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ORIGINAL PAPER

Economic Activity, Fiscal Space and Types of COVID-19 Containment Measures

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Abstract

This paper argues that the type of COVID-19 containment measures affects the trade-offs between infection cases, economic activity and sovereign risk. Using local projection methods and a year and a half of high-frequency daily data covering 44 advanced and emerging economies, we find that smart (e.g. testing) as opposed to physical (e.g. lockdown) measures appear to be best placed to tackle these trade-offs. Initial conditions also matter whereby containment measures can be less disruptive when public health response time is fast and public debt is low. We also construct a database of daily fiscal announcements for Euro area countries, and find that sovereign risk is improved under a combination of large support packages and smart measures.

Keywords COVID-19 · Fiscal measures · Containment measures · Fiscal space · Sovereign risk

Introduction

Researchers and policy makers alike have been studying how containing COVID-19 can save lives and livelihoods. While a number of studies find that more stringent containment measures are associated with lower COVID-19 cases (Hsiang et al. 2020; Deb et al. 2020a; Caselli et al. 2020), other studies report that these are also associated with lower economic activity (Adda 2016; Deb et al. 2020a; Coibion et al. 2020). More recent research shows

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that "smart" measures, such as testing and contact tracing as opposed to physical closures, can soften this trade-off (Fotiou and Lagerborg 2021; Hosny 2021; Islamaj et al. 2021).

Very few studies examine the relationship between COVID-19 infections and fiscal space. Fiscal space is a multifaceted concept and covers mainly two dimensions: long-term sustainability and market access/financing (Caselli et al. 2018; Botev et al. 2016). In the empirical literature, (Kose et al. 2017) report CDS spreads as a proxy for fiscal space hinging on the dimension of market access and focusing on sovereign risk. We follow a similar approach in this paper. A priori, the relationship between containment measures and fiscal space during the COVID-19 pandemic is not clear. In Fig. 1, we plot the cross-country average of the observed sovereign 5-year maturity CDS spreads, and a policy index measuring the stringency of containment measures against waves of COVID-19 infections over time. While tighter containment and CDS spreads moved together during the first wave, the relationship seemed to reverse in consequent waves. This could be because CDS spreads were driven by uncertainty surrounding the beginning of the pandemic, independent from initial policy interventions, while financial markets later internalized such measures during subsequent waves.

This paper aims at studying the effects of different types of COVID-19 containment measures on infection cases, economic activity and fiscal space, using a year and a half of daily data. Our sample uses data at a daily frequency from February 26,2020 to June 30,2021 covering a set of 44 advanced and emerging economies. Using local projection á la (Jordà 2005), an econometric specification that builds on (Deb et al. 2020a) and high-frequency daily data, we study how different containment measures dynamically affect COVID-19 infection cases, economic activity (proxied by NO2 emissions) and fiscal space (proxied by CDS spreads). Drawing on Oxford's Coronavirus Government Response Tracker (OxCGRT), we use three different containment measures indices that range from "physical" closures (e.g., lockdown) to "smart" measures (e.g., contact tracing).[1]

Findings suggest that "smart" containment measures are best placed to tackle the trade-offs between infection cases, economic activity and sovereign risk. First, baseline results suggest that containment measures can limit infection cases but potentially at the expense of economic activity. We find that the degree of this trade-off, however, depends on the type of containment measure. While "physical" measures can be most effective in containing outbreaks, they are also most disruptive to economic activity. "Smart" measures, on the other hand, can contain infections to some degree while safeguarding the economy. Second, on fiscal space, we observe that smart measures may be as effective as physical ones in improving sovereign risk (reducing 5-year CDS spreads). These results combined suggest that smart measures can provide a relatively optimal response in comparison to more physical containment measures provided that infection outbreaks are under control.

We also study how initial conditions can affect these trade-offs. The paper employs various state-dependent local projections to examine the transmission of containment measures onto our variables of interest. Specifically, we find evidence that (i) stricter physical containment measures tend to affect economic activity less and reduce CDS spreads more in EMs versus AEs; (ii) faster public health response time can more quickly normalize economic activity after an initial shock as well as improve the sovereign risk profile; and (iii) onger initial public finances (low public debt) containment measures are associated with an improved economic outlook and lower sovereign risk.

[1] "Physical" measures include non-pharmaceutical interventions that involve closures such as school closing, ban on international and local travel, etc. "Smart" measures include non-pharmaceutical interventions that involve policies aiming at tracing and preventing infections such as contact tracing and mask mandates. See below for details.

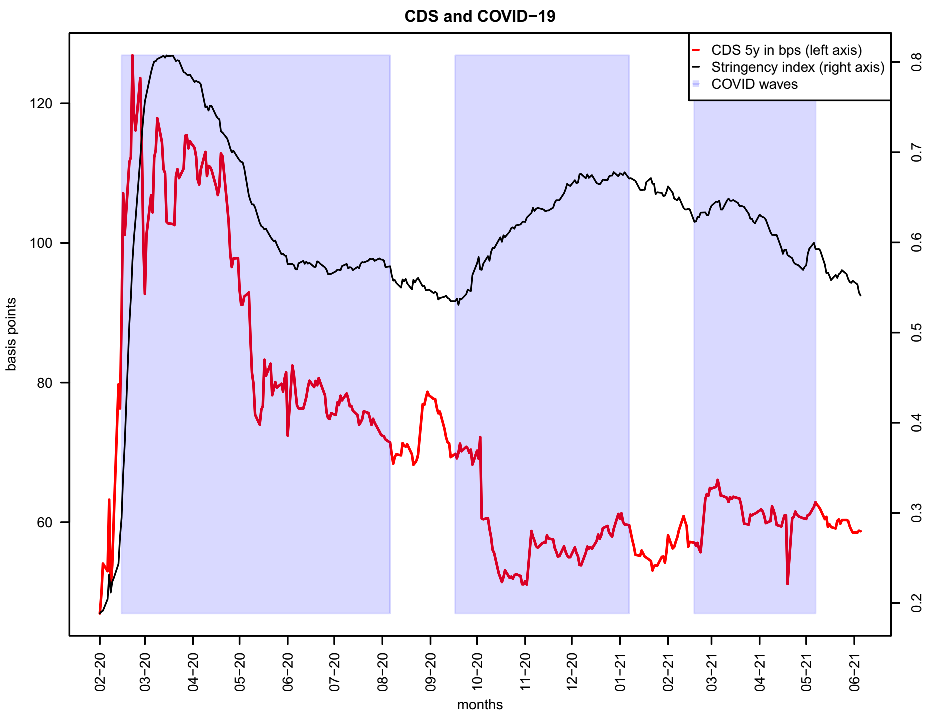

Fig. 1 COVID-19 waves, stringency index and sovereign 5-year CDS spread. Notes: The cross-country average OxCGRT "stringency index" is normalized between [0, 1] on the right y-axis. Cross-country average CDS spreads are measured in basis points on the left axis. Argentina is excluded from the computation of the cross-country average of CDS spreads. Infection (shaded) waves are plotted according to the global pandemic number of new cases tracked by the WHO Coronavirus Dashboard. Specifically, the first and second wave reflects the pandemic evolution observed in Europe and the Americas, while the third wave reflect the infection dynamics reported in Europe, the Americas and South East Asia. The country sample used in Fig. 1 is the one used throughout the empirical analysis. See Section 2 for details. Source: Authors' calculations based on OxCGRT and WHO

Lastly, we construct a new database of "daily" fiscal announcements in response to COVID-19 for EU-19 countries. We study the impact of physical closures and smart measures on CDS spreads conditioning on the size of announced government fiscal support packages, building on the methodology of (Deb et al. 2021). Using state-dependent local projection and interpreting fiscal announcements as unanticipated fiscal shocks á la (Ramey 2011b; 2011a), results suggest that sovereign risk is improved under a combination of large support packages and smart measures.

The paper is structured as follows. We explain our contribution to the relevant literature in "Contribution to the Literature". Data and the empirical strategy are presented in "Data" and "Empirical Strategy", respectively. Empirical results are reported in "Results". Finally, "Concluding remarks" concludes.

Contribution to the Literature

The empirical literature on COVID-19 containment measures has been evolving from studying its impact on infection cases, to economic activity to policy responses. Since the onset of the COVID-19 pandemic, authorities across the world implemented a wide range of non-pharmaceutical interventions (NPIs) to protect livelihoods and to flatten the epidemic curve. As a result, a trade-off started to appear between health and economy outcomes. As lockdowns became prolonged with several waves of infections, a discussion emerged on living with the virus and the appropriate mix of hard vs soft non-pharmaceutical interventions. Moreover, as fiscal and monetary authorities implemented various policy packages, the literature started to discuss the appropriate size and design of such policies, including their interactions with containment measures and initial conditions. The impact on fiscal space, or sovereign risk, was then briefly investigated. As vaccines became more available, the literature naturally started to cover the race between the virus and the vaccine, and its macro-fiscal implications. In what follows, we present how the literature evolved our time, and in each case, how this paper contributes to the existing literature.

The literature initially studied the role of non-pharmaceutical interventions (NPIs) in containing the contagion spread of COVID-19. The literature first used the Susceptible, Infected and Recovered (SIR) epidemiology model and its variants to study the impact of NPIs on health outcomes.[2] Results found in (Kraemer et al. 2020; Chinazzi et al. 2020; Tian et al. 2020; Hsiang et al. 2020; Deb et al. 2020b) highlight that stringent containment measures (e.g., lockdowns) and NPIs effectively contributed to the reduction of confirmed cases and deaths.

Then the literature focused on the trade-off between protecting lives versus stimulating the economy. Notably, (Deb et al. 2020a; Chen et al. 2020; Demirgüç-Kunt et al. 2021) use high-frequency data to study the impact of non-pharmaceutical interventions (NPIs) and containment measures on economic activity. These papers make use of a wide variety of daily frequency economic activity indicators such as nitrogen dioxide (NO2) emissions, electric usage, Google and Facebook mobility indices and also job postings. Specifically, using panel local projection (LP) following (Jordà 2005; Deb et al. 2020a), using daily data until end-Dec 2020, show that implementing maximum stringency (namely, physical lockdowns) implies almost a 100 percent reduction in economic activity measured by NO2 emissions.[3] In this paper, using an extended and high-frequency dataset, we present evidence that this trade-off depends on the type of containment measures.

Some papers show that using smart/soft (e.g. testing) as opposed to physical/hard (e.g. quarantines) containment measures can soften this trade-off, helping protect both lives and livelihoods. Smart NPIs typically refer to contact tracing, public campaign policies, social distancing mandates, etc. (Hosny 2021). Hosny (2021), Deb et al. (2020a), Fotiou and Lagerborg (2021), Islamaj et al. (2021), WEO (2020) find that smart and fast containment measures can reduce infections while also safeguarding economic resources. In this paper, we report empirical evidence that smarter containment measures are less prone to cause a trade-off between protecting lives and stimulating economic activity. Indeed, when we use smart NPIs as a shock in the LP framework, we find that COVID-19 cases slightly decrease while also safeguarding economic activity.

The literature then studied governments' announced fiscal policy responses and their interactions with COVID-19 measures. Using data from the IMF policy tracker, (Deb et al. 2020a) find that fiscal stimulus measures mitigate the economic fallout associated with

[2] See (Acemoglu et al. 2020; Bognanni et al. 2020; Garibaldi et al. 2020) for more on SIR model applications. The original SIR model was first developed by (Kermack and McKendrick 1927).

[3] Using standard panel regression techniques, (Deb et al. 2020a) and the present study report that NO2 and the industrial production index (a proxy for GDP) are significantly and positively correlated. For further details, see Section 2.

COVID-19 crisis. Hosny (2021) and Fotiou and Lagerborg (2021) study the determinants of announced fiscal packages in response to COVID-19, as measured by the IMF's Fiscal Monitor database.[4] Their main finding is that faster and smarter containment measures are associated with lower fiscal responses to COVID-19. Those studies used cross-section methodologies as their dataset contained one observation (size of fiscal package) per country. The literature then introduced the time-series dimension and examined such responses at higher frequency. For instance, (Deb et al. 2021) assemble a novel cross-country daily database of fiscal announcements between Jan-Dec 2020, building on the Yale COVID-19 Financial Response Tracker dataset. They find that fiscal responses can stimulate economic activity. Compared to (Deb et al. 2021), this paper extends the database until end-June 2021, focusing on EU-19 countries and uses it to explore the determinants of CDS spreads during COVID-19.

Fiscal space is a multifaceted concept and covers mainly two dimensions: long-term sustainability and market access (Botev et al. 2016; Metelli and Pallara 2020). (Caselli et al. 2018) defines fiscal space as the room for undertaking discretionary fiscal policy relative to existing plans without endangering market access and debt sustainability. Regarding the long-term fiscal/debt sustainability dimension, fiscal space can be measured as the distance between the actual debt and a fiscal limit for which the government would be unable to roll-over its debt and, then, lose market access. Pallara and Renne (2021) exploit the time-variation of sovereign credit data, namely CDS spreads, to estimate both fiscal limits and fiscal space.[5] Kose et al. (2017) also report CDS spreads as an indicator for fiscal space hinging on the dimensions of market access and perceived sovereign risk.[6] In this paper, we use CDS spreads as an indicator for fiscal space, including because our analysis relies exclusively on high-frequency data, which does not allow for the use of government budget or debt variables to proxy for fiscal space.[7] Hosny (2021) and Fotiou and Lagerborg (2021) control for the role of fiscal space when studying the role of containment measures on fiscal responses, by accounting for EMBI spreads and initial debt levels, respectively.

