INTERNATIONAL MONETARY FUND

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

Amr Hosny and Kevin Pallara

2022
JAN

IMF Working Paper

Fiscal Affairs Department

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

Prepared by Amr Hosny and Kevin Pallara

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.

1. 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., 2020b; Coibion et al., 2020). More recent research shows 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 Figure 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) stronger initial public finances (low public debt) containment measures are associated with an improved economic outlook and lower sovereign risk.

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,a), results suggest that sovereign risk is improved under a combination of large support packages and smart

---

[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.

measures.

The paper is structured as follows. We explain our contribution to the relevant literature in Section 2. Data and the empirical strategy are presented in Sections 3 and 4, respectively. Empirical results are reported in Section 5. Finally, Section 6 concludes.

FIGURE 1. COVID-19 waves, stringency index and sovereign 5-year CDS spread.
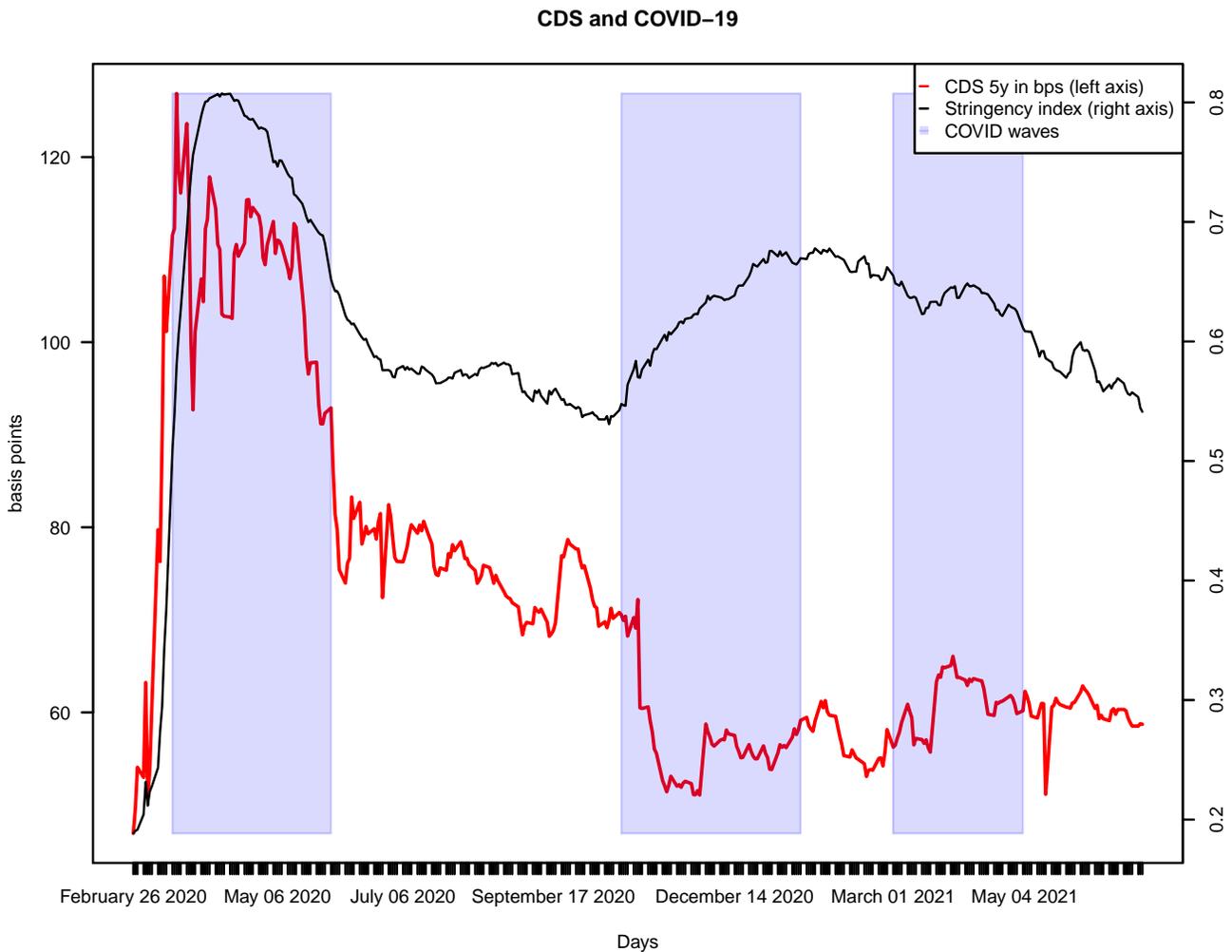
Notes: The cross-country average OxCGRT "stringency index" is normalized between $[0, 1]$ on the right y-axis. Cross-country average CDS spreads are measured in basis points on the left axis. Infection (shaded) waves are those in the Western Hemisphere. Argentina is excluded from the computation of the cross-country average of CDS spreads. The country sample used in Figure 1 is the one used throughout the empirical analysis. See Sec. 4 for details.

