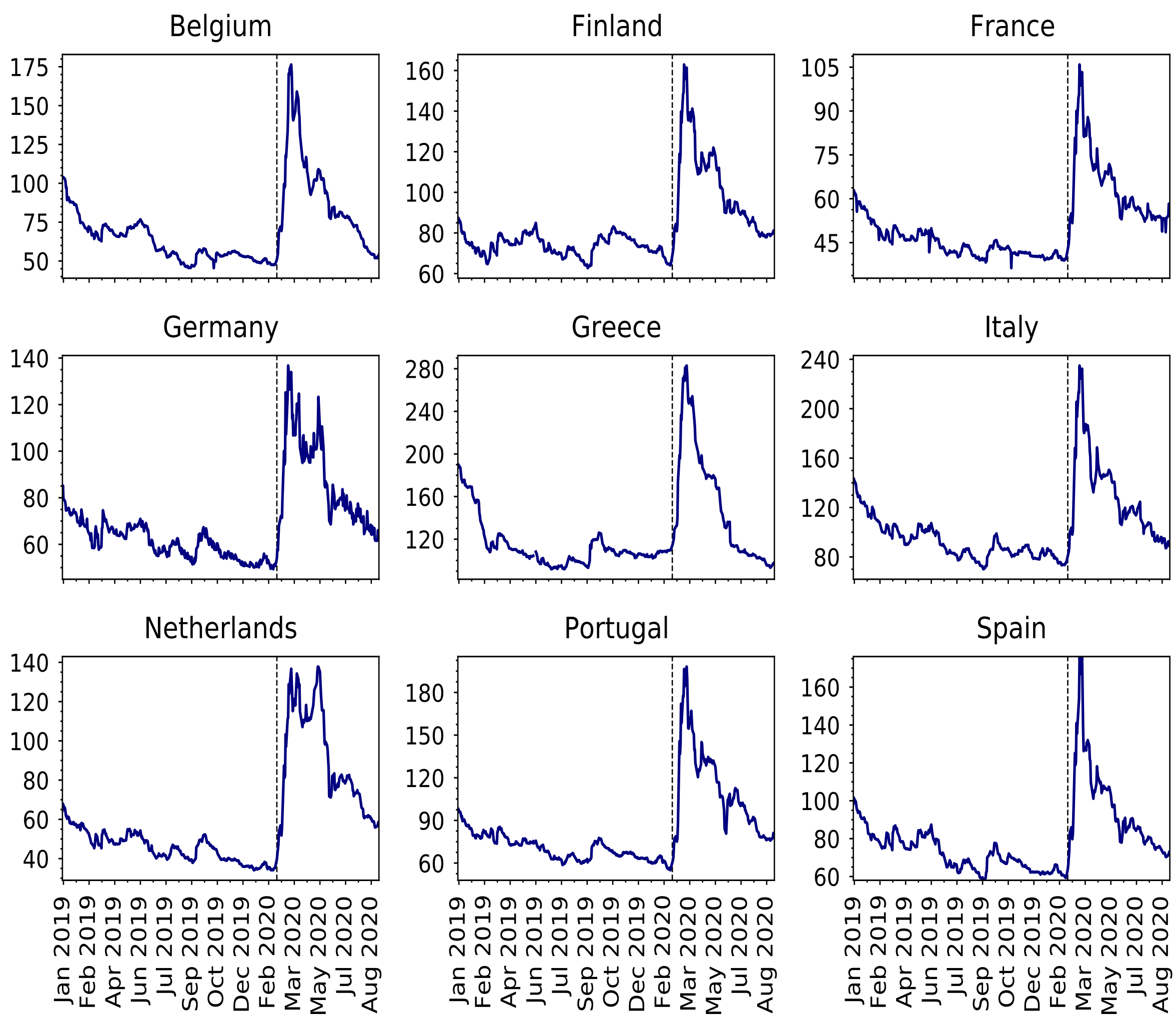

FIGURE 1: **Euro Area corporate CDS**: This figure plots the value-weighted average corporate CDS spread in basis points for firms headquartered in the nine countries in our sample over the period from January 1, 2019 to September 10, 2020 (443 trading days). The dashed vertical line marks the beginning of the first Italian lockdown on February 24, 2020.

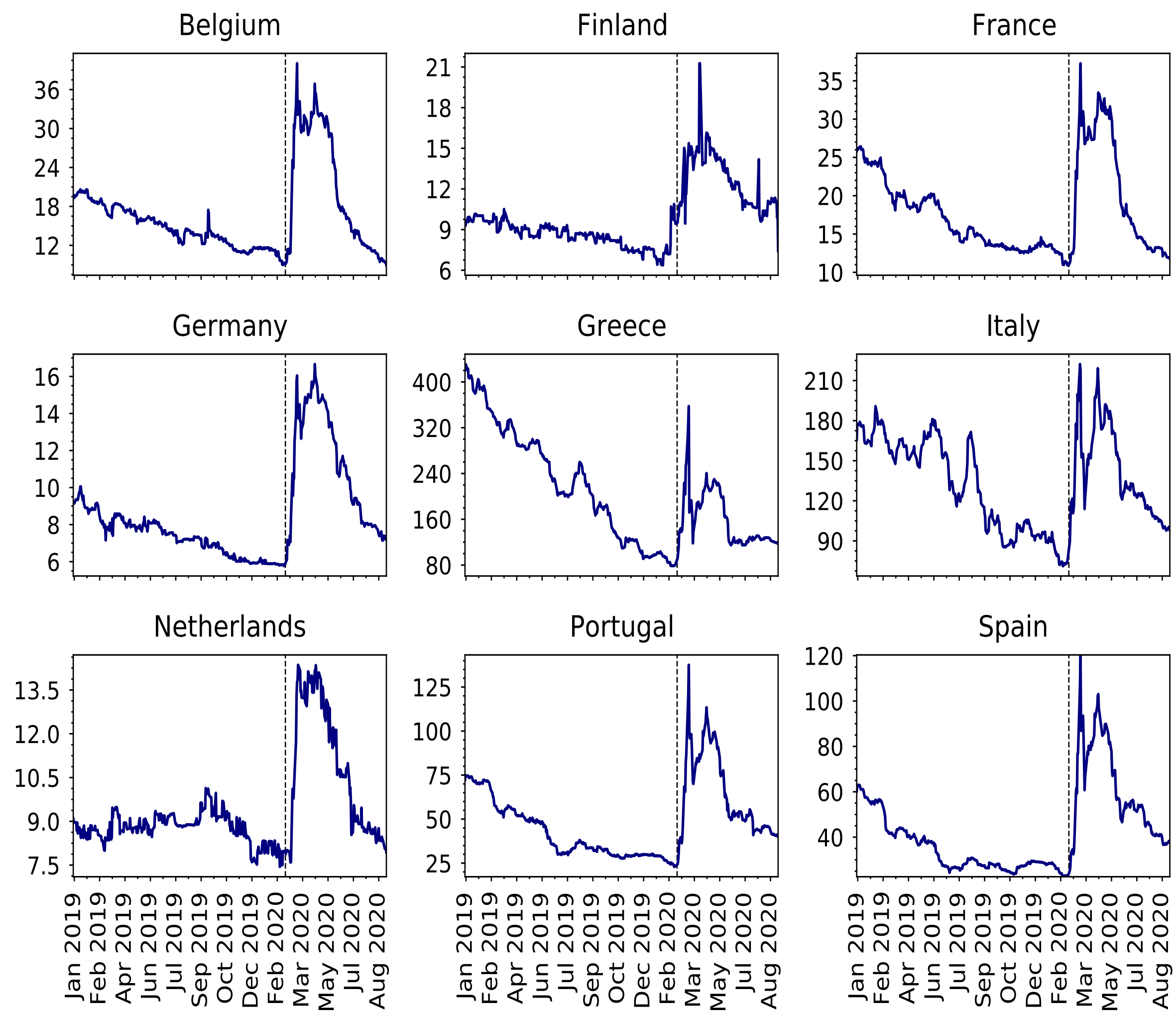

FIGURE 2: **Euro Area sovereign CDS**: This figure plots sovereign CDS spreads in basis points for the nine countries in our sample over the period from January 1, 2019 to September 10, 2020 (443 trading days). The dashed vertical line marks the beginning of the first Italian lockdown on February 24, 2020.