[4]These studies use different vintages of the IMF Fiscal Monitor (FM) database on country fiscal measures in response to COVID-19. The dataset includes announced fiscal measures, in almost all IMF member countries, and are classified into on-budget above-the-line (ATL) health and non-health measures, tax deferrals and off-budget below-the-line (BTL) and contingent labilities (CLs; such as guarantees and quasi-fiscal operations). ATL measures include both forgone revenues and additional spending, mostly to provide support to households, while BTL-CL measures are mostly to support firms. The IMF database is available at https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19.

[5]Another part of the literature focuses on providing structural macroeconomic approaches to assessing fiscal space. This literature builds theoretical models to derive the so-called fiscal limit. This line of work considers the fiscal space as the distance between current public debt and a (theory-based) debt or fiscal limit. The latter represents the maximum expected assets attainable by the government. On one hand, (Ostry et al. 2010; Ghosh et al. 2013; Ostry et al. 2015) compute static estimates for debt limits based on the observation that the higher the levels of debt, the weaker the reaction of primary surpluses ("fiscal fatigue"). On the other hand, in Bi (2012), Leeper (2013), Bi and Leeper (2013), Bi and Traum (2012) and Bi and Traum (2014), the theoretical fiscal limit corresponds to the discounted present value of future maximum primary surpluses. Moreover, (Collard et al. 2015) also exploit the idea of a maximum primary surplus to derive a static measure of debt limit.

[6]The dataset of (Kose et al. 2017) covers many of the core aspects of fiscal space: government debt sustainability, perceived sovereign risk, market access, balance sheet composition, external and private debt considerations.

[7]We acknowledge that CDS spreads do not represent a complete measure of fiscal space, but, given our focus on high-frequency indicators, they stand as the best proxy that can be employed in our analysis.

This paper pertains to the nascent literature on the relationship between COVID-19 and financial variables. For instance, estimating yield curves for a large sample of non-financial and financial corporate bonds for major European countries between Jan-Apr 2020, (Ettmeier et al. 2020) find that the pandemic impacted corporate bond yields across the maturity structure. While, focusing on the impact of the pandemic in Europe on sovereign CDS spreads using an event study methodology, (Andries et al. 2021) study the effect of COVID-19 cases and deaths on sovereign risk premia. They find that the stronger the circulation of the virus, the higher the uncertainty among investors and, thus, the larger the risk premia. Similarly, (Esteves and Sussman 2020) observe a rise in the emerging economies' borrowing costs with higher COVID-19 infections. Augustin et al. (2021) find a positive and significant sensitivity of sovereign default risk to the intensity of the virus' spread for fiscally constrained governments for a sample of 30 developed countries.[8] In this paper, we focus on the sovereign CDS market for both advanced and emerging economies. Moreover, we study the effect of various containment measures on sovereign risk using daily data extending through end-June 2021.

In this paper, we highlight that implementing containment measures, jointly with managing fear and uncertainty, relaxes fiscal space/sovereign risk. Cevik and Ozturkkal (2020), using daily data from January to June 2020, report a significant positive correlation between COVID-19 cases and CDS spreads.[9] Interacting COVID cases with a measure of stringency of domestic lockdowns, they argue that the impact of COVID-19 infections on sovereign CDS spreads can be lower in countries with more stringent containment measures, although they caveat their results given the short time period covered in their analysis. Compared to that study, this paper uses high-frequency daily data for an extended period of time from Feb2020 till end-June 2021 and includes a much wider set of control variables. We find that containing infection cases via stricter containment is associated with lower CDS spreads. Smart measures, however, were associated with a reduction in CDS spreads that is quantitatively comparable to physical containment measures.

Data

We build a dataset at daily frequency for 44 countries spanning from February 26 2020 until June 30 2021.[10] Our dataset includes COVID-19-related variables (including vaccinations), economic activity indicators, meteorological variables and financial variables.[11] Moreover, for the countries part of the EU-19, we build a novel database collecting their fiscal policy announcements, also at a daily frequency.

COVID-19-related data and containment measures. We draw data related to COVID-19 infection cases, deaths, tests and vaccinations from the Coronavirus Resource Center

[8] Supporting the fiscal channel, (Augustin et al. 2021) confirm the results for Eurozone countries and U.S. states, for which monetary policy can be held constant.

[9] Using annual panel data between 2004-2020, they first find no link between previous infectious outbreaks and sovereign spreads.

[10] The countries included in our sample are United States, United Kingdom, Norway, Switzerland, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Spain, Netherlands, Portugal, Ireland, Cyprus, Japan, South Korea, Sweden, Israel, Iceland, New Zealand, Greece, Hong Kong, Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Hungary, India, Mexico, Philippines, Poland, Romania, Russia, South Africa, Thailand and Turkey.

[11] More details regarding the data employed in the empirical analysis are also provided in Appendix 2.

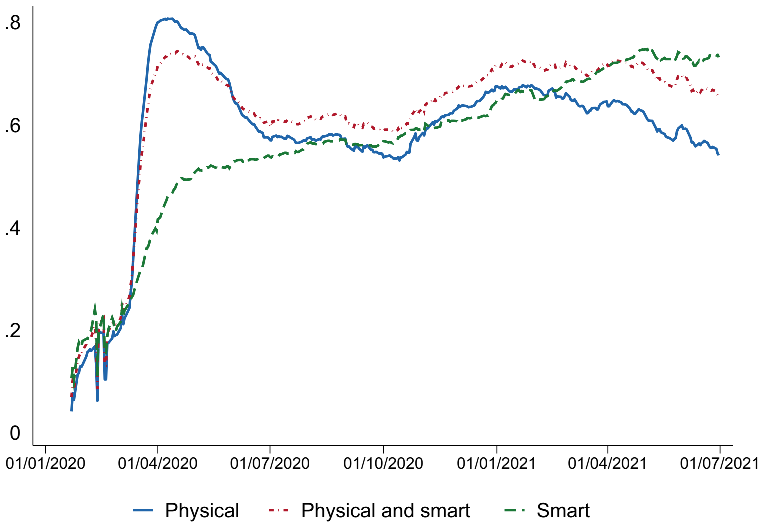

Fig. 2 Containment measures indices: physical, physical and smart, smart. Notes: The figure reports the three containment measures indices as defined in "Data": physical, physical and smart, smart. All indices are normalized to be between 0 and 1. Source: Authors' calculations based on OxCGRT

of Johns Hopkins University.[12] Regarding containment measures, we build on Oxford's Coronavirus Government Response Tracker (OxCGRT).[13] The OxCGRT database constructs different indices of containment measures using country-level information on closure policies, economic policies, health system policies and vaccination policies. Specifically:

- OxCGRT reports a "stringency index" that includes exclusively physical closure policies across eight dimensions: school closing, workplace closing, public events cancelling, restrictions on gatherings, closing public transport, stay at home requirements, restrictions on internal movement and international travel controls. In this paper, we refer to this index as the "physical" index (Fig. 2).
- Another OxCGRT index is the "containment and health index", which expands the stringency index above by also including "soft" or "smart" measures such as testing policy, contact tracing, facial coverings and vaccination policy. We name this the "physical and smart" index (Fig. 2).
- Finally, we construct a "smart" index that includes only the so-called smart containment measures (Fig. 2). In all three indices, we normalize the values to be between 0 and 1 for ease of interpretation when used as shocks in the empirical strategy, to gauge the effect of different types of containment measures on COVID-19 cases, economic activity and fiscal space (see "Empirical Strategy").

Economic activity indicators. We draw NO2 emissions at daily frequency across major cities from the Air Quality Open Data Platform of the World Air Quality Index (WAQI),

[12]The John Hopkins University Coronavirus Resource Center can be accessed via https://coronavirus.jhu.edu/. Moreover, we draw the aforementioned data from https://github.com/owid/covid-19-data/tree/master/public/data.

[13]The OxCGRT (Blavatnik School of Government) database can be accessed at the following link: https://www.bsg.ox.ac.uk/research/research-projects/covid-19-government-response-tracker.

Table 1 Panel regression, monthly frequency: industrial production on NO2 emissions

	$\Delta \log(IPI)$
$\Delta \log(NO2)$	0.137**
	(2.67)
Constant	0.00362***
	(4.25)

t statistics in parentheses;
*p<0.1, **p<0.05, ***p<0.01

as a proxy for economic activity.[14] This is in line with (Deb et al. 2020a) who show that high-frequency NO2 emissions are highly correlated with low-frequency economic activity indicators such as industrial production. Specifically, in Table 1, we report the panel regression of $\Delta \log(IPI)$ on $\Delta \log(NO2)$ at monthly frequency, where IPI represents the industrial production index.[15] We find a positive and significant correlation, where a 1 percent change in NO2 emissions implies a 0.137 percent variation in the IPI index. Other high-frequency indicators are also available, but are often industry-specific (such as number of flights per day). We use humidity, temperature and particulate matter 10 μm (pm10) from WAQI as controls in our empirical analysis. Meteorological variables, including NO2 emissions, are collected by city-specific stations that report data three times per day. We use the median reported values.[16]

Financial variables. As a proxy for fiscal space, we draw sovereign yields and CDS spreads at different maturities (1, 3, 5 and 10 years). We use the 5-year maturity CDS spread as the benchmark variable of interest, while other maturities' are used as controls.[17] In the same fashion, we use sovereign yields as controls in the empirical analysis. Data comes from Refinitiv Eikon Datastream and Bloomberg.[18]

Fiscal announcements. Starting from Yale's COVID-19 Financial Response Tracker (CFRT) and following the methodology implemented in (Deb et al. 2021), we construct a dataset reporting fiscal announcements in EU-19 countries at a "daily" frequency between Feb 26 2020-June 30 2021.[19] Yale's CFRT reports policy measures taken during the COVID-19 pandemic by monetary, fiscal and governmental authorities. For each measure, the dataset indicates the announcement date, size, type of policy measure, coverage, and the relevant weblinks/press releases. Focusing on fiscal announcements, we cross-check every reported measure with information reported by the IMF Policy Tracker and other sources, revising entries day-by-day and one-by-one as needed for a set of EU-19 countries representing the bulk of fiscal responses worldwide.[20] We include European institutions'

[14] https://aqicn.org/data-platform/covid19/

[15] We include country fixed effects and we cluster the standard errors at the country level.

[16] NO2 emissions are measured in parts per billion (ppb), which is the US environmental protection agency standards.

[17] The 5-year maturity for CDS spreads is close to the average maturity for sovereign debts across our country sample.

[18] Data are downloaded through the Eikon and Bloomberg portals, which are private data providers and, thus, we cannot publicly share the data. Upon request, we can provide the Excel extraction files for Refinitiv Eikon Datastream data that can be used to download the data conditional on the type of subscription with the data provider.

[19] More details on the Yale's CFRT database can be found at https://som.yale.edu/faculty-research-centers/centers-initiatives/program-on-financial-stability/covid-19-crisis.

[20] More details on the IMF Policy Tracker database can be found at https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19.

announcements not included at the individual country level. We define all measures in percentage of national (2020 and 2021) GDP.[21] Furthermore, we expand the CFRT database by categorizing the reported policy instruments into more structured macro-categories; namely emergency lifeline and demand-support, as well as health and non-health measures. Specifically, following the IMF FM database on fiscal responses, we define lifeline measures as those that provide cashflow support both to firms and households (such as credit guarantees and loans). On the other hand, demand-support includes measures aiming at increasing the income of firms and households (such as wage subsidies and tax payment forbearances). These series of fiscal announcements can be interpreted as fiscal news so that we can identify unanticipated fiscal policy shocks/instruments as in (Ramey 2011b; 2011a), who builds a series of estimated changes in expected present value of government purchases caused by military events: the so-called Ramey news shock series. See Appendix 2 for more details and an illustration of our (expanded) dataset compared to the raw CFRT database.

Empirical Strategy

This section presents the empirical methodology and specification employed to estimate the effects of various containment measures on economic activity and CDS spreads.

The estimation methodology uses Local Projection. Firstly introduced by (Jordà 2005), local projections (LPs) have become increasingly popular to estimate impulse response functions (IRFs) compared to more standard methods such as structural vector autoregression (VAR) models. VARs provide a global approximation of the IRFs, while LPs approximate the IRFs locally.[22] Interestingly, the LP responses are equivalent to VAR ones if the data generating process (DGP) is a VAR.[23] Moreover, LPs deal with non-linearities easily given they employ subsequent single equation estimations rather than a system estimation. In general, in a cross-country setting, the linear panel local projections we are interested in estimating can be written as:

$$y_{i,t+h} = \alpha_i + \beta_h \eta_{i,t} + \Psi_h \mathbf{X}_{i,t} + \Phi_h(L) y_{i,t} + \varepsilon_{i,t+h} \quad h = 0, 1, 2, \ldots, H, \tag{1}$$

where $y_{i,t}$ stands for the dependent variable, $\eta_{i,t}$ represents the shock variable of interest (that is, in our case, containment measures), $X_{i,t}$ is a vector of control variables. α_i represents country fixed effects; Ψ_h and $\Phi_h(L)$ stand for the coefficient matrix of the control

[21] For instance, among many others, fiscal policy instruments that we report are wage supplements, cash transfers, unemployment benefits, tax relief, targeted transfers, sector support, salary compensations, reduction of social security contributions, infrastructure spending, credit guarantees, liquidity and equity injections.