Source: Authors' calculations based on OxCGRT and WHO.

2. 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. (2020c) 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

---

[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).

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); 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 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

---

[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 Sec. 3.

[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.

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.

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

---

[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) and 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.

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.

---

[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.

3. 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. 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 of Johns Hopkins University.[11] Regarding containment measures, we build on Oxford's Coronavirus Government Response Tracker (OxCGRT).[12] 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

---

[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]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.

[12]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.

gauge the effect of different types of containment measures on COVID-19 cases, economic activity and fiscal space (see Sec. 4).

FIGURE 2. Containment measures indices: physical, physical and smart, smart.
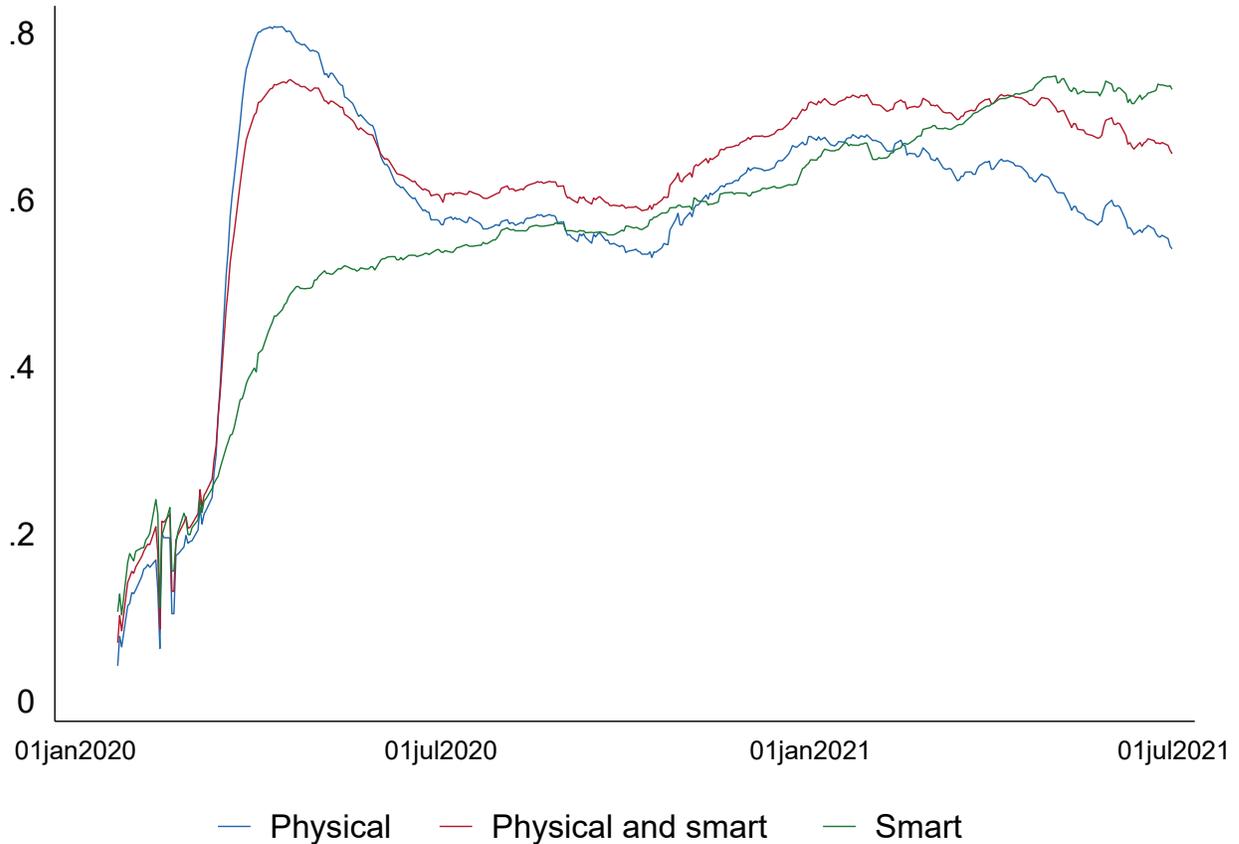
Notes: The figure reports the three containment measures indices as defined in Sec. 3: physical, physical and smart, smart. All indices are normalized to be between 0 and 1.