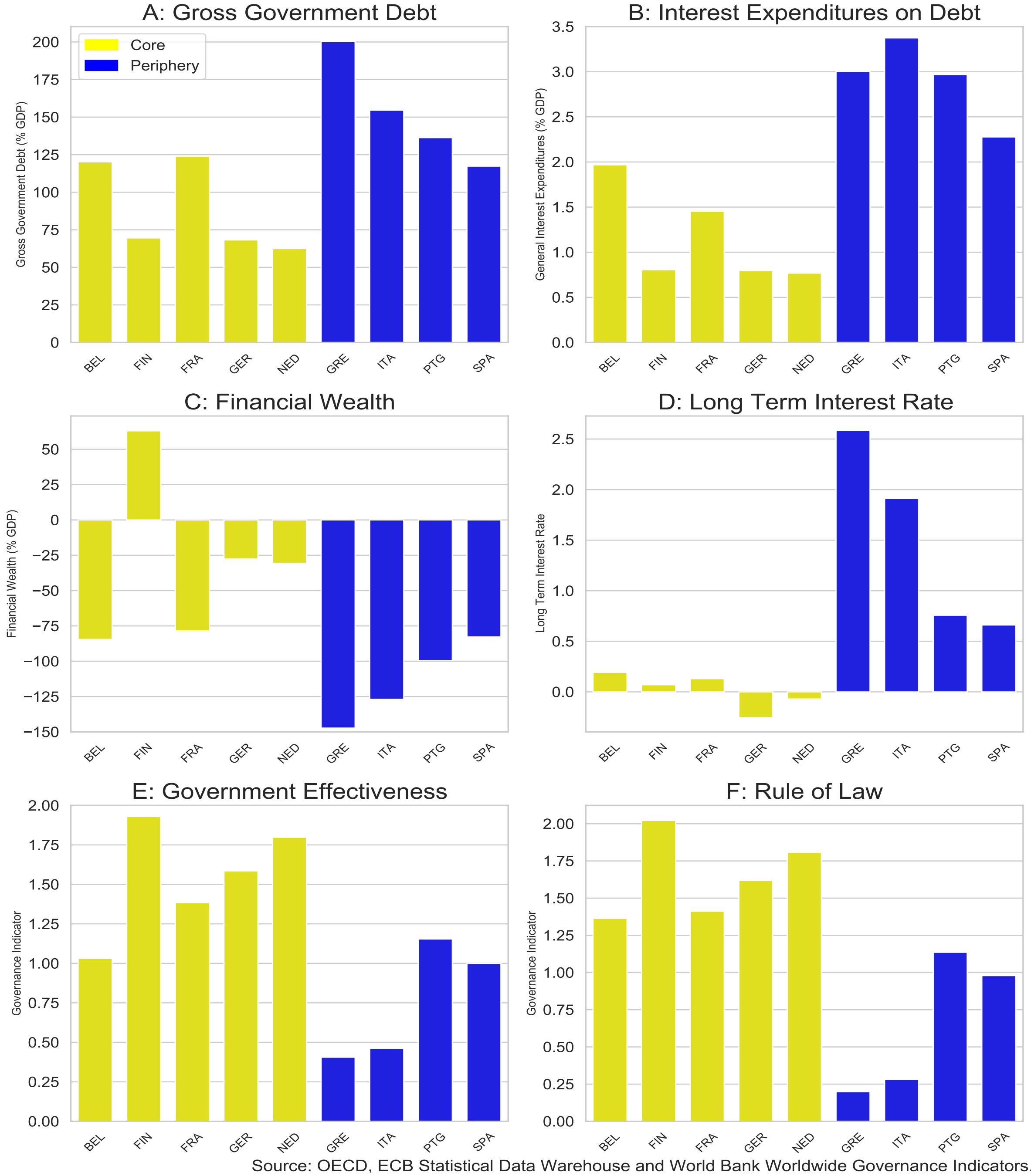

FIGURE 3: **Fiscal capacity measures**: This figure plots several measures of fiscal capacity for the nine Euro Area countries included in the sample as of December 2019. Panel A reports gross government debt over GDP. Panel B considers interest expenditures on debt over GDP. Panel C represents financial wealth, defined as financial assets minus outstanding liabilities. Panel D displays bond implied long-term interest rates. Panels E and F report, respectively, World Bank indexes for government effectiveness, e.g., quality of policy, and rule of law, e.g., enforcement of property rights.