[22] As one can see from Eq. 1, the main difference between LPs and VARs resides in LPs not assuming any data generating processes (DGP) for the data at hand, making them a less parametric tool than VARs which instead are fully parametric. As a direct consequence, if one believes the economy to be structurally well characterized by a set of stochastic equations as in a VAR, then estimating IRFs with a VAR will for sure yield more reliable and more efficient estimates. However, if the researcher does not have a strong belief for the data to be generated by a VAR, then a case exists for estimating IRFs with nonparametric methods as LPs. Therefore, when model uncertainty is a concern, LPs possibly represent a better option as opposed to VARs which by construction cannot account for uncertainty in the DGP, but only for uncertainty in parameters conditional on a given DGP.

[23] Recently, (Plagborg-Møller and Wolf 2021) find that linear LPs and VARs estimate (in theory) the same IRFs. This only holds true, however, when no constraint is imposed on the lag structure, meaning that only IRFs from linear VARs and linear LPs with an infinite number of lags coincide.

variables and the lag-coefficient matrix of the dependent variable. The estimation is carried out independently for each horizon and the IRFs are defined by the sequence $\beta_{h=0}^{H}$. Moreover, inference is performed with country-clustered standard errors.

Model specification. Our baseline approach relies on estimating Eq. 1 and our specification builds on (Deb et al. 2020a). The dependent variables $y_{i,t+h}$ in Eq. 1 that we focus on are COVID-19 cases, NO2 emissions (as proxy for economic activity) and 5-year maturity sovereign CDS spreads (as proxy for fiscal space). Dependent variables are defined in log deviations from their past values $(t-1)$.[24] Regarding the set of controls ($X_{i,t}$ in Eq. 1), we include COVID-19 deaths, vaccinations, vaccination policy, temperature, humidity, pm10, 1,3,10-years maturity CDS spreads (in logs), 1 and 10-years maturity sovereign yields.[25,26,27]

When the dependent variable is either the economic activity or the fiscal space indicator, we also include COVID-19 cases in the set of controls. We use containment measures indices as shock variables. Specifically, we use the physical index, the physical and smart index and the (newly created) smart index as defined in Section 2. Given that these indices are scaled to be between 0 and 1, the unitary impulse shock in each of the containment measure indices equals a 0 to 100 percent increase in the policy index. For example, a unitary shock in the physical index is equivalent to the implementation of maximum physical stringency, namely full lockdown.

In general, capturing causality between containment measures, economic activity and CDS spreads is complicated. As outbreaks and stringency measures evolve jointly, it could be problematic for a dynamic analysis to treat these variables as exogenous, as noted in (Maloney and Taskin 2020) and (Deb et al. 2020a). We acknoweledge this issue and try to mitigate it in two ways. First, by interacting our physical index with a seasonality factor, which is measured as a ratio of non-seasonally adjusted economic indicator and its seasonally adjusted counterpart.[28] We adopt this strategy given that in a winter season, for instance, if activities tend to naturally decline, the man-made lockdown is then less likely to affect the economy. Moreover, seasonality is in the information set of policy makers. Lastly, it aims at reducing the confounding effects of pure lockdowns and voluntary social distancing given that they both contribute to a decline in economic activities during the

[24] E.g., in the case of NO2 emissions, $y_{i,t+h} = \log(NO2_{i,t+h}) - \log(NO2_{i,t-1})$ for each h.

[25] As regards the number of deaths, it represents a good predictor for the severity of the pandemic wave, so we need to include it to control also for the voluntary social distancing and self-isolation. The fact that a surge in deaths may push people to stay at home due to fear even if the physical containment measures are not extremely restrictive. Thus, it is crucial to control also for the number of deaths. As correctly pointed out also in (Deb et al. 2020a), containment measures have not been introduced to explicitly target economic activity but their implementation depends on the dynamics of the virus that can have a feedback effect on economic activity and mobility (Maloney and Taskin 2020). This means that studying causality calls for controlling for the endogenous response that could bias the estimated effects of containment measures. Hence, we use daily data and control for the contemporaneous number of infections (in the models in which the dependent variable is not the COVID-19 cases) and deaths that summarize the dynamics and severity of the virus on top of other controls.

[26] "Vaccination policy" records policies for vaccine delivery for different groups, which spans from unavailability to universal availability that are associated with numeric values equal to 0 and 5, respectively. While, with "vaccinations", we mean the total number of vaccinations rolled out. See (Deb et al. 2021a; 2021b) for empirical analysis on the role of vaccinations on economic and health outcomes.

[27] As a robustness check, we also include the VIX to control for global volatility. Results do not vary including VIX as control. We draw the VIX from Cboe Exchange, Inc. at www.cboe.com.

[28] Seasonal adjustment of the daily economic activity indicator is carried out by regressing it on days of the week dummies, quarter dummies, main holidays dummies and on its lags (in total seven, namely one week).

pandemic. Second, we include lags of the dependent variable and include time trends for each country to capture the timeline of the infection outbreak within each country.[29]

We also employ various state-dependencies. Non-linearities can be examined by using a dummy indicator to separate two different states (defined as D_t below). In our context, we investigate the extent to which containment measures are transmitted differently under two different regimes (say, regimes A and B). We employ the same state-dependency methodology for LPs as the one carried out by (Ramey and Zubairy 2018) and is represented as follows:[30]

$$\begin{aligned} y_{i,t+h} &= \mathcal{D}_t\left[\alpha_{A,i} + \beta_{A,h}\eta_{i,t} + \Psi_{A,h}\mathbf{X}_{i,t} + \Phi_{A,h}(L)y_{i,t}\right] \\ &\quad +(1-\mathcal{D}_t)\left[\alpha_{B,i} + \beta_{B,h}\eta_{i,t} + \Psi_{B,h}\mathbf{X}_{i,t} + \Phi_{B,h}(L)y_{i,t}\right] + \varepsilon_{i,t+h} \\ h &= 0, 1, 2, \ldots, H \end{aligned} \tag{2}$$

where the interpretation of the parameters and variables is the same as in Eq. 1 except that A and B represent different states as defined by the dummy indicator D_t. Specifically, we study the dynamic responses of economic activity and CDS spreads to containment measures' changes under the regimes of advanced/emerging economies, slow/fast public health response time and high/low public debt.

Results

This section presents the empirical results. We start with baseline results on the dynamic effects of various containment measures on COVID-19 cases, economic activity and CDS spreads using linear local projection (Eq. 1). Then, we report state-dependent LP (Eq. 2). In what follows, IRFs are estimated over a 30-days (1-month) projection horizon, with a 95 percent (shaded) confidence interval.

Baseline Results

Baseline results, reported in Fig. 3, show the responses of COVID-19 cases, economic activity and fiscal space (along the column dimension) to shocks in physical, physical and smart, and smart containment measures (along the row dimension). Specifically, the plots report the estimated impulse response functions (IRFs) from linear local projection (Eq. 1) of COVID-19 cases, NO2 emissions (proxy for economic activity) and 5-year CDS spreads (proxy for fiscal space) (moving along the column dimension), by using, in turn, the physical index, physical and smart index and smart index as shock variables (moving along the row dimension). Responses of variables of interest are reported in log-deviations from their past values. Shaded green areas represent the 95 percent confidence intervals, while

[29] Results are robust using one day lag, or also one week or two weeks lag.

[30] Other authors - e.g. (Tenreyro and Thwaites 2016) - have opted for smooth transition local projections, which allow parameters to smoothly switch between the two regimes, instead of letting them change abruptly around a threshold. While a smooth transition is desirable, for this model - first developed in (Granger and Terasvirta 1993) - to be employed one needs to calibrate two key curvature and location parameters, whose choice turns out to be quite important in terms of the final set of IRFs that are obtained. In principle, those parameters could be estimated, but in order to do so reliably the researcher would need a lot of data around the transition of the state variable, something that is virtually never the case in macroeconomic applications. (Teräsvirta 1994) discusses those estimation issues in detail. We therefore decided to stick with the easier to interpret (and more robust) discrete indicator variable, which nonetheless yields a cleaner interpretation of the coefficients as exact average causal effects within a given state.

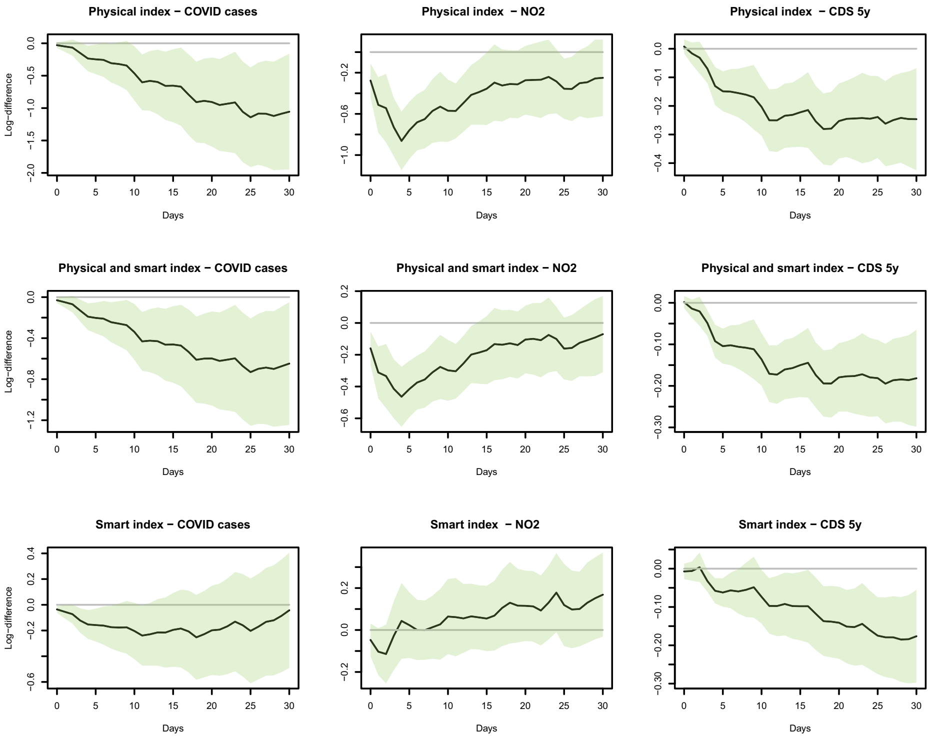

Fig. 3 Baseline results. Notes: As we move along the columns of plots, we observe the responses of COVID-19 cases, NO2 emissions and CDS spreads. While, as we move along the rows of plots, we observe the dynamic effects of the "physical", "physical and smart", and the "smart" index as defined above. Responses are reported in log-deviations from their past values. Shaded green areas represent the 95 percent confidence intervals, while the black solid lines represent the median IRFs. Sources: Authors' calculations.

the black solid lines represent the median IRFs. The projection horizon covers 30 days after a unitary change in the containment indices.[31]

First, results suggest a trade-off between fighting the virus and its impact on the economy. Estimated IRFs suggest that more physical lockdowns are associated with lower COVID-19 cases (see first column), but typically at the expense of lower economic activity (second column). The impacts are strongest when using physical lockdowns (first row) compared to other forms of containment measures (second and third rows). Specifically:

- On COVID-19 cases (first column), a unitary shock in the "physical" and "physical and smart" indices is associated with a 90 percent drop in COVID-19 cases at peak (see first two rows), in line with (Deb et al. 2020a). The reduction in cases under the "physical and smart" index is milder (second row) as smart measures potentially compensate for the need for strict physical lockdowns.[32]

[31] As regards the length of the projection horizon, we follow (Deb et al. 2020a; 2020b). Longer projection horizons would be costly in terms of loss in observations and would not be reliable.

[32] In Fig. 12 in Appendix 2, we report that a unitary shock in the "physical" and "physical and smart" indices is associated with a strong and persistent drop in COVID-19-related new deaths, hospitalized patients and

- On economic activity (second column), a unitary shock in the "physical" index is associated with a peak 90 percent drop in NO2 emissions after a few days (see first row). This is in line with (Deb et al. 2020a) who show that NO2 emissions are cut by almost 100 percent at peak response. A milder plunge in NO2 emissions is observed when using the "physical and smart" index (second row).

Smart measures appear to soften this health-economy trade-off. Physical lockdowns (first row) are associated with the strongest reduction in COVID-19 cases, but also the strongest reduction in economic activity. When smart measures are introduced alongside physical lockdowns (second row), the impact on both is softened. Smart measures alone (third row) seem to be associated with a milder reduction in COVID-19 cases while at the same time safeguarding economic activity. Specifically, following a unitary shock in the "smart" index, COVID-19 cases drop by 20 percent (at peak) without any statistically significant drop in NO2 emissions.

Second, there is evidence that physical and smart measures are almost equally effective in reducing sovereign risk. We have established above that more physical containment measures are associated with stronger reductions in cases (first column) and output (second column). Focusing on fiscal space (third column), we find that CDS spreads drop by about 20 percent on average across the three types of containment measures, and the IRFs are consistently negative throughout the projection horizon.[33] Results suggest that introducing smarter measures (e.g. testing as in rows 2 and 3) are almost as effective as physical measures (e.g. lockdowns as in row 1) in terms of the associated improvement in fiscal space (reduction in sovereign spreads). This seems to suggest that smart measures are as effective as physical ones in terms of managing the contagion of fear, improving confidence, and thereby lowering default risk provided that infection outbreaks are under control (namely, as previously observed, cases decrease, even if mildly, under the implementation of smart measures).