Source: Authors' calculations based on OxCGRT.

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), as a proxy for economic activity.[13] 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 3, we report the panel regression of $\Delta \log(IPI)$ on $\Delta \log(NO2)$ at monthly frequency, where IPI represents the industrial production index. We find a positive and significant correlation, where a 1 percent change in NO2

---

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

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.[14]

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

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.[15] In the same fashion, we use sovereign yields as controls in the empirical analysis. Data comes from Refinitiv Eikon Datastream and Bloomberg.

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.[16] 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

---

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

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

[16]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.

bulk of fiscal responses worldwide.[17] We include European institutions' announcements not included at the individual country level. We define all measures in percentage of national (2020 and 2021) GDP.[18] 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 cash-flow 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,a), 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 A for more details and an illustration of our (expanded) dataset compared to the raw CFRT database.

4. 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

---

[17]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.

[18]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.

the IRFs locally.[19] Interestingly, the LP responses are equivalent to VAR ones if the data generating process (DGP) is a VAR.[20] 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 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 $(t-1)$.[21] 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.[22,23]

---

[19]As one can see from equation 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.

[20]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.

[21]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.

[22]"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,b) for empirical analysis on the role of vaccinations on economic and health outcomes.

[23]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.

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 3. 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.[24] 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 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.[25]

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:[26]

---

[24]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).

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

[26]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

$$y_{i,t+h} = \mathcal{D}_t \left[\alpha_{A,i} + \beta_{A,h} \eta_{i,t} + \Psi_{A,h} \mathbf{X}_{i,t} + \Phi_{A,h}(L) y_{i,t} \right] +$$

$$+ (1 - \mathcal{D}_t) \left[\alpha_{B,i} + \beta_{B,h} \eta_{i,t} + \Psi_{B,h} \mathbf{X}_{i,t} + \Phi_{B,h}(L) y_{i,t} \right] + \varepsilon_{i,t+h} \qquad (2)$$

$$h = 0, 1, 2, \ldots, H$$

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.

5. 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 90 percent (shaded) confidence interval.

Baseline Results

Baseline results, reported in Figure 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 90 percent confidence intervals, while the black solid lines represent the median IRFs. The projection horizon covers 30 days after a unitary

---

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.

change in the containment indices.[27]

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.[28]
- 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

---

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

[28]In Figure 12 in Appendix B, 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 ICU patients. The reduction of deaths and hospitalized/ICU patients is milder under the adoption of "smart" measures, but still persistent and substantial.

percent on average across the three types of containment measures, and the IRFs are consistently negative throughout the projection horizon.[29] 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).

---

[29]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 Figure 13 in Appendix B.