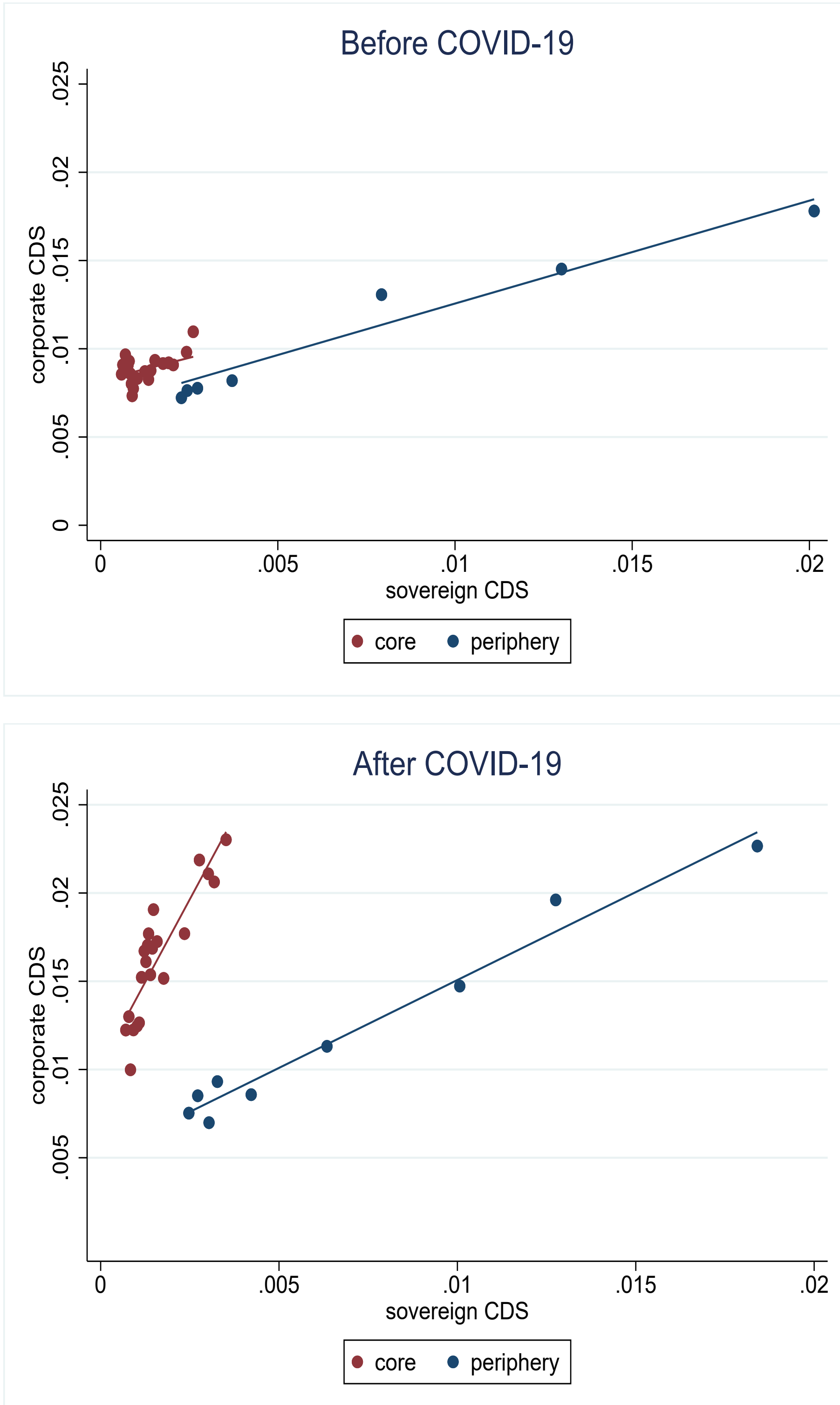

FIGURE 4: **Credit risk comovement**: This figure shows a binned scatterplot of sovereign and corporate CDS spreads per unit of notional, before and after the COVID-19 shock (top and bottom panel, respectively). Observations are first grouped into equal-width bins. Data points in the diagram correspond to within-bin averages of the x-axis and y-axis variables.

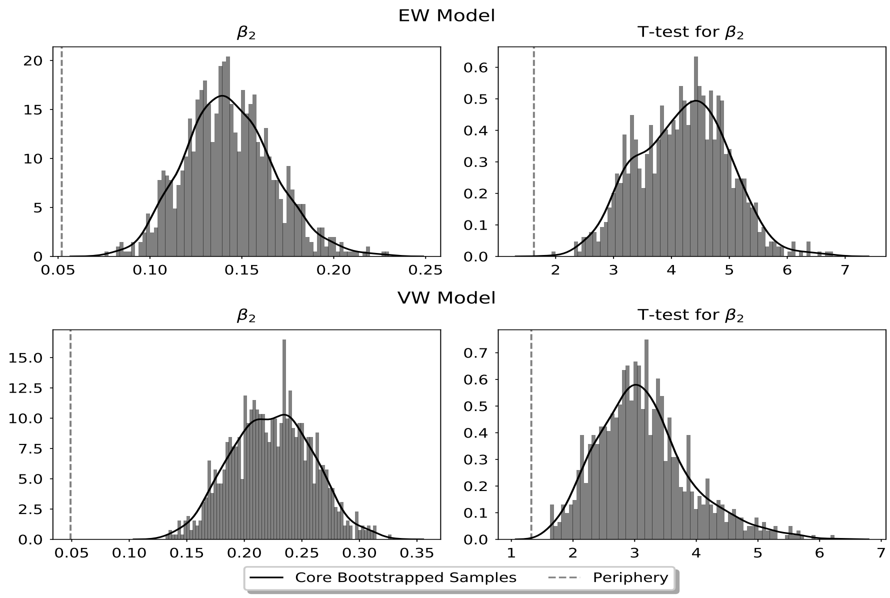

FIGURE 5: **Bootstrapped samples**: In each bootstrap run, we match every firm in the periphery with a random firm in the core in same sector classification. We then estimate our baseline panel regression on this randomized sample of core firms, whose size and industrial composition match (by design) those in the periphery, store the resulting coefficients and standard errors, and repeat the procedure 1,000 times. The figure plots the distributions of the β_2 coefficient (left panels) and its t-statistic (right panels) for the equally weighted (top panels) and market cap-weighted models across the 1,000 randomized core samples. The dotted line in each panel marks the corresponding estimate for the actual periphery from Table 2.

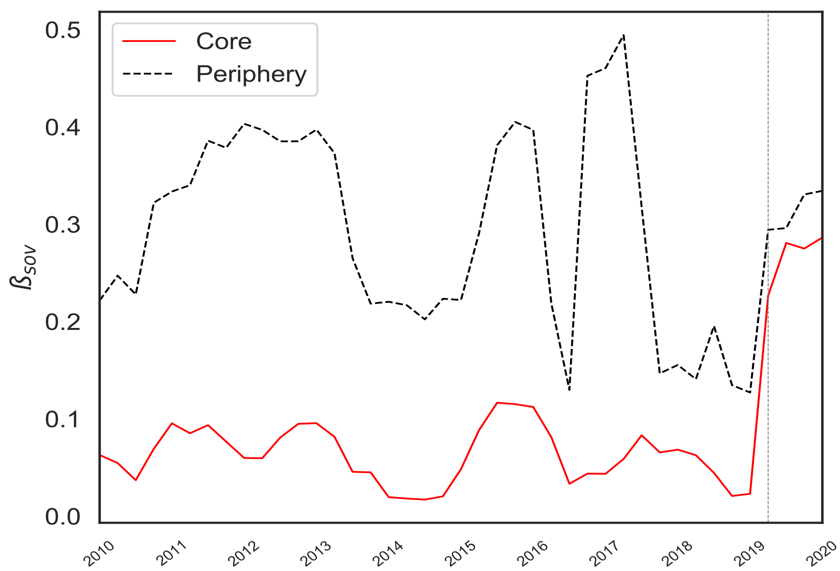

FIGURE 6: **Rolling regressions**: We estimate the panel regression in Eq.(1) – without interaction terms with the E dummy – separately for core and peripheral countries on one-year windows of data that are rolled forward after one quarter over the Jan 1, 2010 to Sept 10, 2020 sample period. The figure plots the coefficient relating changes in log corporate CDS spreads to changes in log CDS spreads of the corresponding sovereign by region. Each coefficient is plotted in correspondence to the begin date of its estimation window, and the dashed vertical line marks the first sample that includes COVID-19 data.