These results combined suggest that smart measures are best placed to contain infection cases, while safeguarding economic activity and reducing sovereign risk. Specifically, empirical results suggest that smart measures (row 3) such as testing and contact tracing can be sufficient enough to be empirically associated with a slight reduction in COVID-19 infection cases (column 1), while being least disruptive to economic activity (lowest reduction in NO2 emissions in column 2) and at the same time providing enough assurance to financial markets to improve sovereign risk (statistically comparable reduction in CDS spreads in column 3).

State-dependencies

Initial conditions can affect the trade-offs between economic activity, fiscal space and containment measures. This subsection examines the role of country characteristics and initial conditions; namely advanced versus emerging economies, fast versus slow public health response time and high versus low public debt.

ICU patients. The reduction of deaths and hospitalized/ICU patients is milder under the adoption of "smart" measures, but still persistent and substantial.

[33] This corresponds to approximately a 25 basis points drop in CDS spreads in our sample. The result also holds under the sub-indices of the OxCGRT stringency index (e.g., stay at home requirements). See Fig. 13 in Appendix 2.

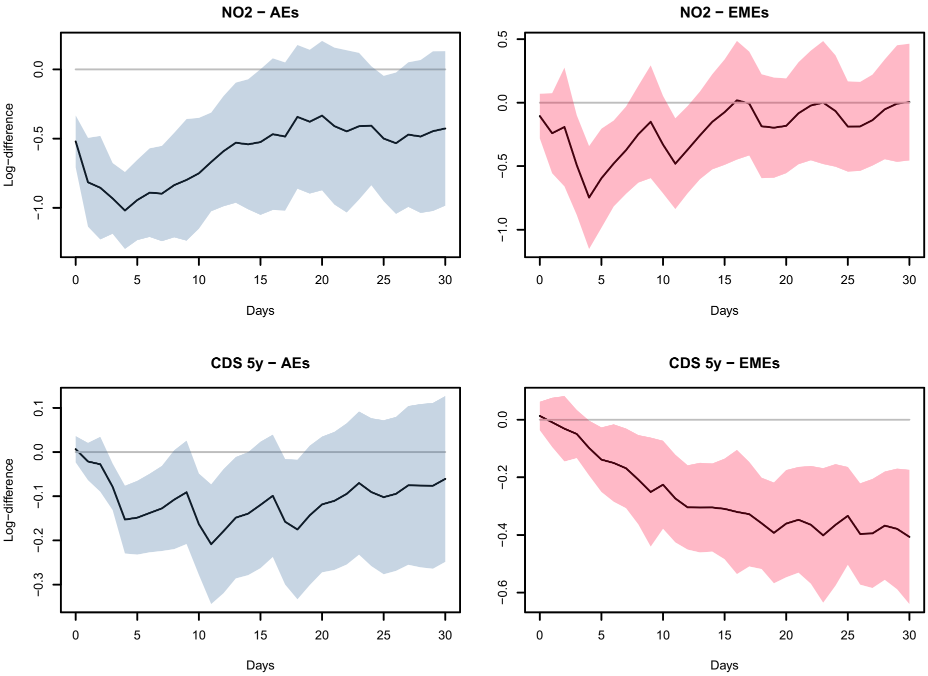

Fig. 4 Advanced/Emerging economies - Physical index. Notes: LHS (RHS) plots IRFs under the AE (EM) state whose confidence intervals are shaded in blue (red). Median IRFs are represented by black solid lines. Responses are reported in log-deviations from the dependent variables' past values. Sources: Authors' calculations

- **Advanced/Emerging economies.** Advanced economies (AEs) typically have lower perceived sovereign risk than emerging markets (EMs).[34] Fig. 4 examines whether such characteristics can change how containment measures affect economic activity and fiscal space. The state dummy indicator (D_t in Eq. 2) is equal to 1 (0) when in AEs (EMs). Results suggest that a tightening of the physical index implies a stronger drop in NO2 emissions (peaking at -100 percent) under the AE state, potentially reflecting weaker compliance in EMs (first row). Moreover, CDS spreads under the AE regime tend to drop less than under the EM regime (second row), in which spreads decrease consistently throughout the projection horizon.[35] This may imply that financial markets reward EMs more for taking difficult policy actions and/or that sovereign risk in AEs is typically affected more by fundamentals rather than transitory containment impacts.

- **Fast/Slow public health response time (PHRT).** Figure 5 plots the IRFs under the slow (fast) PHRT state whose confidence intervals are shaded in blue (red). Following

[34]We follow the IMF World Economic Outlook (WEO) in defining AEs vs EMs. See https://www.imf.org/external/pubs/ft/weo.

[35]That is equal to a 30 percent reduction of CDS spreads on average across the projection horizon. Results hold in Figs. 14 and 15 in Appendix 2 when using the "physical and smart" and the "smart" indices as shock variables.

Fig. 5 Fast/Slow public health response time - Physical index. Notes: LHS (RHS) plots IRFs under the slow (fast) PHRT state whose confidence intervals are shaded in blue (red). Median IRFs are the black solid lines. Responses are reported in log-deviations from the dependent variables' past values. Sources: Authors' calculations

(Hosny 2021), we define PHRT as the number of days needed to reach maximum stringency after a major COVID-19 outbreak (100 COVID-19 cases) within the country. The state dummy indicator (D_t in eq. 2) equals one when PHRT is above the median (slow), and zero if below the median (fast). While a tightening of the physical index is associated with an initial drop in NO2 emissions in both regimes, the shock dissipates faster under the fast PHRT regime (first row). Regarding sovereign risk, CDS spreads are statistically reduced only under the fast PHRT regime. Similar results are obtained using alternative definitions of PHRT as well as under using other containment measures indices as shock variables (see Figures 16-23 in Appendix 2).[36]

- **High/Low public debt.** We define states of high public debt in two different ways: (i) that above a cut-off of debt-to-GDP at 90 percent of GDP, and (ii) observations above the 75th percentile of the public debt sample distribution. The state dummy indicator (D_t in Eq. 2) is equal to 1 (0) when public debt is high (low). In Fig. 6, the LHS (RHS) plots IRFs under the high (low) public debt state whose confidence intervals are shaded

[36] A number of papers use 100 cases as the definition of a significant outbreak (Deb et al. 2020a; Fotiou and Lagerborg 2021). We adopt two alternative definitions of PHRT as robustness checks. The first is defined as the number of days to reach maximum stringency after 250 COVID-19 cases per 100 thousands inhabitants outbreak. The second is defined as the number of days to reach a 1 percent tightening in the stringency index after 100 cases outbreak. See (Hosny 2021) for a comparison of different definitions of PHRT in the empirical literature.

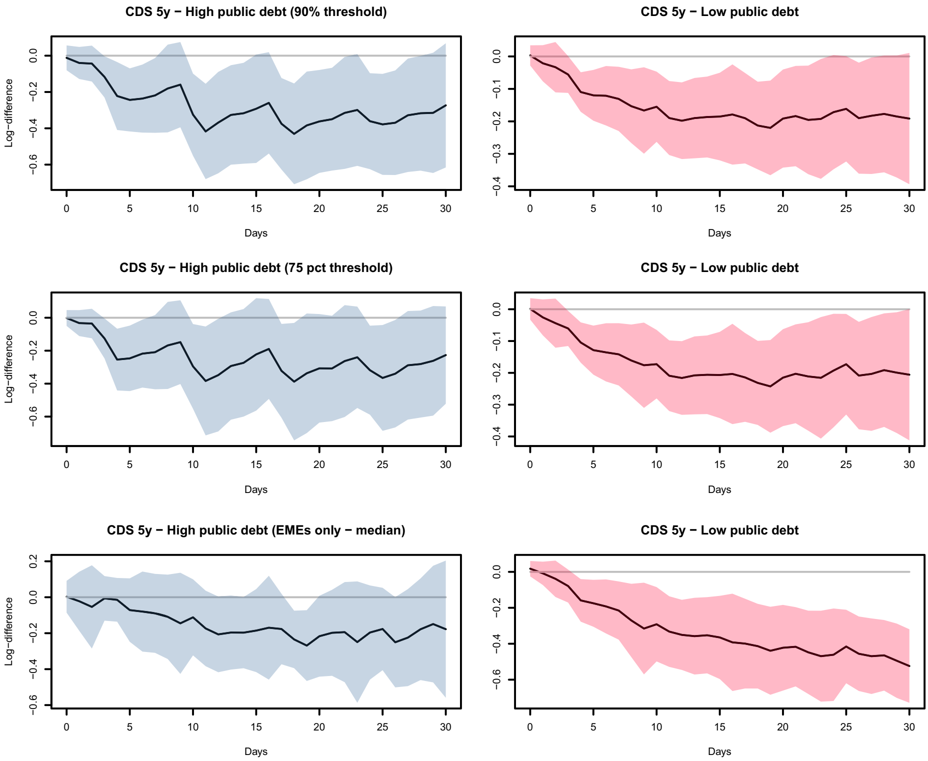

Fig. 6 High/Low public debt - Physical index. Notes: LHS (RHS) plots IRFs under high (low) public debt whose confidence intervals are shaded in blue (red). Median IRFs are the black solid lines. Responses are reported in log-deviations from the dependent variable's past value. Sources: Authors' calculations

in blue (red). Results suggest that 5-year CDS spreads decrease significantly throughout the projection horizon only when public debt is low. The peak response, equal to about -20 percent, takes place at around 20 days after the shock. If we consider EMs only (third row), the decrease in CDS spreads peaks to -50 percent at the end of the projection horizon when public debt is low. This implies that containment measures can be more effective in reducing sovereign risk when initial conditions are stronger. This is in line with (Augustin et al. 2021) who find that financial markets penalize sovereigns with low fiscal capacity, thereby impairing their resilience to external shocks.[37]

Fiscal Announcements

In this subsection, we briefly investigate how fiscal policy responses affect economic activity and fiscal space in a sample of EU-19 countries. The time span is the same as in the main analysis. In Table 2, using linear local projection (Eq. 1), we show the results of a fiscal announcement shock on 5-year CDS spreads and NO2 emissions on impact and

[37] We consider also the effects on economic activity under the aforementioned states. Results, reported in Fig. 24 of Appendix 2, suggest that, the cut in NO2 emissions is more subdued under low public debt.

Table 2 Effect of fiscal policy announcement shock on CDS and NO2 on impact and after 4 weeks

	CDS on impact	CDS after 4 weeks	NO2 on impact	NO2 after 4 weeks
FPA	0.0378	**0.223***	-0.201	**2.070**
	(0.93)	(3.18)	(-1.14)	(2.48)

FPA: fiscal policy announcement shock; *t* statistics in parentheses;
*p<0.1, **p<0.05, ***p<0.01

4 weeks after the shock.[38] On average, the effect of an increase in fiscal support (the fiscal announcement shock) in response to COVID-19 is associated with a (statistically significant) mild rise in CDS spreads 4 weeks after the shock. This is in line with (Deb et al. 2021). However, the same shock yields a doubling in NO2 emissions 4 weeks after the impulse shock. This implies that fiscal policy interventions can support the economy but at the cost of slightly worsening sovereign risk.

State-dependencies of large versus low fiscal announcements. We estimate Eq. 2 using this state-dependency to gauge the impact of a tightening of containment ("physical" and "smart") measures on CDS spreads. Figure 7 shows the dynamic responses of 5-year maturity CDS spreads to a physical index shock (LHS) and to a smart measures index shock (RHS) under large versus low fiscal announcements.

Fiscal space improves when a mix of "large" fiscal support and "smart" measures are in place. Results suggest that the size of fiscal announcements did not matter for the transmission of the effects of physical index shocks on CDS spreads, which were in median negative (LHS). However, fiscal space improves when a mix of "large" fiscal support and "smart" measures are in place (RHS). This seems to suggest that while large support packages may be expected to worsen public finances and therefore future default risks embedded in 5-year CDS spreads, the confidence boost and the expected more positive outlook from the fiscal support, accompanied by the introduction of containment measures which rely on smart testing and avoid physical lockdowns which contain infections and avoid disruptions to the economy, seem to reduce expected sovereign risk.

Concluding remarks

This paper uses daily data to examine how different types of COVID-19 containment measures can impact infection cases, economic activity and sovereign risk. We use daily data from February 2020 to June 2021 for a set of 44 advanced and emerging economies. We use OxCGRT indices, NO2 emissions and CDS spreads as high-frequency proxies of containment measures, economic activity and fiscal space, respectively. We use local projection á la (Jordà 2005) and an econometric specification that builds on (Deb et al. 2020a) to analyze the dynamic responses of COVID-19 infection cases, NO2 emissions and CDS spreads following different types of containment measures ranging from physical (e.g., lockdowns) to smart (e.g., testing and contact tracing) measures.

Results suggest that "smart" containment measures are best placed to tackle the trade-offs between infection cases, economic activity and sovereign risk. Baseline

[38] We take the cross-country fiscal announcement series in percentage of GDP so to be comparable across countries. An example is provided in Fig. 10 in Appendix 2.