FIGURE 3. Baseline results
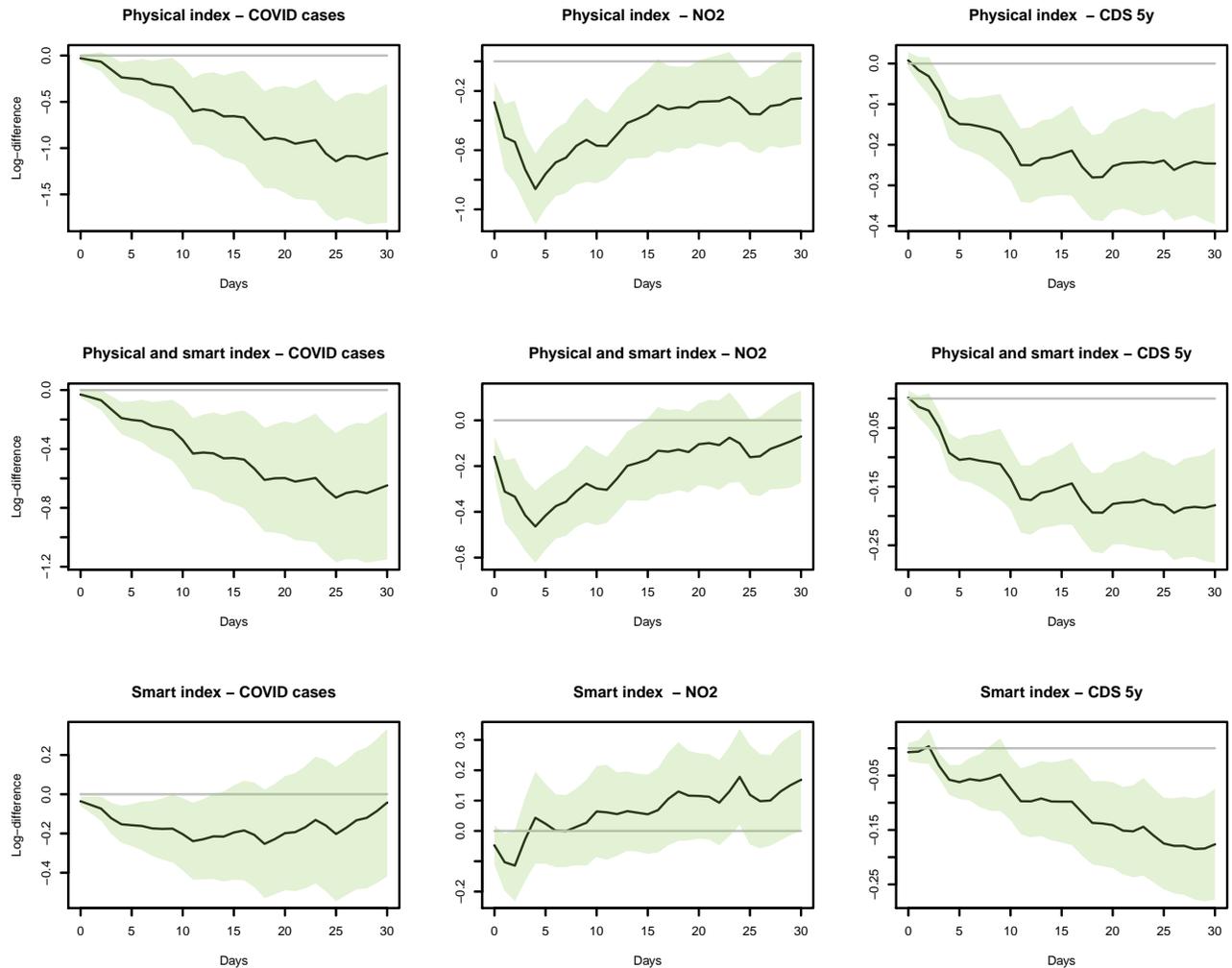
Notes: As we move along the columns of plots, we observe the responses of COVID-19 cases, NO2 emissions and CDS spreads. While, as we move along the rows of plots, we observe the dynamic effects of the "physical", "physical and smart", and the "smart" index as defined above. Responses are reported in log-deviations from their past values. Shaded green areas represent the 90 percent confidence intervals, while the black solid lines represent the median IRFs.

Sources: Authors' calculations.

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.

- **Advanced/Emerging economies.** Advanced economies (AEs) typically have lower perceived sovereign risk than emerging markets (EMs). Figure 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.[30] 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.

---

[30]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 B when using the "physical and smart" and the "smart" indices as shock variables.