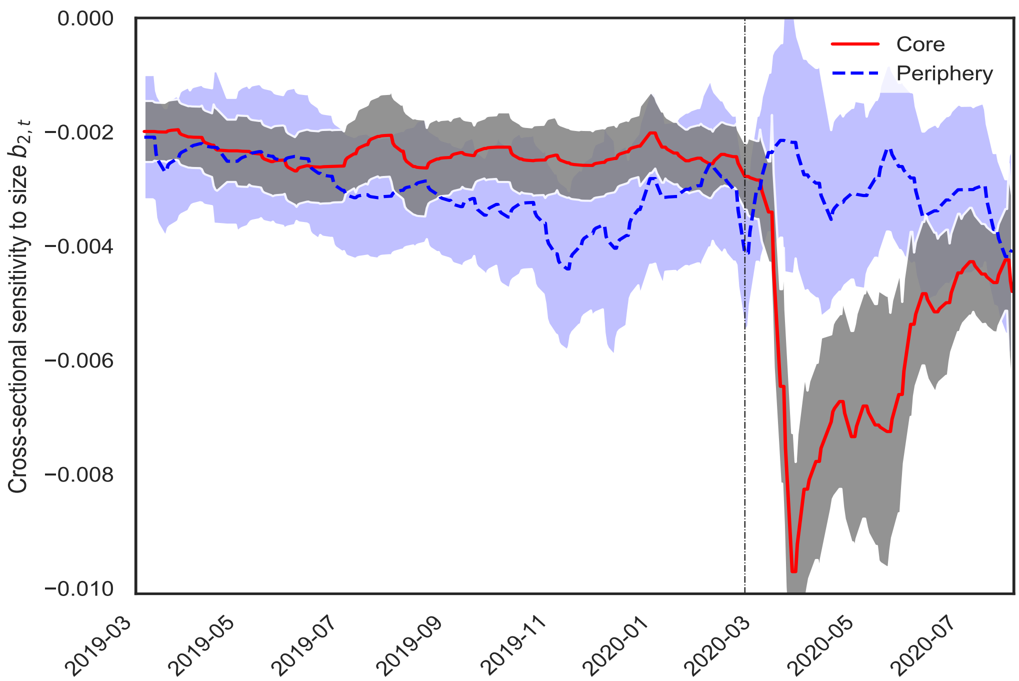

FIGURE 7: **Deviations of CDS from fundamental credit risk as function of size**: We calculate the model-implied CDS rate from the Merton (1974) model using Bharath and Shumway's (2008) measure of distance to default (DD). We then estimate cross-sectional weekly regressions of the form $\text{CDS}_{it} = a_t + b_{1t}\text{Merton Spread}_{it} + b_{2t}\text{Size}_{it} + b_{3t}\text{Leverage}_{it} + \varepsilon_{it}$, separately for observations in the core and periphery. The plot displays the four-week trailing average relative to the time series of the resulting coefficient on size, b_{2t}, with shaded areas denoting one standard deviation bands. The dash-dot vertical line marks the begin of the COVID-19 sample on February 24, 2020.

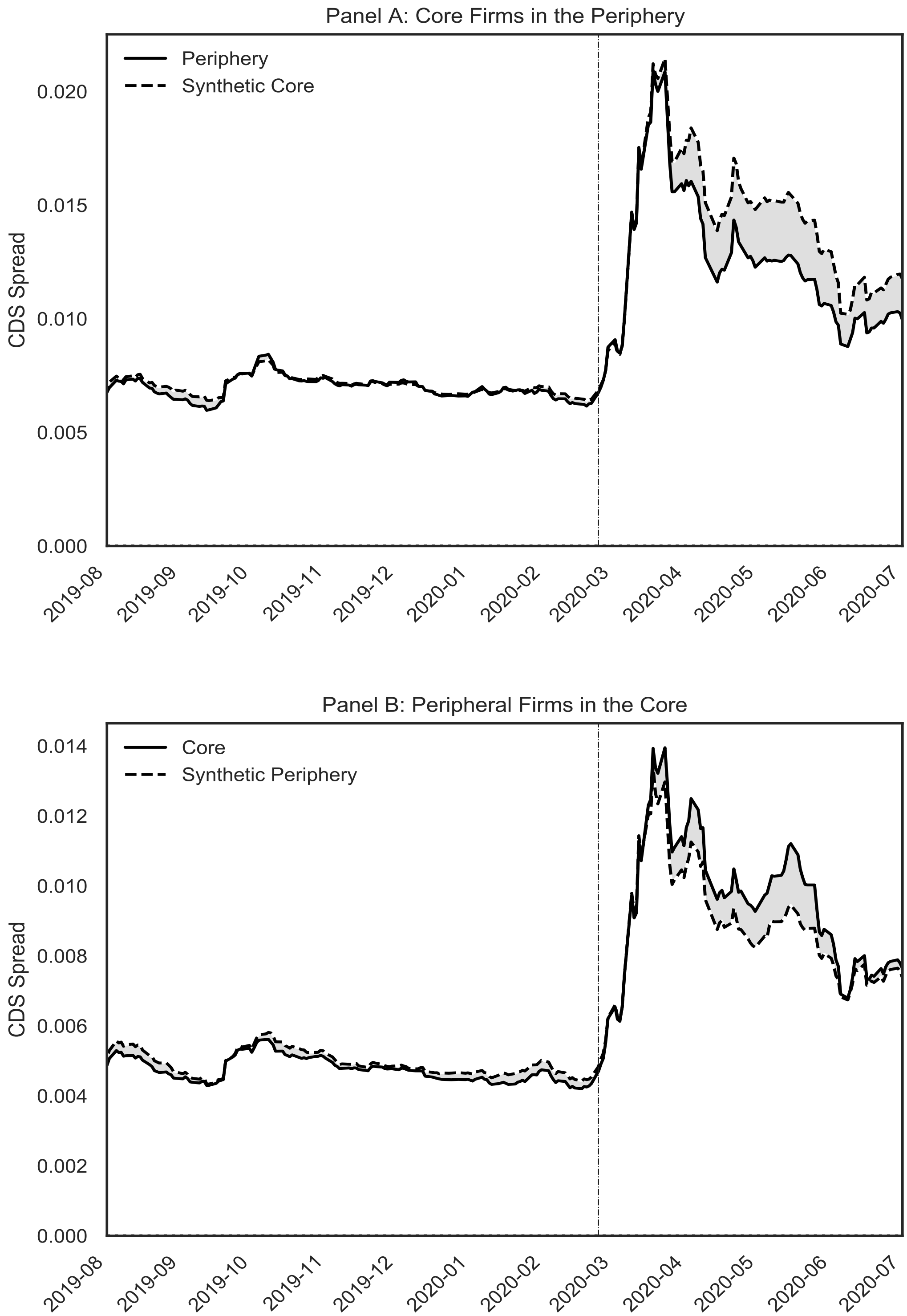

FIGURE 8: **Synthetic control method**: This figure plots the value-weighted average CDS spread (solid line) and its synthetic counterfactual (dashed line), which estimates the value-weighted average pricing of firms' credit risk had they been headquartered in the other region of the Euro Area. Panel (A) shows firms in the periphery of the Union. Panel (B) refers to firms in core countries. The dash-dot vertical line marks the begin of the COVID-19 sample on February 24, 2020.

TABLE 1: **Summary statistics**

The table presents summary statistics of the sample. Panel A reports statistics of 5-year CDS spreads for our sample of non-financial firms and their sovereigns organized by country and region. Core countries are Belgium, Finland, France, Germany, and the Netherlands, while countries in the periphery are Greece, Italy, Portugal, and Spain. The data are daily from January 1, 2019 to September 10, 2020 (443 trading days), and the source is Markit. Panel B presents growth rates of 5-years tenor corporate and sovereign CDS spreads. Panel C outlines country and regional averages of firms' balance sheet characteristics that are used in our analysis, as of fiscal year 2019. Volatility and market beta from Refinitiv refer to a firm's equity return.

Panel A: CDS spreads

	Corporate					Sovereign		
Country	Obs.	Firms	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Belgium	2,573	6	0.0101	0.0067	0.0078	0.0017	0.0014	0.0006
Finland	3,340	8	0.0113	0.0084	0.0100	0.0010	0.0009	0.0002
France	17,233	40	0.0121	0.0057	0.0270	0.0018	0.0016	0.0006
Germany	13,824	33	0.0120	0.0073	0.0174	0.0008	0.0008	0.0003
Netherlands	5,195	12	0.0064	0.0039	0.0062	0.0009	0.0009	0.0002
Core	42,165	99	0.0112	0.0063	0.0205	0.0012	0.0011	0.0006
Greece	862	2	0.0255	0.0257	0.0178	0.0204	0.0191	0.0092
Italy	4,705	11	0.0156	0.0090	0.0129	0.0134	0.0131	0.0035
Portugal	866	2	0.0085	0.0071	0.0041	0.0049	0.0045	0.0021
Spain	3,897	9	0.0091	0.0064	0.0060	0.0043	0.0038	0.0019
Periphery	10,330	24	0.0133	0.0087	0.0119	0.0107	0.0088	0.0084
Total	52,495	123	0.0116	0.0067	0.0191	0.0054	0.0020	0.0073

Panel B: Δ log(CDS spreads)