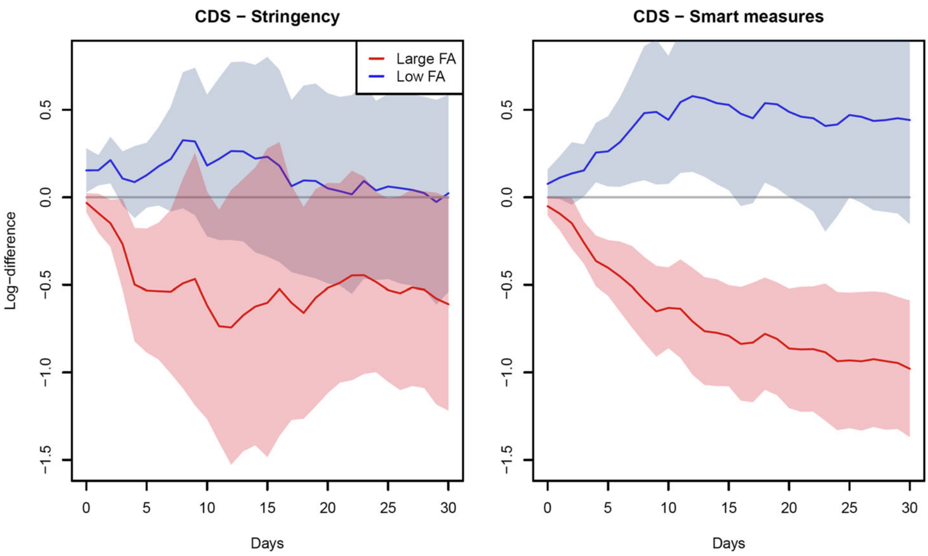

Fig. 7 Large/low fiscal announcements. Notes: This figure shows the dynamic responses to a physical (LHS) and smart measures index shock (RHS) of 5-year maturity CDS spreads under large (low) fiscal announcements states whose median IRFs and 95 percent confidence intervals are shaded in red (blue). Responses are reported in log-deviations from the dependent variable's past value. Sources: Authors' calculations

results suggest that containment measures can limit infection cases but potentially at the expense of economic activity. This paper presents empirical evidence, however, that this trade-off between health and the economy depends on the type of containment measures, whereby more physical lockdowns may be effective in reducing infection cases but can also be disruptive to the economy. "Smart" measures, on the other hand, can ease this trade-off, by controlling infections to some degree while safeguarding economic activity at the same time. Furthermore, on fiscal space, we find that smart measures are statistically as effective as physical ones in improving sovereign risk (reducing 5-year CDS spreads). These results combined suggest that smart measures can be relatively optimal in terms of containing infections, while avoiding disruptions to economic activity and improving sovereign risk, thereby hitting more than one bird with the same stone.

Initial conditions can affect these trade-offs. Using state-dependent local projection, we find evidence that (i) in EMs versus AEs, stricter physical containment measures tend to affect economic activity less and reduce CDS spreads more; (ii) in fast versus slow public health response time, economic activity is more quickly normalized after an initial shock and the sovereign risk profile is improved; and (iii) in low versus high initial public debt, containment measures are associated with an improved economic outlook and lower sovereign risk.

Lastly, we find evidence that sovereign risk improves when a mix of large fiscal support and smart measures are in place. We construct a new dataset of government fiscal policy announcements in response to COVID-19 at a "daily" frequency for a sample of EU-19 countries between February 2020-June 2021, building on Yale's CFRT database and the methodology of (Deb et al. 2021). We study the impact of physical closures and smart measures on CDS spreads conditioning on the size of announced government fiscal support packages. Using state-dependent local projection and interpreting fiscal announcements as unanticipated fiscal shocks á la (Ramey 2011b; 2011a), results suggest that sovereign risk is improved under a combination of large support packages and smart measures. Future research could further exploit the fiscal announcement dataset, including by expanding its coverage, to gauge the effects of fiscal news on fiscal space and economic activity during COVID-19.

Appendix A: Data

The countries included in our sample are United States, United Kingdom, Norway, Switzerland, Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Italy, Spain, Netherlands, Portugal, Ireland, Cyprus, Japan, South Korea, Sweden, Israel, Iceland, New Zealand, Greece, Hong Kong, Argentina, Brazil, Bulgaria, Chile, China, Colombia, Croatia, Hungary, India, Mexico, Philippines, Poland, Romania, Russia, South Africa, Thailand and Turkey.

Table 3 reports the summary statistics and source of the main variables used in the empirical analysis described in Section 2. Specifically, among the summary statistics, we report the mean, the standard deviation (SD), maximum and minumum value, and the number of observations.

The monthly data used for the regression table reported in Section 2 (Table 1), namely the industrial production index and the NO2 emissions are drawn from Refinitiv Eikon Datastream and from the Air Quality Open Data Platform of the World Air Quality Index (WAQI), respectively.

Table 3 Main variables used in the empirical analysis - summary statistics

Name	Mean	SD	Min	Max	N	Source
$\log(CDS\text{-}5y)$ (Fiscal Space proxy)	3.83	1.18	1.84	10.24	14914.00	Refinitiv Eikon Datastream/Bloomberg
$\log(NO_2)$ (Economic Activity proxy)	2.03	0.56	-2.30	3.91	14914.00	Air Quality Open Data Platform (WAQI)
Physical stringency index	0.60	0.19	0.00	1.00	14907.00	Oxford's Coronavirus Government Response Tracker
Physical and Smart containment index	0.64	0.17	0.00	1.00	14906.00	Oxford's Coronavirus Government Response Tracker
Smart containment index	0.58	0.18	0.00	1.00	14906.00	Oxford's Coronavirus Government Response Tracker
Vaccination Policy index	0.18	0.30	0.00	1.00	14898.00	Oxford's Coronavirus Government Response Tracker
Infections (in millions)	1.22	3.71	0.00	33.66	14806.00	Coronavirus Resource Center of Johns Hopkins University
Deaths (in thousands)	30.38	72.94	0.00	604.64	14129.00	Coronavirus Resource Center of Johns Hopkins University
Vaccinations (in millions)	6.69	47.21	0.00	1244.68	14914.00	Coronavirus Resource Center of Johns Hopkins University

Table 3 (continued)

Name	Mean	SD	Min	Max	N	Source
Temperature	14.93	8.33	-22.42	33.50	14914.00	Air Quality Open Data Platform (WAQI)
Humidity	70.57	12.59	18.50	98.70	14914.00	Air Quality Open Data Platform (WAQI)
$pm10$	22.10	16.09	1.00	219.25	14914.00	Air Quality Open Data Platform (WAQI)
$\log(CDS\text{-}1y)$	2.69	1.42	0.64	10.55	14914.00	Refinitiv Eikon Datastream/Bloomberg
$\log(CDS\text{-}3y)$	3.36	1.30	1.21	10.35	14914.00	Refinitiv Eikon Datastream/Bloomberg
$\log(CDS\text{-}10y)$	4.29	1.04	2.48	10.09	14914.00	Refinitiv Eikon Datastream/Bloomberg
Sovereign Yield (1-year)	2.33	6.23	-0.90	55.41	14914.00	Refinitiv Eikon Datastream
Sovereign Yield (10-year)	2.94	6.53	-1.02	57.72	14914.00	Refinitiv Eikon Datastream

Note: CDSs are expressed in basis points; NO2 emissions are expressed in μg/m3; temperature is measured in celsius degrees; humidity is reported in percent of air saturation; $pm10$ is reported in μg/m3; yields are reported in percent

Appendix B: Fiscal Announcements Dataset

Starting from Yale's COVID-19 Financial Response Tracker (CFRT) and following the methodology implemented in (Deb et al. 2021), we construct a high-frequency daily dataset of fiscal announcements in EU-19 countries for the period Feb2020 to end-June2021. The information from the Yale CFRT is supplemented by, and cross-checked with, announcements provided by the IMF Policy Tracker and other reports, especially where numbers quoted by CFRT do not match those reported elsewhere. Given the focus on EU-19 countries and the fact that several measures were implemented at the EU-level, we distribute the fractions of the EU-wide fiscal measures by each country's GDP.

We categorize each fiscal announcement by policy instrument, then aggregate by various macro-categories following the classification in the IMF's Fiscal Monitor database of country fiscal measures in response to the COVID-19 pandemic: lifeline and demand (spending and revenue) support, above and below-the-line, as well as health and non-health measures.[39]

- Lifeline measures include liquidity injections, loans in general, umbrella guarantees, credit guarantees, government provisions of loans, equity injections, asset purchases, targeted loans (support to damaged business/worst hit business). Demand-support measures include wage subsidies, targeted transfers, grants, unemployment benefits, wage supplements, support to families with children, deferrals of tax and social security contributions, tax relief, social security support, and grants to small and medium enterprises (SMEs).
- Above-the-line measures include unemployment benefits, grants and transfers, tax cuts and relief measures, tax or social security contribution payment deferrals, payment

[39] IMF's Fiscal Monitor database can be accessed at https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19

Date	Country	Country Other	Implementing Institution	Implementing Institution Othe	Institutional Role	Institutional Role Other	Policy Tool	Magnitude	Order of Magnitude
3/13/2020	Austria		Ministry of Labor, Family, and Youth		Regulatory Authority		Other rules		
3/18/2020	Austria		Ministry of Finance		Fiscal Authority		Tax relief	10	Billion
3/20/2020	Austria		Ministry of Labor, Family, and Youth		Fiscal Authority		Grants		
4/9/2020	Austria		Ministry of Labor, Family, and Youth		Fiscal Authority		Grants	30	Million
4/14/2020	Austria		Ministry of Finance		Fiscal Authority		Tax relief		
5/23/2020	Austria		European Commission		Fiscal Authority		Grants	8	Billion
7/6/2020	Austria		European Commission		Regulatory Authority		Lending	150	Million
8/6/2020	Austria		European Commission		Fiscal Authority		Lending	665	Million
11/25/2020	Austria		European Commission		Regulatory Authority		Grants	9	Million
3/29/2021	Austria		European Investment Bank		Fiscal Authority		Lending	200	Million

Fig. 8 Original dataset for fiscal announcements in Austria

forbearances and support to SMEs (grants). These can also be categorized by health and non-health measures. Below-the-line measures include any form of loans, capital injections, asset purchases and guarantees, government guarantees to banks, firms, households, and equity injections to firms.

Figure 8 reports raw fiscal announcements for Austria as reported in the CFRT. Figure 9 shows how we expanded the dataset after cross-checking the day-by-day entries and granularly categorizing announced fiscal measures by policy instrument, and reporting the size of the shock in percent of national GDP. These series of fiscal announcements can be interpreted as unanticipated fiscal news/shocks in the same fashion as in (Ramey 2011b; 2011a). In Fig. 10, we report the (static average) divisions across categories of the fiscal announcements. In Fig. 11, we show the set of policy instruments under the demand support category as an illustration.