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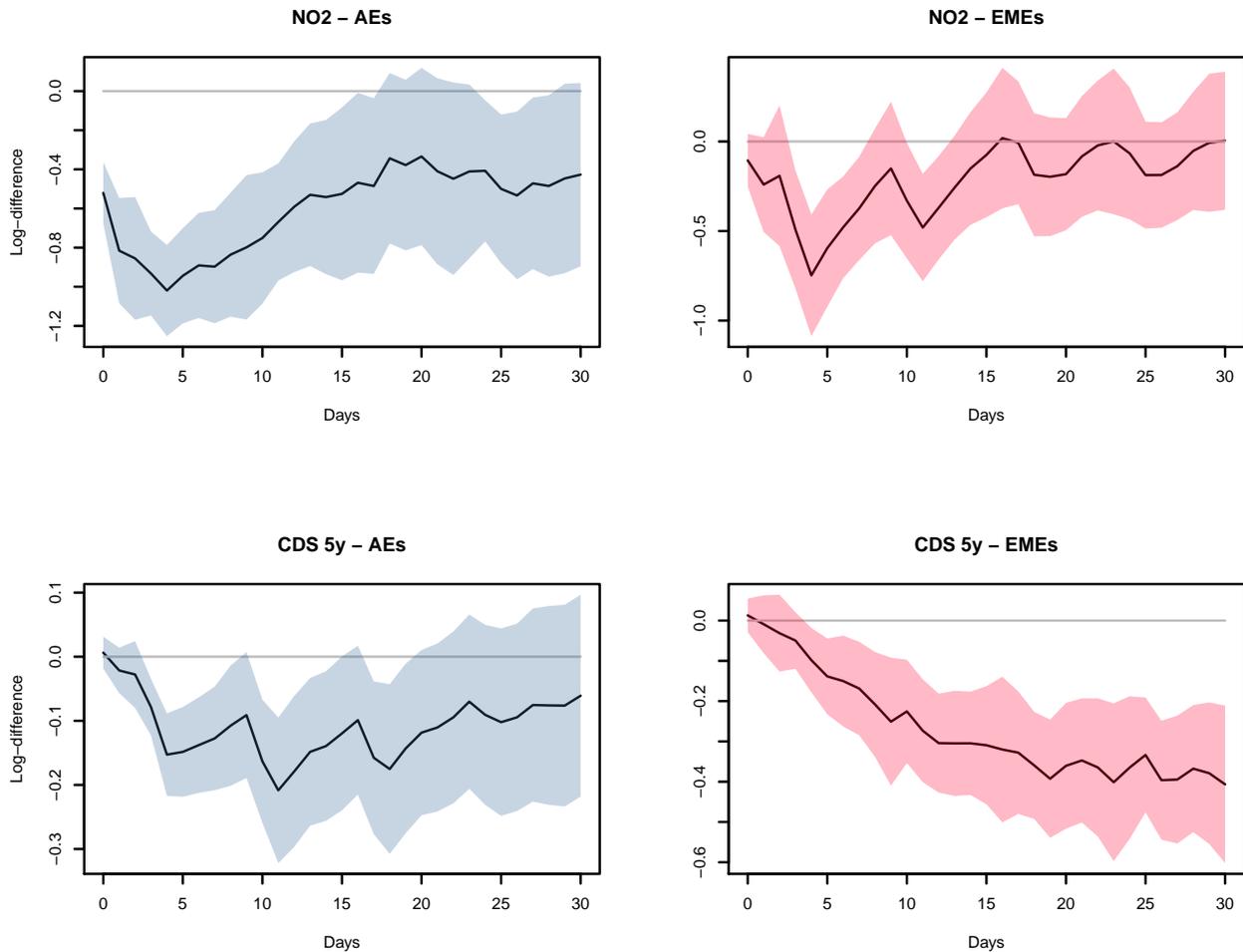
Notes: LHS (RHS) plots IRFs under the AE (EM) state whose confidence intervals are shaded in blue (red). Median IRFs are represented by black solid lines. Responses are reported in log-deviations from the dependent variables' past values.

Sources: Authors' calculations.

- **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 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 B).[31]

---

[31]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.