	Corporate					Sovereign		
Country	Obs.	Firms	Mean	Median	Std. Dev.	Mean	Median	Std. Dev.
Belgium	2,567	6	-0.0005	-0.0000	0.0268	-0.0018	-0.0020	0.0481
Finland	3,332	8	-0.0004	-0.0004	0.0304	-0.0005	-0.0002	0.0594
France	17,193	40	-0.0003	-0.0001	0.0391	-0.0018	-0.0033	0.0354
Germany	13,791	33	-0.0003	-0.0002	0.0404	-0.0005	-0.0005	0.0323
Netherlands	5,183	12	-0.0011	-0.0032	0.0401	-0.0003	-0.0002	0.0326
Core	42,066	99	-0.0004	-0.0002	0.0384	-0.0010	-0.0005	0.0426
Greece	860	2	-0.0012	-0.0000	0.0299	-0.0030	-0.0028	0.0549
Italy	4,694	11	-0.0003	-0.0000	0.0317	-0.0012	-0.0028	0.0340
Portugal	864	2	-0.0005	-0.0031	0.0386	-0.0014	-0.0031	0.0455
Spain	3,888	9	-0.0009	-0.0006	0.0345	-0.0011	-0.0020	0.0438
Periphery	10,306	24	-0.0006	-0.0001	0.0332	-0.0017	-0.0027	0.0463
Total	52,372	123	-0.0004	-0.0001	0.0374	-0.0013	-0.0010	0.0442

Panel C: Firm characteristics

	Debt/Assets		Market Cap (bn €)		Equity Volatility		Equity Beta		Rating
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Median
Belgium	33.34	14.53	46.34	58.90	0.2230	0.0420	0.9063	0.5355	AA
Finland	21.11	12.14	10.64	6.71	0.30715	0.0902	1.366	0.5632	AA
France	30.29	11.70	32.37	41.90	0.2453	0.0654	0.9666	0.3521	AA
Germany	29.04	13.29	29.49	27.86	0.2839	0.0683	0.9968	0.3979	AA
Netherlands	31.93	16.97	29.07	25.67	0.2589	0.0789	1.036	0.3576	AA
Core	29.45	13.50	29.71	35.45	0.2642	0.0735	1.0176	0.4137	AA
Greece	34.03	1.66	5.85	2.06	0.3001	0.0959	0.7778	0.2326	AA
Italy	34.56	14.89	21.08	24.55	0.2598	0.0694	0.8420	0.2815	AA
Portugal	36.43	5.71	13.20	0.8456	0.2198	0.0211	0.7694	0.0095	AA
Spain	42.05	10.02	22.67	14.67	0.2085	0.0351	0.6849	0.2267	AA
Periphery	38.09	12.18	20.11	18.77	0.2350	0.0620	0.7601	0.2498	AA
Total	31.04	13.68	27.94	33.22	0.2588	0.0724	0.9702	0.4014	AA

TABLE 2: **Corporate-sovereign nexus, baseline model**

The table reports estimates from the panel regression in Eq.(1), relating changes in log corporate CDS spreads to changes in log CDS spreads of the corresponding sovereigns and firm-specific and aggregate variables. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. Results are reported for the equally weighted model (columns 1 and 2), for the equity market capitalization-weighted model (columns 3 and 4), and for the entropy-balanced model (columns 5 and 6). The models are estimated separately for countries in the core (Belgium, Finland, France, Germany, and the Netherlands) and the periphery (Greece, Italy, Portugal, and Spain). Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Equally Weighted		Value Weighted		Entropy Balanced	
Variables	Core	Periphery	Core	Periphery	Core	Periphery
$\Delta log(\text{CDS sovereign})_{jt}$	0.127***	0.208***	0.170***	0.325***	0.126***	0.294***
	(0.013)	(0.036)	(0.015)	(0.037)	(0.013)	(0.040)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.125***	0.052	0.151***	0.049	0.124***	0.008
	(0.016)	(0.032)	(0.025)	(0.037)	(0.016)	(0.044)
$\Delta log(\text{CDS corp})_{ijt-1}$	0.162***	0.133***	0.095***	0.168***	0.165***	0.149***
	(0.040)	(0.043)	(0.022)	(0.013)	(0.041)	(0.020)
$\Delta log(\text{CDS corp})_{ijt-1} \times E$	-0.029	0.020	0.024	-0.017	-0.030	0.039
	(0.042)	(0.044)	(0.027)	(0.025)	(0.043)	(0.023)
Stock Returns_{it}	-0.290***	-0.119	-0.402***	-0.232**	-0.297***	-0.106
	(0.035)	(0.071)	(0.046)	(0.090)	(0.035)	(0.097)
Stock $\text{Returns}_{it} \times E$	-0.175***	-0.165**	-0.090**	-0.269***	-0.178***	-0.282***
	(0.039)	(0.060)	(0.039)	(0.084)	(0.040)	(0.090)
$\Delta log(\text{VIX})_t$	0.064***	0.054***	0.069***	0.069***	0.063***	0.070***
	(0.004)	(0.009)	(0.007)	(0.009)	(0.004)	(0.010)
$\Delta log(\text{VIX}_t) \times E$	0.040***	0.010	0.036***	0.011	0.040***	0.024
	(0.005)	(0.008)	(0.007)	(0.010)	(0.005)	(0.015)
E	0.001***	-0.000	0.001***	-0.000	0.001***	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	41,967	10,282	41,536	10,282	40,685	9,420
R-squared	0.274	0.285	0.315	0.434	0.278	0.386
Firms	99	24	98	24	96	22
p-value for $\left(\beta_2^{Core} = \beta_2^{\text{Periphery}}\right)$	0.019		0.006		0.010	

TABLE 3: **Corporate-sovereign nexus, analysis by country and sector**

The table reports estimates from the panel regression in Eq.(1), relating changes in log corporate CDS spreads to changes in log CDS spreads of the corresponding sovereigns and firm-specific and aggregate variables separately for each of the nine countries in our sample in Panel A and for each sector (including financials, which are excluded from the analysis in Table 2) in Panel B. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. The industry classification follows Refinitiv Eikon. Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Panel A: Estimates by Country

	Core					Periphery			
Variables	BEL	FIN	FRA	GER	NED	GRE	ITA	PTG	SPA
$\Delta log(\text{CDS sov})_{jt}$	0.076**	0.018***	0.210***	0.146***	0.121***	0.130	0.158***	0.264**	0.326***
	(0.023)	(0.005)	(0.019)	(0.026)	(0.012)	(0.122)	(0.046)	(0.015)	(0.064)
$\Delta log(\text{CDS sov})_{jt} \times E$	0.121**	0.076***	0.136***	0.156***	0.158***	-0.051	0.060	0.130	0.000
	(0.042)	(0.019)	(0.027)	(0.034)	(0.018)	(0.080)	(0.036)	(0.073)	(0.032)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	2,561	3,324	17,153	13,758	5,171	858	4,683	862	3,879
R-squared	0.303	0.233	0.312	0.260	0.299	0.186	0.276	0.528	0.324
Firms	6	8	40	33	12	2	11	2	9

Panel B: Estimates by Sector

Variables	Energy and Utilities	Industrial	Technology	Goods and Services	Financials
$\Delta log(\text{CDS sov})_{jt}$	0.169***	0.110***	0.125***	0.146***	0.170***
	(0.039)	(0.024)	(0.040)	(0.015)	(0.036)
$\Delta log(\text{CDS sov})_{jt} \times E$	0.106***	0.104***	0.055**	0.120***	0.047*
	(0.032)	(0.030)	(0.025)	(0.026)	(0.027)
Controls	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes
No. Obs.	9,155	14,705	6,271	18,965	17,948
R-squared	0.318	0.274	0.218	0.278	0.218
Firms	22	36	16	47	43