Informa	Date	Impleme	End Date	Countr	Countr	Implem	Implem	Institut	Institut	Policy T	FP_inst	FP_inst	Policy I	Policy I	Magnitude	Magnitude	Magnit	Order o	Metric	Ultimat	Ultimat	Target	Target	Condui	Condui	Flag	Flag Otl	Notes	Link 1	Links 2
Adoption	3/6/2020			Austria	EU: Memb	European Commissio		Fiscal Authority		Lending	Healthcare spending				0.000003	0.001403	37.5	Million	Euro (EUR)	Non-financial busines		Industry-specific						Following t	https://ec.europa.e	
Proposal	3/16/2020			Austria		European Investment		Fiscal Authority		Credit gua	Credit guarantees				0.001499	0.627170	20	Billion	Euro (EUR)	Banks								The EIB Gr	https://www.eib.or	
Proposal	3/16/2020			Austria		European Investment		Fiscal Authority		Lending	Liquidity ir	Support to	Other (ple:	Liquidity li	0.000750	0.313585	10	Billion	Euro (EUR)	Banks								The EIB Gr	https://www.eib.or	
Proposal	3/16/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Asset purc	Asset purc	Risk transfer			0.000750	0.313585	10	Billion	Euro (EUR)	Banks						Asset-backed securiti		The EIB Gr	https://www.eib.or	
Adoption	3/18/2020			Austria		Ministry of Finance		Fiscal Authority		Tax relief	Tax relief				0.026627	10.833532	10	Billion	Euro (EUR)	Non-financial busines		Small- and medium-si		National governments				The measu	https://wv	https://
Adoption	3/19/2020			Austria	EU: Memb	European Commissio		Regulatory Authority		Grants	Healthcare spending				0.000004	0.001506	50	Million	Euro (EUR)	National governments								the Europ	https://ec.europa.e	
Adoption	4/2/2020	4/2/2020		Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Sector support		Other (ple:	Financing S	0.000052	0.021528	19.70735	Million	Euro (EUR)	Non-financial busines		Industry-specific						The Europ	https://www.eib.or	
Adoption	4/6/2020			Austria		European Commissio		Regulatory Authority		Credit gua	Credit gua	Support to SMEs, mid-caps throu			0.000600	0.243212	8	Billion	Euro (EUR)	Non-financial businesses								The Europ	https://ec.europa.e	
Adoption	4/9/2020	4/9/2020		Austria		Ministry of Labor, Fan		Fiscal Authority		Grants	Unemployment bene		Unemployment bene		0.000080	0.032816	30	Million	Euro (EUR)	Individuals		Families with children		National governments				At least on	https://www.bmafj	
Adoption	4/9/2020			Austria	EU: Memb	European Commissio		Regulatory Authority		Credit gua	Credit gua	Mixed package measures			0.039940	16.407788	15	Billion	Euro (EUR)	Non-financial businesses				Banks,Special purpose vehicles (SPVs)				The Europ	https://ec.europa.e	
Adoption	4/16/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Credit gua	Credit guarantees				0.001874	0.767531	25	Billion	Euro (EUR)	National governments								Following	https://www.eib.or	
Adoption	4/23/2020	4/23/2020		Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Targeted k	Support to damaged businesses			0.000150	0.060969	2	Billion	Euro (EUR)	Non-financial busines		Industry-specific,Small- and medium-sized enterprises (SMEs)						The Europ	https://www.eib.or	
Adoption	5/12/2020			Austria	EU: Memb	European Commissio		Regulatory Authority		Grants	Healthcare spending				0.000009	0.003582	117	Million	Euro (EUR)	Non-financial businesses								The Comm	https://ec.europa.e	
Adoption	5/15/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Healthcare	Vaccine development and manuf			0.000013	0.005480	180	Million	Euro (EUR)	National governments								The Europ	https://www.eib.or	
Adoption	5/19/2020			Austria	EU: Memb	European Commissio		Fiscal Authority		Lending	Healthcare spending				0.000009	0.003760	122	Million	Euro (EUR)	National governments								The Comm	https://ec.europa.e	
Adoption	5/23/2020			Austria		European Commissio		Fiscal Authority		Grants	Targeted k	Support to damaged businesses			0.021301	8.712414	8	Billion	Euro (EUR)	Non-financial businesses				National governments				The Europ	https://ec.europa.e	
Adoption	5/26/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Credit guarantees				0.001874	0.766720	25	Billion	Euro (EUR)	National governments								The Board	https://www.eib.or	
Adoption	6/8/2020			Austria	EU: Memb	European Commissio		Fiscal Authority		Grants	Healthcare spending				0.000024	0.009990	314	Million	Euro (EUR)	National governments								The Comm	https://ec.europa.e	
Adoption	6/11/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Healthcare spending				0.000382	0.192056	5.1	Billion	Euro (EUR)	National governments								The Board	https://www.eib.or	
Adoption	7/3/2020	5/26/2020	12/31/2021	Austria	EU: Memb	European Investment		Fiscal Authority		Credit gua	Credit gua	Loans to SI	Other (ple:	Pan-Europ	0.001874	0.791287	25	Billion	Euro (EUR)	Non-financial busines		Small- and medium-si		Banks				On April 3r	https://wv	https://
Adoption	7/6/2020			Austria		European Commissio		Regulatory Authority		Lending	Sector support				0.000399	0.169762	150	Million	Euro (EUR)	Non-financial busines		Industry-specific						The Europ	https://ec.europa.e	
Adoption	7/24/2020			Austria		European Commissio		Fiscal Authority		Credit gua	Credit gua	Support to SMEs			0.000030	0.013091	400	Million	Euro (EUR)	Non-financial busines		Small- and medium-si		National governments				The EIF an	https://ec.europa.e	
Adoption	8/6/2020			Austria		European Commissio		Fiscal Authority		Lending	Sector support				0.001771	0.787560	665	Million	Euro (EUR)	Non-financial busines		Other (ple:	Non-profit organizations					The Europ	https://ec.europa.e	
Adoption	11/25/2020			Austria		European Commissio		Regulatory Authority		Grants	Sector support				0.000024	0.010710	9	Million	Euro (EUR)	Non-financial busines		Industry-specific						The Europ	https://ec.europa.e	
Adoption	12/16/2020			Austria		European Investment		Fiscal Authority		Lending	Infrastructure spending				0.000293	0.000110	2.6	Billion	Euro (EUR)	Non-financial businesses,National governments								The Europ	https://www.eib.or	
Adoption	12/16/2020			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Infrastructure spending				0.000016	0.007116	208	Million	Euro (EUR)	Non-financial businesses,National governments								The Europ	https://www.eib.or	
Adoption	1/19/2021			Austria		European Investment		Fiscal Authority		Lending	Credit gua	Guarantees to loans to SMEs			0.000329	0.157658	130	Million	Euro (EUR)	Non-financial busines		Small- and medium-si		Banks				The EIB Gr	https://www.eib.or	
Adoption	1/19/2021			Austria		European Investment		Fiscal Authority		Lending	Credit gua	Support to SMEs			0.000346	0.157658	130	Million	Euro (EUR)	Non-financial busines		Small- and medium-si		Banks				The EIB Gr	https://www.eib.or	
Adoption	2/3/2021			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Targeted loans				0.000107	0.050796	1.5	Billion	Euro (EUR)	Non-financial businesses				National governments				The Europ	https://www.eib.or	
Adoption	2/3/2021			Austria	Austria, Fr	European Investment		Fiscal Authority		Lending	Targeted loans				0.000224	0.106183	1.9	Billion	Euro (EUR)	Non-financial businesses				National governments				The Europ	https://www.eib.or	
Adoption	3/10/2021			Austria	EU: Memb	European Commissio		Fiscal Authority		Lending	Targeted transfers				0.000730	0.343373	9	Billion	Euro (EUR)	Non-financial businesses,Individuals				National governments				The Europ	https://ec.europa.e	
Adoption	3/11/2021			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Targeted loans				0.000183	0.082230	2.4	Billion	Euro (EUR)	Non-financial businesses				National governments				The Board	https://www.eib.or	
Adoption	3/11/2021			Austria	EU: Memb	European Investment		Fiscal Authority		Lending	Infrastructure spending				0.000050	0.023573	688	Million	Euro (EUR)	Non-financial businesses				National governments				The Board	https://www.eib.or	
Adoption	3/29/2021			Austria		European Investment		Fiscal Authority		Lending	Loans to SMEs				0.000506	0.235269	200	Million	Euro (EUR)	Non-financial busines		Small- and medium-si		Banks				The EIB Gr	https://www.eib.or	
Adoption	3/11/2021			Austria	EU: Memb	European Commissio		Fiscal Authority		Lending	Healthcare spending				0.000043	0.020329	530	Million	Euro (EUR)	National governments								Today, the	https://ec.europa.e	

Fig. 9 Newly constructed dataset for fiscal announcements in Austria

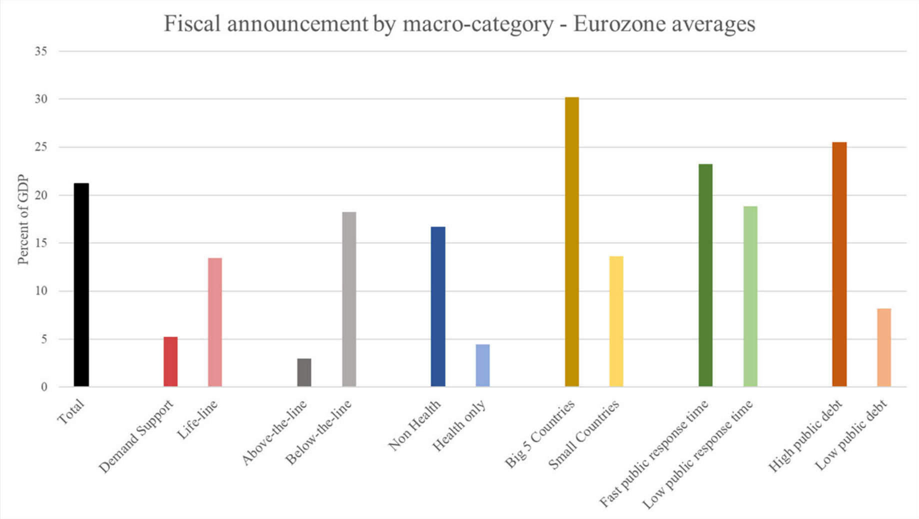

Fig. 10 This figure reports fiscal announcements as % of GDP divided in subcategories (e.g., demand support/life-line) and state-dependencies (e.g., high/low public debt). "Big 5 Countries" stand for the biggest countries in terms of GDP size in the EU-19 group: Germany, France, Italy, Spain and the Netherlands

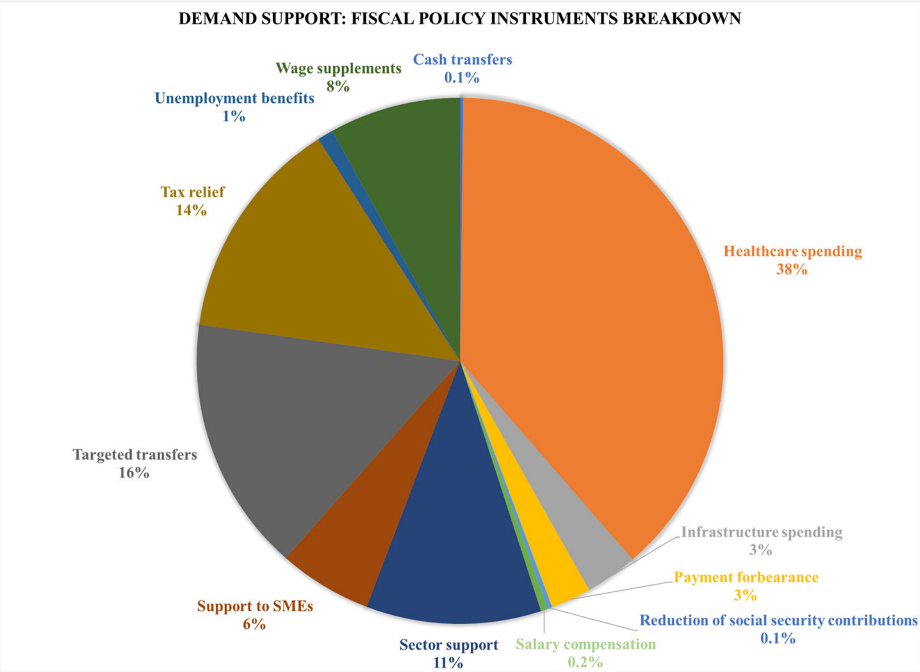

Fig. 11 This figure reports the break-down of policy instruments contained within the demand support category of the fiscal announcements dataset

Appendix C: Additional Results (Figures and Tables)

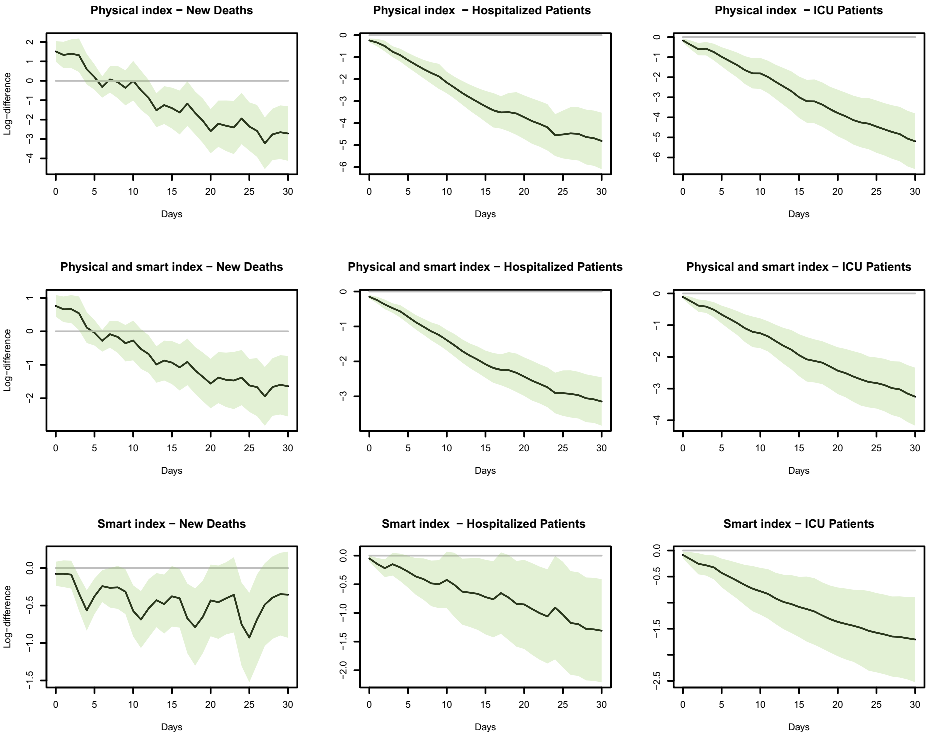

Fig. 12 IRFs of Covid-19-related deaths, hospitalized patients and ICU patients - Physical, physical and smart, smart indices. This figure reports the impulse response functions from linear local projection (Eq. 1) of new daily deaths, hospitalized patients and ICU patients following a unitary change in the physical, physical and smart and only smart measures indices. The response of our variables of interest are reported in log-deviations from their past values. The shaded green areas stand for the 95% confidence intervals, while the black solid lines represent the median IRFs