TABLE 4: **Corporate-sovereign nexus, robustness checks**

The table reports robustness checks from alternative specifications of the panel regression in Eq.(1), relating changes in log corporate CDS spreads to changes in log CDS spreads of the corresponding sovereigns and firm-specific and aggregate variables. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. Results are reported for the following specifications: adding firm-level ATM option-implied volatility (columns 1 and 2); restricting the sample to the subset of issuers not eligible for the ECB Pandemic Emergency Purchase Programme (columns 3 and 4); restricting the disaster sample to one month after the Italian lockdown (columns 5 and 6); accounting for Nickell bias through the system GMM procedure of Arellano–Bover/Blundell–Bond (columns 7 and 8); estimating the model on weekly data (columns 9 and 10); selecting the cum-restructuring clause for corporate CDS (columns 11 and 12); restricting the cross-section of firms to those with higher average pre-pandemic credit spreads than that of their sovereign (columns 13 and 14); restricting the cross-section of firms to those whose government ownership is below sample average (columns 15 and 16); and adding the first principal component of sovereign CDS spreads of the other region (columns 17 and 18). Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Implied Volatility		Non-PEPP		End March 24, 2020	
Variables	Core	Periphery	Core	Periphery	Core	Periphery
$\Delta log(\text{CDS Sov})_{jt}$	0.132***	0.219***	0.073**	0.186***	0.127***	0.208***
	(0.014)	(0.041)	(0.031)	(0.045)	(0.013)	(0.036)
$\Delta log(\text{CDS Sov})_{jt} \times E$	0.125***	0.032	0.109**	0.065	0.153***	0.058
	(0.016)	(0.036)	(0.047)	(0.049)	(0.020)	(0.041)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	38,297	8,374	10,582	5,579	30,273	7,480
R-squared	0.286	0.279	0.224	0.246	0.330	0.313
Firms	92	20	25	13	99	24

	(7)	(8)	(9)	(10)	(11)	(12)
	Arellano–Bover/Blundell–Bond		Weekly Aggregation		CR Clause	
Variables	Core	Periphery	Core	Periphery	Core	Periphery
$\Delta log(\text{CDS Sov})_{jt}$	0.135***	0.268***	0.149***	0.161***	0.134***	0.246***
	(0.013)	(0.037)	(0.022)	(0.035)	(0.013)	(0.038)
$\Delta log(\text{CDS Sov})_{jt} \times E$	0.159***	-0.013	0.155***	0.071	0.127***	0.006
	(0.021)	(0.031)	(0.030)	(0.044)	(0.014)	(0.033)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	32,957	8,096	8,458	2,075	35,848	7,319
R-squared	-	-	0.405	0.376	0.288	0.330
Firms	99	24	99	24	84	17

	(13)	(14)	(15)	(16)	(17)	(18)
	Sovereign Ceiling		Government Ownership		Cross-Spillovers	
Variables	Core	Periphery	Core	Periphery	Core	Periphery
$\Delta log(\text{CDS Sov})_{jt}$	0.127***	0.237***	0.146***	0.234***	0.128***	0.181***
	(0.013)	(0.048)	(0.019)	(0.045)	(0.013)	(0.033)
$\Delta log(\text{CDS Sov})_{jt} \times E$	0.125***	0.050	0.127***	0.025	0.073***	0.035
	(0.016)	(0.036)	(0.019)	(0.039)	(0.016)	(0.029)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	41,967	6,872	19,733	6,854	41,078	10,066
R-squared	0.274	0.284	0.327	0.333	0.217	0.221
Firms	99	16	46	16	99	24

TABLE 5: **Corporate-sovereign nexus, firm-level characteristics**

The table reports estimates from the panel regression in Eq. (1), where the covariates are augmented with firm-specific characteristics that proxy for firm sensitivity to the shock. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. Columns 1 and 2 augment the baseline regression with profit per employee (profit before taxes over employees). Columns 3 and 4 control for the liquidity ratio (current assets minus stocks divided by current liabilities). Columns 5 and 6 account for loans (log of loans from financial institutions divided by total debt). Following standard practice, all ratios are industry-year adjusted. The ratios enter the regression both in level and interacted with changes in sovereign CDS spreads. The models are estimated separately for core countries (Belgium, Finland, France, Germany, and the Netherlands) and peripheral countries (Greece, Italy, Portugal, and Spain). Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Core	Periphery	Core	Periphery	Core	Periphery
Variables	$Z = PPE$		$Z = Liquidity$		$Z = Loans$	
$\Delta log(\text{CDS sovereign})_{jt}$	0.142***	0.253***	0.136***	0.216***	0.136***	0.207***
	(0.013)	(0.060)	(0.013)	(0.038)	(0.013)	(0.040)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.114***	0.045	0.120***	0.063	0.117***	0.056
	(0.014)	(0.041)	(0.014)	(0.039)	(0.015)	(0.037)
Z_{it}	-0.000	-0.001	0.000	0.000	-0.003	-0.002
	(0.000)	(0.001)	(0.000)	(0.001)	(0.003)	(0.004)
$\text{Z}_{it} \times E$	-0.000	-0.001	-0.000	-0.002*	0.003	0.008
	(0.000)	(0.001)	(0.000)	(0.001)	(0.002)	(0.009)
$\Delta log(\text{CDS sovereign})_{jt} \times Z_{it}$	-0.009***	-0.023	-0.015***	0.028	0.172	-0.403
	(0.003)	(0.031)	(0.002)	(0.030)	(0.176)	(0.404)
$\Delta log(\text{CDS sovereign})_{jt} \times Z_{it} \times E$	0.027	0.135	-0.009***	0.185**	0.088	-0.595
	(0.031)	(0.140)	(0.003)	(0.068)	(0.676)	(1.539)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs.	35,498	8,479	36,282	8,833	35,420	8,833
R-squared	0.283	0.323	0.282	0.330	0.279	0.331
Firms	85	21	86	21	84	21

TABLE 6: **Corporate-sovereign nexus, country-level characteristics**

The table reports estimates from a pooled version of the panel regression in Eq. (1), where all countries are included in the estimation and we interact log changes in sovereign CDS with a Core_j dummy that equals one if country j is core (Belgium, Finland, France, Germany, and the Netherlands) and zero otherwise. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. Column 1 is the baseline specification, which is then augmented with the following country-specific characteristics (source is the OECD, World Bank, and Oxford COVID-19 Government Response Tracker databases): trade openness (measured as import plus exports over GDP) in column 2; number of hospital beds per thousand inhabitants in column 3; the Government Policy Tracker index in column 4; and the share of GDP generated by tourism per country and year in column 5. Columns 6 and 7 saturate the baseline model with, respectively, week $\times$ sector and week $\times$ country fixed effects. Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\text{Core}_j \times \Delta log(\text{CDS sovereign})_{jt}$	-0.061	-0.061	-0.061	-0.059	-0.061	-0.052	-0.094**
	(0.044)	(0.044)	(0.044)	(0.044)	(0.044)	(0.043)	(0.044)
$\text{Core}_j \times \Delta log(\text{CDS sovereign})_{jt} \times E$	0.113***	0.113***	0.113***	0.109***	0.113***	0.095**	0.119***
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.038)	(0.043)
$\Delta log(\text{CDS sovereign})_{jt}$	0.189***	0.189***	0.189***	0.187***	0.189***	0.149***	0.193***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.042)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.020	0.020	0.020	0.020	0.020	0.060*	0.049
	(0.036)	(0.036)	(0.036)	(0.036)	(0.036)	(0.034)	(0.038)
$\text{Trade Openness}_{jt}$		0.003					
		(0.012)					
$\text{Hospital Beds}_{jt}$			-0.079				
			(0.254)				
Oxford GPT_{jt}				-0.020***			
				(0.002)			
Tourism_{jt}					-0.036		
					(0.060)		
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Week $\times$ Sector FE	No	No	No	No	No	Yes	No
Week $\times$ Country FE	No	No	No	No	No	No	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	52,249	52,249	52,249	52,249	52,249	52,249	52,249
R-squared	0.272	0.272	0.272	0.275	0.272	0.322	0.319
Firms	123	123	123	123	123	123	123

TABLE 7: **Corporate-sovereign nexus, fiscal capacity measures**

The table reports estimates of the pooled panel regression from column 1 of Table 6, where the Core_j dummy is alternatively replaced with the fiscal capacity measures from Figure 3 (signed so that higher values reflect healthier government) and their first principal component, labeled PC1. The dependent variable is log changes in corporate CDS credit spreads, and the fiscal capacity measure is reported in the corresponding column header. Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$FiscalCap_j$ measure						
	$-$ Debt	$-$ Debt Exp.	Wealth	$-$ LT Rate	Rule of Law	Govt. Eff.	PC1
$FiscalCap_j \times \Delta log(\text{CDS sov})_{jt}$	-0.081*	-0.024	-0.080***	-0.008	-0.056*	-0.057	-0.015*
	(0.041)	(0.019)	(0.020)	(0.024)	(0.033)	(0.035)	(0.009)
$FiscalCap_j \times \Delta log(\text{CDS sov})_{jt} \times E$	0.119**	0.049**	0.032	0.079***	0.085**	0.097**	0.023**
	(0.052)	(0.021)	(0.031)	(0.019)	(0.035)	(0.040)	(0.010)
$\Delta log(\text{CDS sovereign})_{jt}$	0.059	0.105***	0.102***	0.136***	0.220***	0.219***	0.154***
	(0.040)	(0.027)	(0.010)	(0.013)	(0.053)	(0.055)	(0.017)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.229***	0.182***	0.120***	0.137***	-0.013	-0.025	0.088***
	(0.057)	(0.035)	(0.020)	(0.016)	(0.052)	(0.057)	(0.017)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
No. Obs	52,249	52,249	52,249	52,249	52,249	52,249	52,249
R-squared	0.272	0.272	0.273	0.274	0.272	0.272	0.272
Firms	123	123	123	123	123	123	123

TABLE 8: **Corporate-sovereign nexus, bond sample**

The table reports estimates from running the panel regression in Eq. (1) on corporate bonds credit spreads in place of CDS. For each corporate issuer, yield to maturity and modified duration are averages across issues weighted on amount outstanding. We use ECB benchmark rates based on triple A governments nominal spot rates to measure risk-free rates at different horizons. We then compute a firm credit spread 'CS' by subtracting from its yield to maturity the risk-free rate corresponding to its modified duration bucket. We then relate changes in log corporate spreads to their lag, changes in log CDS spreads of the corresponding sovereign, modified duration, and firm-specific and aggregate variables. The dummy E equals one during the COVID-19 period (defined as the days after February 24, 2020) and zero otherwise. Results are reported at the daily frequency (columns 1 and 2), and at the weekly resolution (columns 3 and 4). The models are estimated separately for countries in the core (Belgium, Finland, France, Germany, and the Netherlands) and the periphery (Greece, Italy, Portugal, and Spain). Robust standard errors clustered at the firm level are reported in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)	(3)	(4)
	Daily		Weekly	
Variables	Core	Periphery	Core	Periphery
$\Delta log(\text{CDS sovereign})_{jt}$	0.022*	0.102***	0.104***	0.122***
	(0.011)	(0.012)	(0.017)	(0.015)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.172***	0.048**	0.160***	-0.020
	(0.023)	(0.020)	(0.021)	(0.029)
Firm FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
No. Obs.	81,333	25,571	16,641	5,242
R-squared	0.076	0.047	0.067	0.123
Firms	194	61	194	61

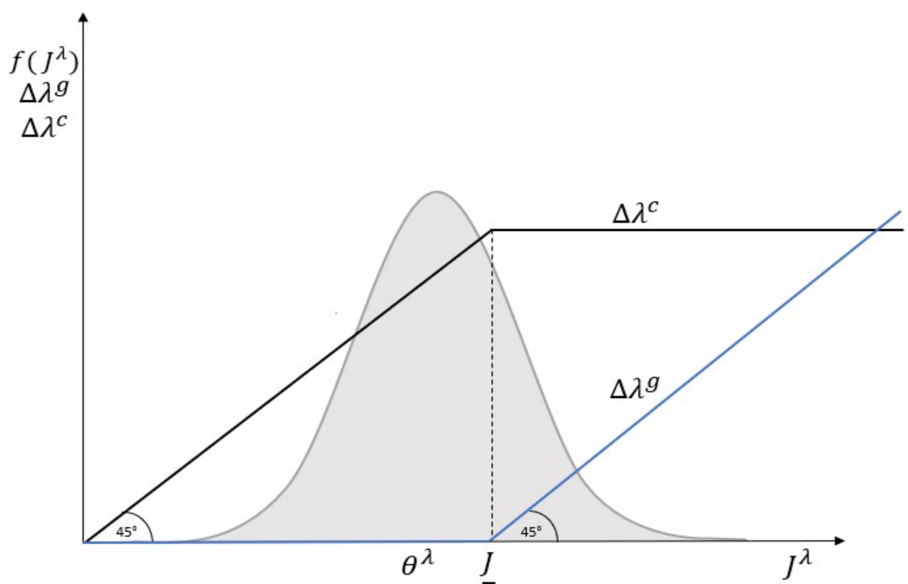

FIGURE A.1: **Government support policy**: This figure plots increases in default intensities of claims referencing corporate and government entities conditionally on the occurrence of a disaster J^λ, whose probability distribution is represented by the gray shaded area. All the losses below $\underline{J}$ are borne by the private sector alone, to reflect the idea that governments intervene for severe catastrophes, in which case default intensity for the private sector is capped.

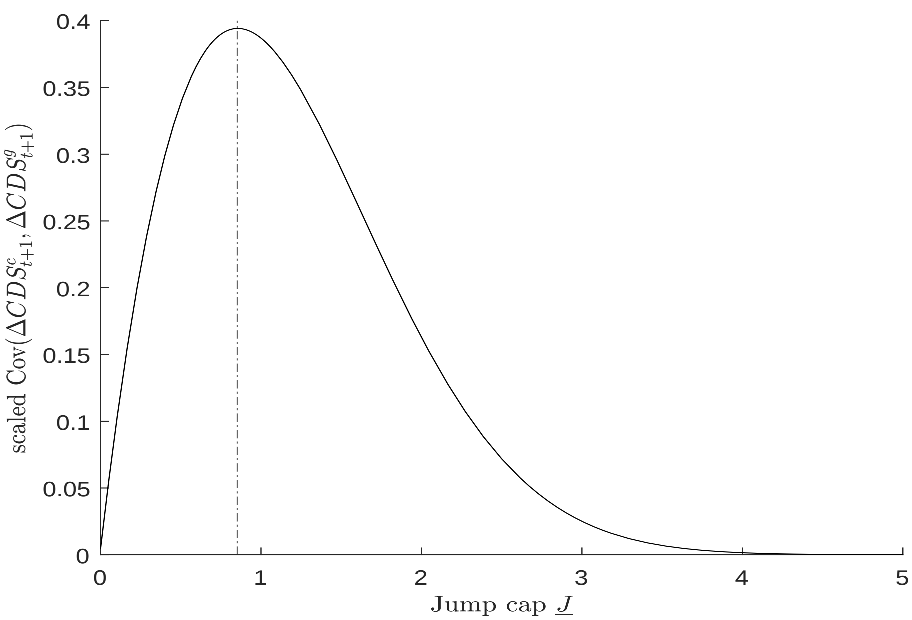

FIGURE A.2: **Government support policy**: This figure shows the disaster-induced corporate-sovereign nexus resulting from government guarantees, up to the exogenous term $(1 - R)^2 \kappa_c p_i$. For illustration purposes, we set $\theta_\lambda = 1$ and $p_i = 0.05$. The parameter restriction required by Corollary I is satisfied to the right of the dash-dotted vertical line corresponding to $\underline{J} = .5(\theta_\lambda + \frac{\phi}{1-\Phi})$.