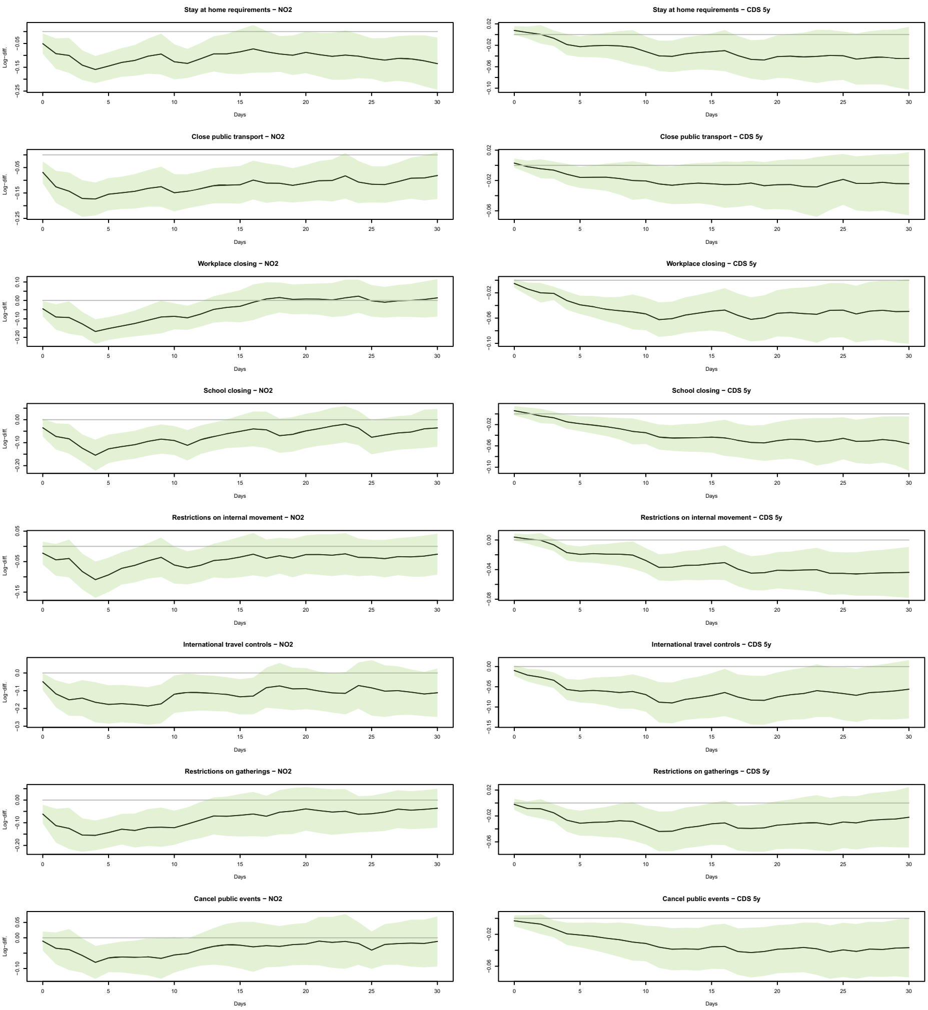

Fig. 13 IRFs of NO_2 emissions and CDS spreads - Stingency index: sub-indices. This figure reports the impulse response functions from linear local projection (Eq. 1) of NO_2 emissions (economic activity indicator) and 5-year CDS spreads (fiscal space indicator) by using, in turn, the sub-indices contained in the stringency index (physical closures) as shock variable. The response of our variables of interest are reported in log-deviations from their past values. The shaded green areas stand for the 95% confidence intervals, while the black solid lines represent the median IRFs.

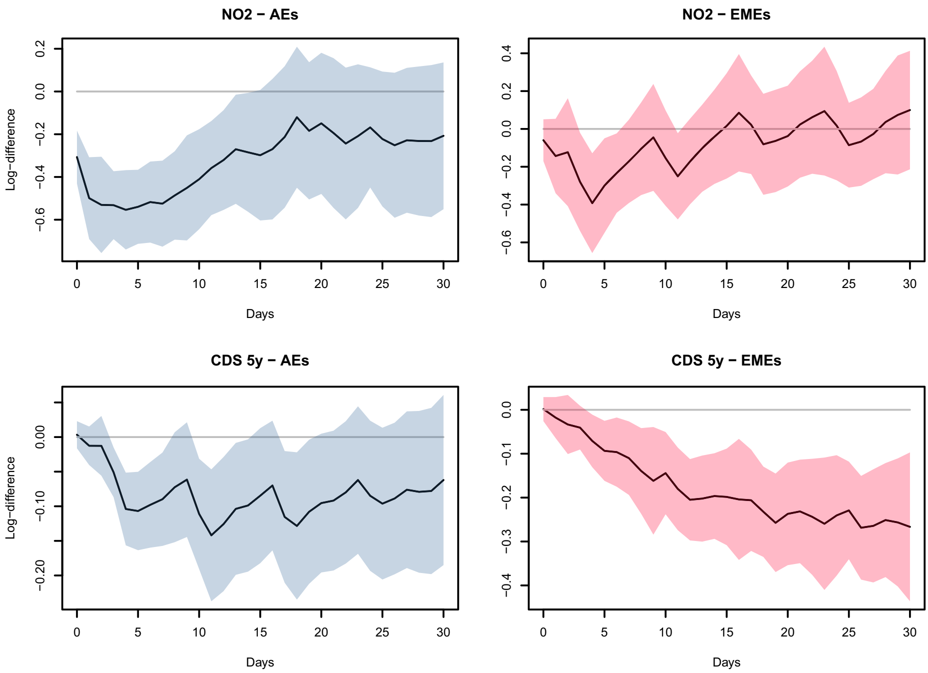

Fig. 14 Advanced/emerging economies - Physical and smart index. This figure shows on the left hand side plots the dynamic responses to a containment health index shock of both NO_2 emissions and CDS spreads under the advanced economy state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the emerging economy state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

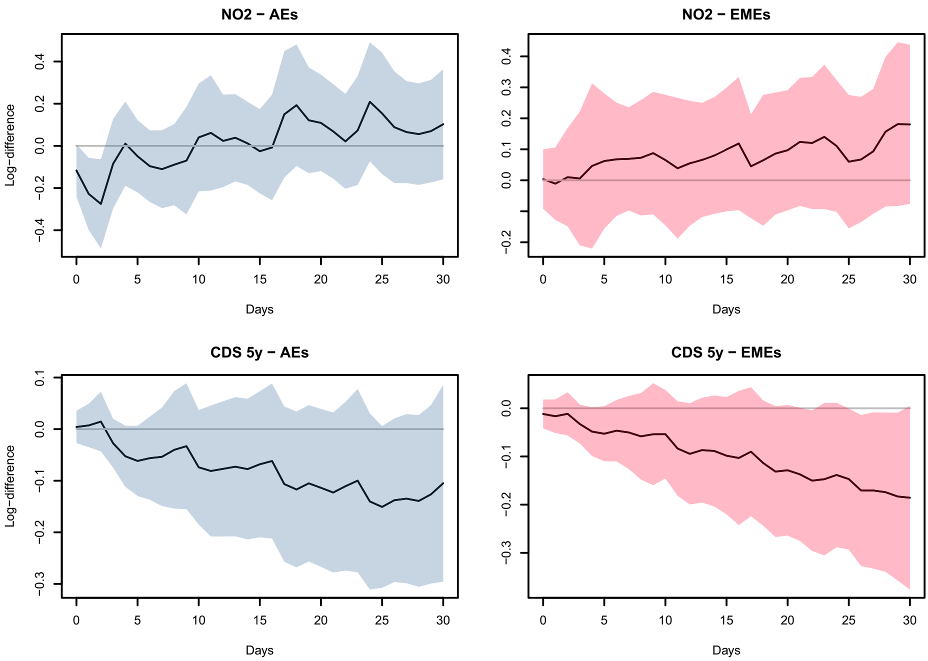

Fig. 15 Advanced/emerging economies - Smart index. This figure shows on the left hand side plots the dynamic responses to a smart containment measures index shock of both NO_2 emissions and CDS spreads under the advanced economy state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the emerging economy state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

Fig. 16 Fast/slow public health response time - Physical and smart index. This figure shows on the left hand side plots the dynamic responses to a containment health index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

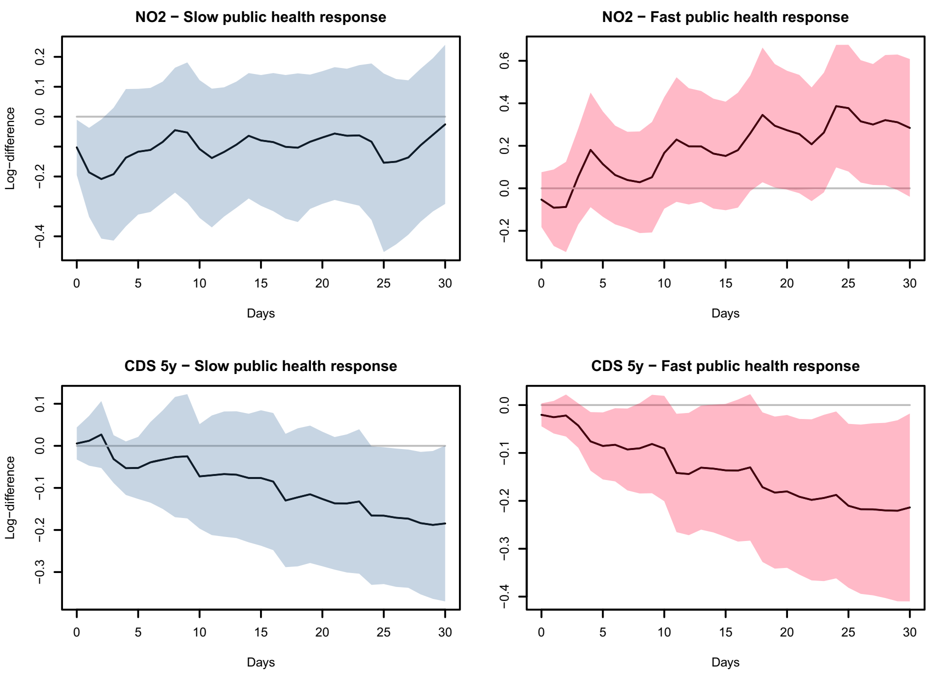

Fig. 17 Fast/slow public health response time - Smart index. This figure shows on the left hand side plots the dynamic responses to a smart containment measures index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

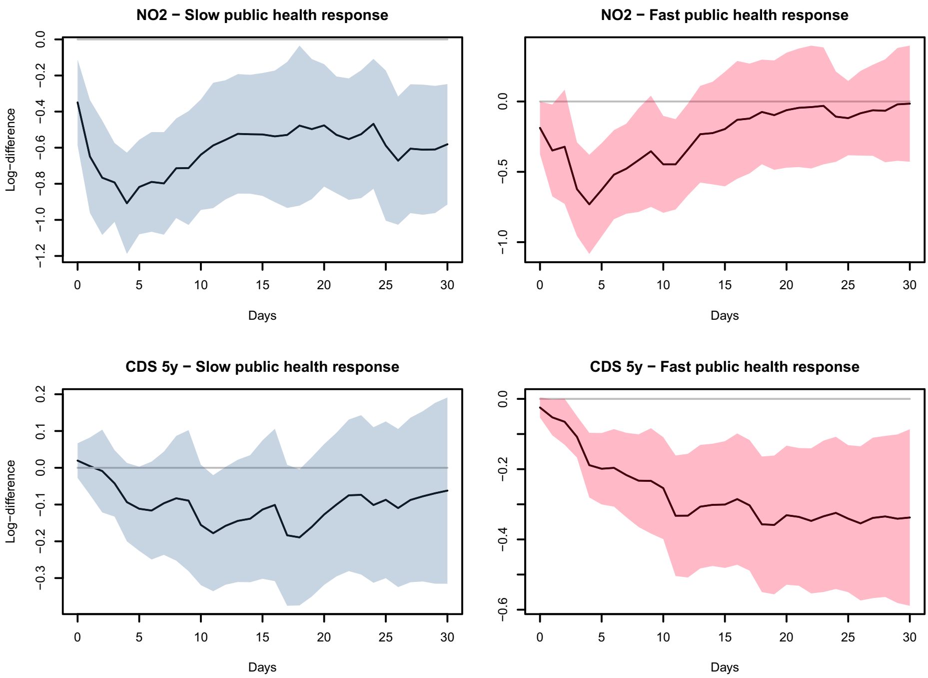

Fig. 18 Fast/slow public health response time (first alternative definition) - Physical index. This figure shows on the left hand side plots the dynamic responses to a stringency index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