TABLE A.1: **Top 100 non-financial firms**

This table reports the top 100 non-financial firms by market capitalization (as of the end of 2019) in our sample. Source: Markit and Refinitiv.

Name	Country	Rank	Name	Country	Rank
LVMH	France	1	Michelin	France	51
L’Oréal	France	2	Legrand	France	52
SAP SE	Germany	3	Peugeot S.A	France	53
Anheuser-Busch InBev	Belgium	4	Nokia Oyj	Finland	54
Total SE	France	5	Capgemini SE	France	55
Sanofi	France	6	Akzo Nobel N.V.	Netherlands	56
Airbus Group	Netherlands	7	Wolters Kluwer N.V.	Netherlands	57
Volkswagen Group	Germany	8	Atlantia S.p.A.	Italy	58
Siemens AG	Germany	9	UPM-Kymmene Oyj	Finland	59
Kering	France	10	Sodexo	France	60
Enel S.p.A.	Italy	11	Cellnex Telecom SA	Spain	61
Bayer AG	Germany	12	Bouygues	France	62
Deutsche Telekom AG	Germany	13	EDP - Energias de Portugal	Portugal	63
BASF SE	Germany	14	EnBW Energie Baden-Württemberg AG	Germany	64
Air Liquide	France	15	Hapag-Lloyd AG	Germany	65
Iberdrola	Spain	16	UCB	Belgium	66
Adidas AG	Germany	17	CNH Industrial N.V.	Netherlands	67
Vinci SA	France	18	Veolia Environnement S.A.	France	68
Heineken N.V.	Netherlands	19	HeidelbergCement AG	Germany	69
Daimler AG	Germany	20	Galp Energia SGPS S.A.	Portugal	70
Schneider Electric SE	France	21	Groupe Renault	France	71
Eni S.p.A.	Italy	22	Terna - Rete Elettrica Nazionale S.p.A.	Italy	72
BMW Group	Germany	23	Carrefour S.A.	France	73
Danone	France	24	Telecom Italia S.p.A.	Italy	74
Merck KGaA	Germany	25	Accor S.A.	France	75
Pernod Ricard	France	26	Koninklijke KPN N.V.	Netherlands	76
Deutsche Post AG	Germany	27	Solvay S.A.	Belgium	77
Henkel AG & Co. KGaA	Germany	28	Stora Enso Oyj	Finland	78
Koninklijke Philips N.V.	Netherlands	29	Red Eléctrica de España	Spain	79
Orange	France	30	Publicis Groupe	France	80
Engie	France	31	Alstom SA	France	81
Telefónica	Spain	32	Proximus	Belgium	82
Électricité de France	France	33	Hochtief AG	Germany	83
Vivendi	France	34	ThyssenKrupp AG	Germany	84
Fresenius SE & Co. KGaA	Germany	35	Elisa Oyj	Finland	85
Fiat Chrysler Automobiles N.V.	Netherlands	36	Deutsche Lufthansa AG	Germany	86
Endesa S.A.	Spain	37	Valeo	France	87
E.ON SE	Germany	38	Hellenic Telecommunications Organization S.A.	Greece	88
Koninklijke Ahold Delhaize N.V.	Netherlands	39	Faurecia	France	89
Continental AG	Germany	40	Schaeffler Group	Germany	90
Naturgy Energy Group S.A	Spain	41	MAN SE	Germany	91
Grifols S.A.	Spain	42	TUI Group	Germany	92
STMicroelectronics N.V.	Netherlands	43	Leonardo S.p.A.	Italy	93
Porsche Automobil Holding SE	Germany	44	Rémy Cointreau	France	94
Repsol S.A.	Spain	45	Edison S.p.A.	Italy	95
Koninklijke DSM N.V.	Netherlands	46	Elia System Operator	Belgium	96
Compagnie de Saint-Gobain S.A.	France	47	Metso	Finland	97
Thales Group	France	48	Pirelli & C. S.p.A.	Italy	98
Fresenius Medical Care AG & Co. KGaA	Germany	49	Lanxess AG	Germany	99
Fortum Oyj	Finland	50	Casino Guichard-Perrachon	France	100

TABLE A.2: **Entropy-balancing covariates**

The table reports the first three moments of credit risk-relevant variables stratified by region of the Euro Area. Panel A presents unweighted summary statistics. Panel B shows the corresponding moments when each observation is reweighted, following Hainmueller (2012). Entropy balancing optimally determines weights to achieve exact moment matching while keeping the distribution of observations as close as possible to the data in an entropy sense.

Panel A: Unweighted Sample

	Core			Periphery		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Market Capitalization	3.03×10^{7}	1.40×10^{15}	2.332	1.90×10^{7}	$3.34\text{e}\times10^{14}$	1.538
Total Debt to Total Assets	30.64	237	1.184	40.15	108.9	-0.318
Equity Volatility (5-yr)	0.264	0.005	0.853	0.245	0.006	1.964
Market to Book	2.100	2.535	1.076	2.095	2.321	2.039

Panel B: Weighted Sample

	Core			Periphery		
	Mean	Variance	Skewness	Mean	Variance	Skewness
Market Capitalization	3.03×10^{7}	1.40×10^{15}	2.332	3.03×10^{7}	6.30×10^{14}	0.4907
Total Debt to Total Assets	30.64	237	1.184	30.66	84.82	0.4818
Equity Volatility (5-yr)	0.264	0.005	0.853	0.264	0.012	1.230
Market to Book	2.100	2.535	1.076	2.099	3.217	1.915

TABLE A.3: **Additional robustness checks**

The table reports estimates from the baseline panel regression, including a quadratic term in firm-level stock returns (columns 1 and 2), and estimating the model in first differences (columns 3 and 4), i.e., relating changes in corporate CDS spreads to changes in CDS spreads of the corresponding sovereigns and firm-specific and aggregate variables. Robust standard errors clustered at the firm level are in parentheses. One, two, and three asterisks denote statistical significance at the 0.10, 0.05, and 0.01 levels, respectively.

	(1)	(2)		(3)	(4)
	Squared Equity Returns			First Differences	
Variables	Core	Periphery		Core	Periphery
$\Delta log(\text{CDS sovereign})_{jt}$	0.127***	0.208***	ΔCDS sovereign$_{jt}$	0.818***	0.136***
	(0.013)	(0.036)		(0.158)	(0.047)
$\Delta log(\text{CDS sovereign})_{jt} \times E$	0.115***	0.042	ΔCDS sovereign$_{jt} \times E$	1.814**	0.004
	(0.016)	(0.029)		(0.908)	(0.054)
Controls	Yes	Yes		Yes	Yes
Firm FE	Yes	Yes		Yes	Yes
Observations	41,967	10,282		24,158	5,942
R-squared	0.285	0.294		0.040	0.125
Firms	99	24		99	24