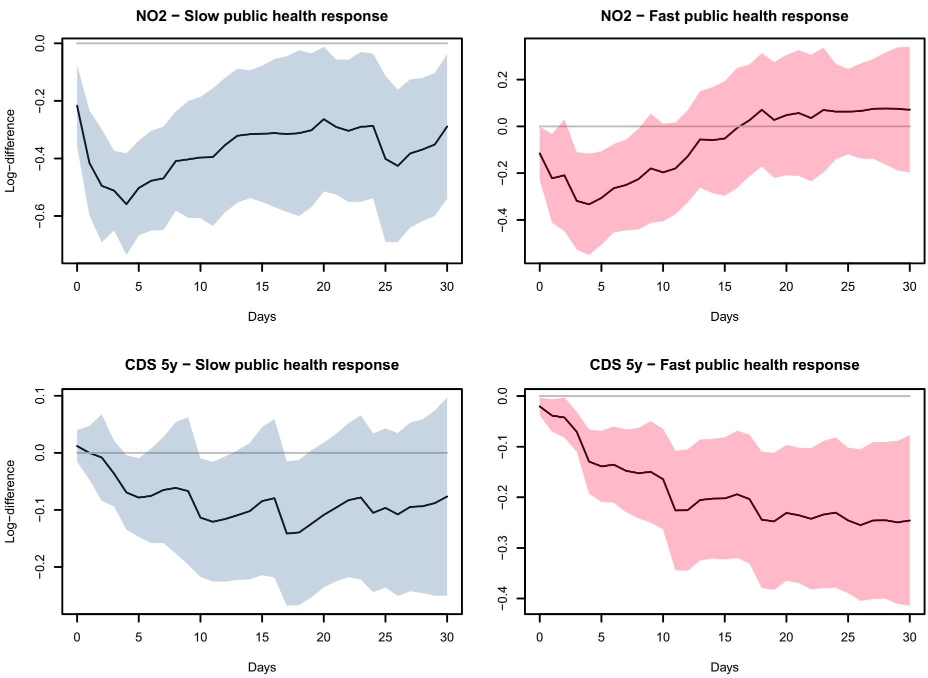

Fig. 19 Fast/slow public health response time (first alternative definition) - Physical and smart index. This figure shows on the left hand side plots the dynamic responses to a containment health index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

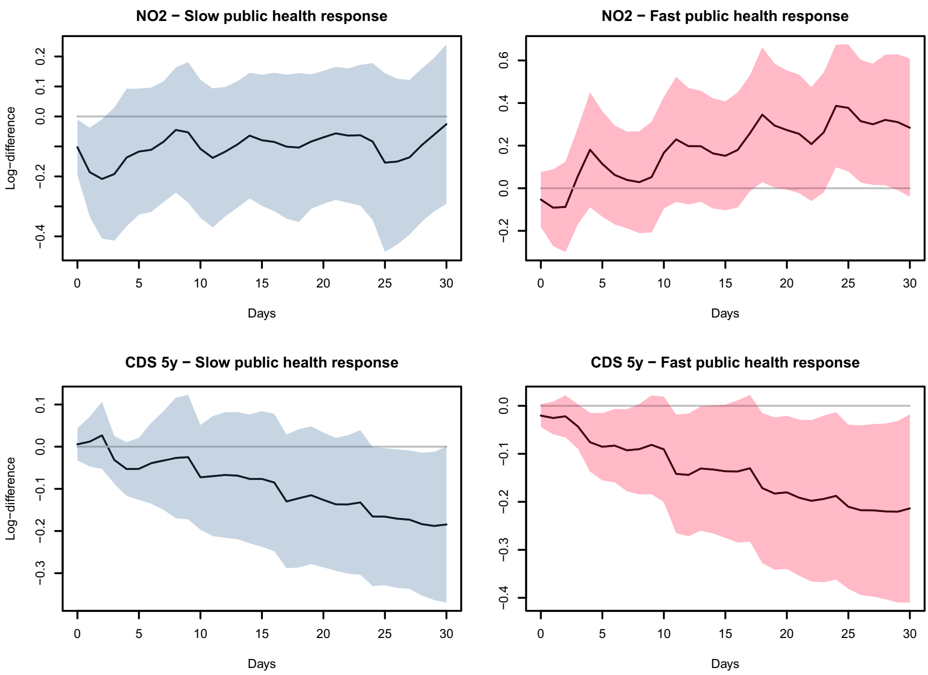

Fig. 20 Fast/slow public health response time (first alternative definition) - Smart index. This figure shows on the left hand side plots the dynamic responses to a smart containment measures index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

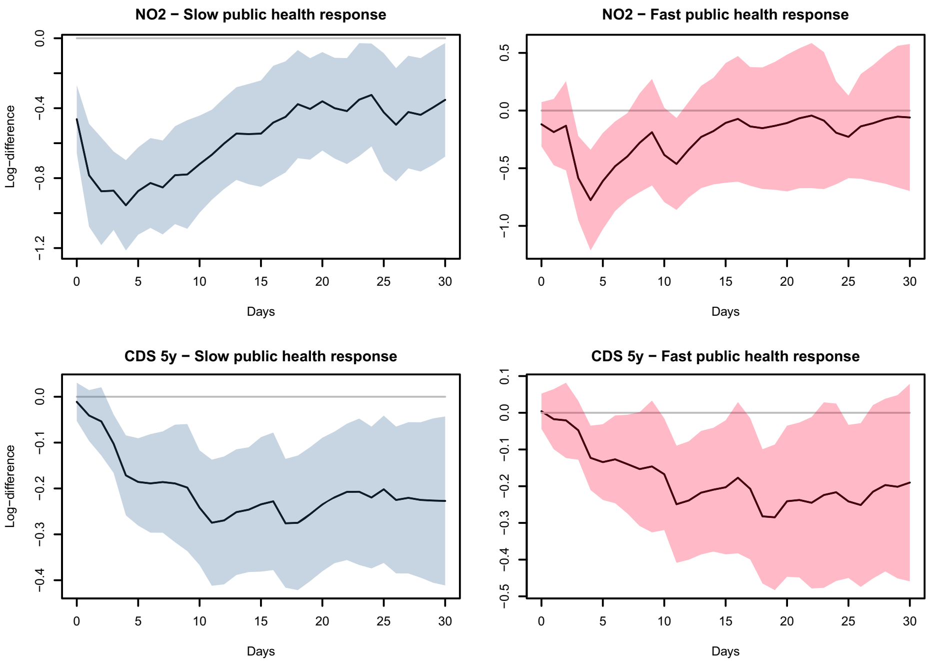

Fig. 21 Fast/slow public health response time (second alternative definition) - Physical index. This figure shows on the left hand side plots the dynamic responses to a stringency index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

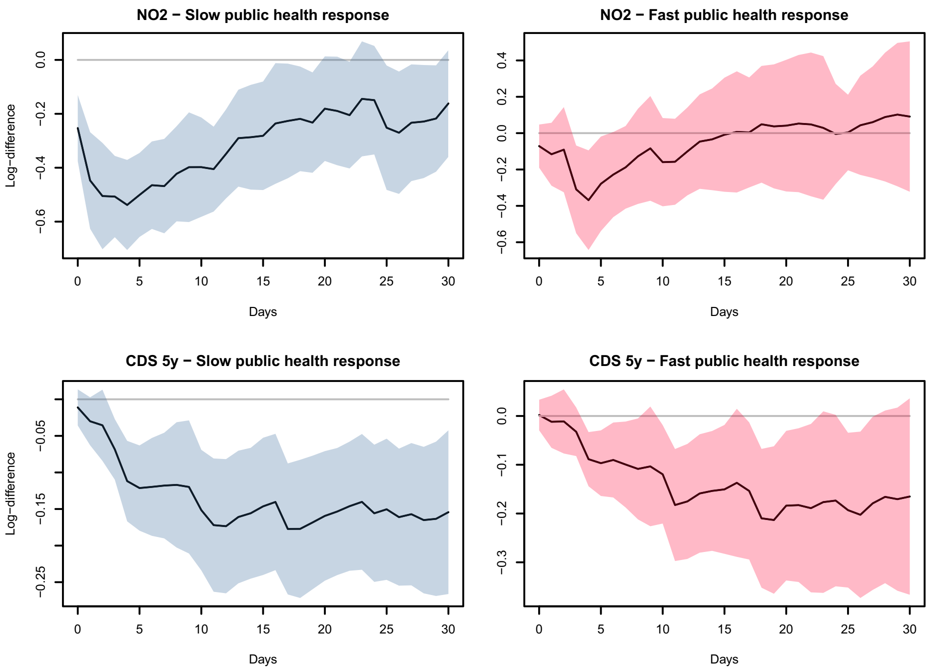

Fig. 22 Fast/slow public health response time (second alternative definition) - Physical and smart index. This figure shows on the left hand side plots the dynamic responses to a containment health index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

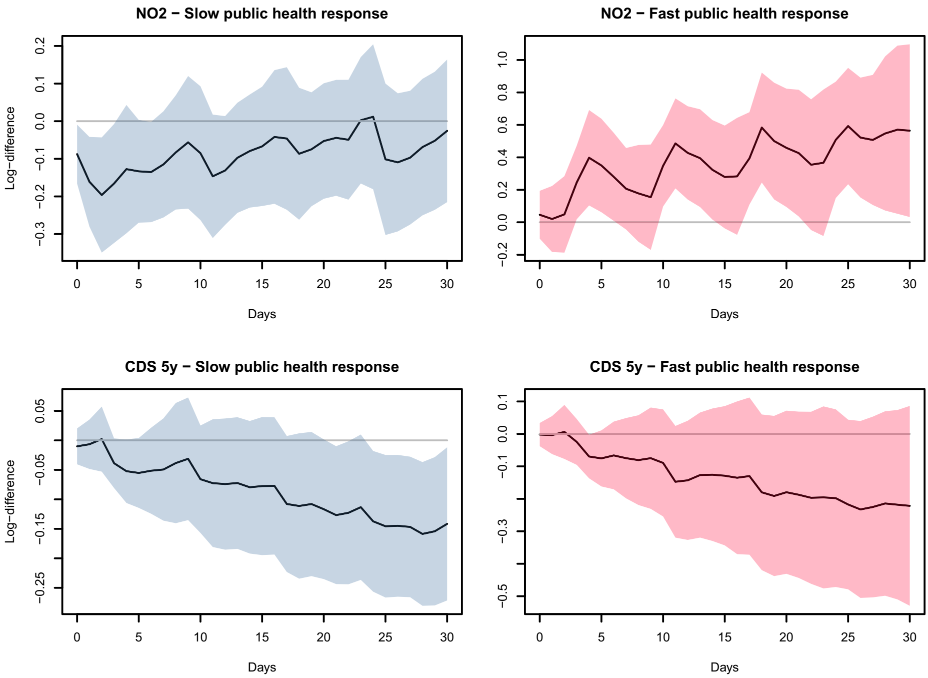

Fig. 23 Fast/slow public health response time (second alternative definition) - Smart index. This figure shows on the left hand side plots the dynamic responses to a smart containment measures index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both NO_2 emissions and CDS spreads under the fast public health response time state whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variables' past values

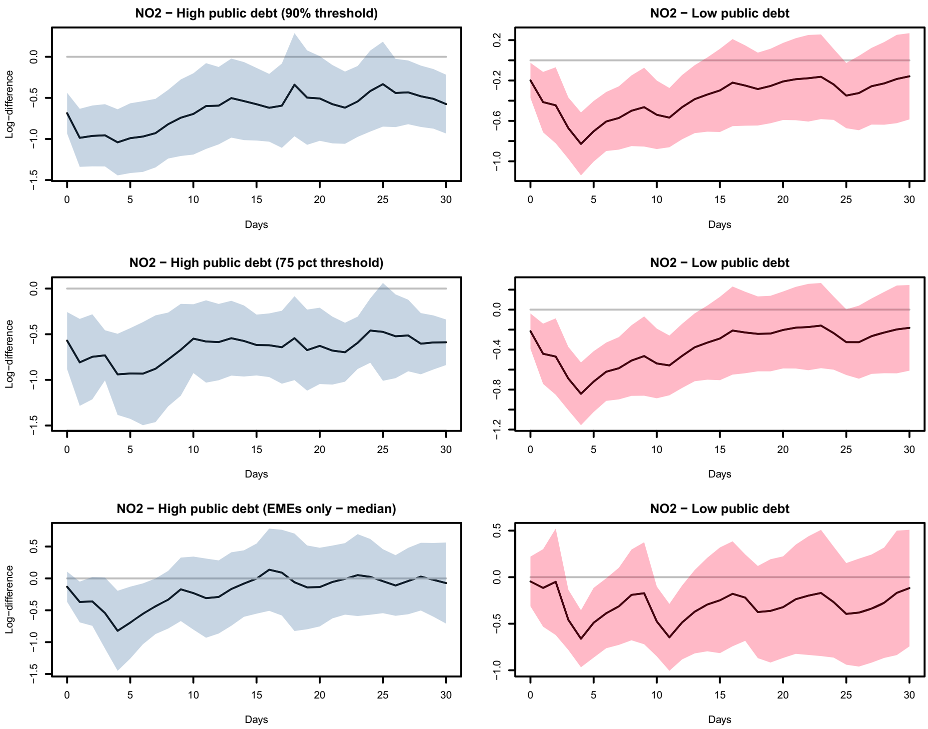

Fig. 24 High/low public debt - IRFs of NO_2 emissions - Physical index. This figure shows on the left hand side plots the dynamic responses to a stingency index shock of NO_2 emissions under high public debt states whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of NO_2 emissions under low public debt states whose confidence intervals are shaded in red. The median IRFs are represented by black solid lines in the plots. Responses are reported in log-deviations from the dependent variable's past value

Author Contributions All authors contributed to the study conception, design, analysis and writing.

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Data Availability The datasets generated during and/or analysed during the current study are partially publicly available given that part of the dataset has been drawn from a third party private repository (*Refinitiv Eikon Datastream*). However, datasets from third parties that are publicly available can be accessed via sources provided in the manuscript. The dataset on *fiscal policy announcements* is available from the corresponding author on reasonable request.

Declarations

Conflict of Interests The authors have no relevant financial or non-financial interests to disclose.

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