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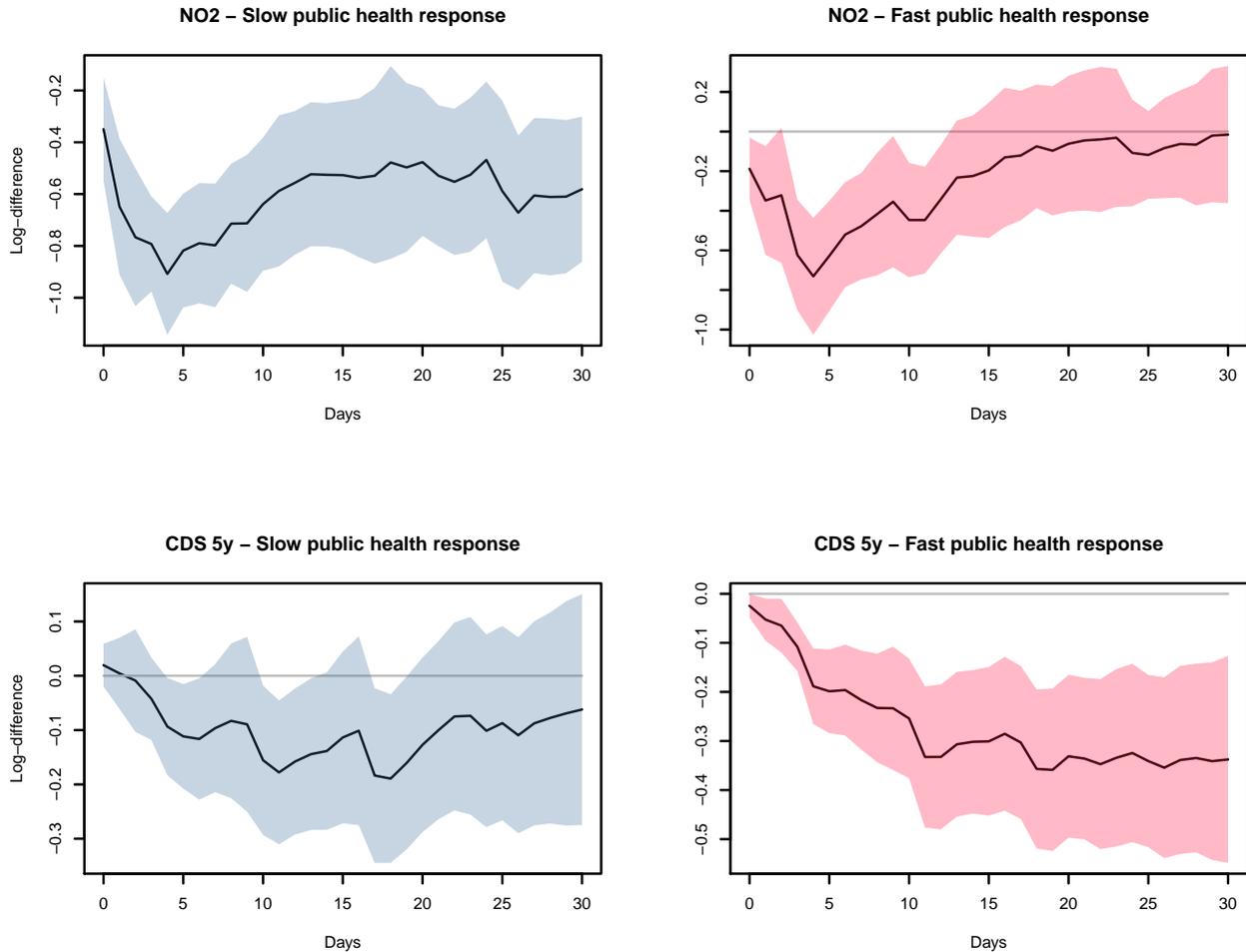
Notes: LHS (RHS) plots IRFs under the slow (fast) PHRT state whose confidence intervals are shaded in blue (red). Median IRFs are the black solid lines. Responses are reported in log-deviations from the dependent variables' past values.

Sources: Authors' calculations.

- **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 Figure 6, the LHS (RHS) plots IRFs under the high (low) public debt state whose confidence intervals are shaded 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.[32]

---

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

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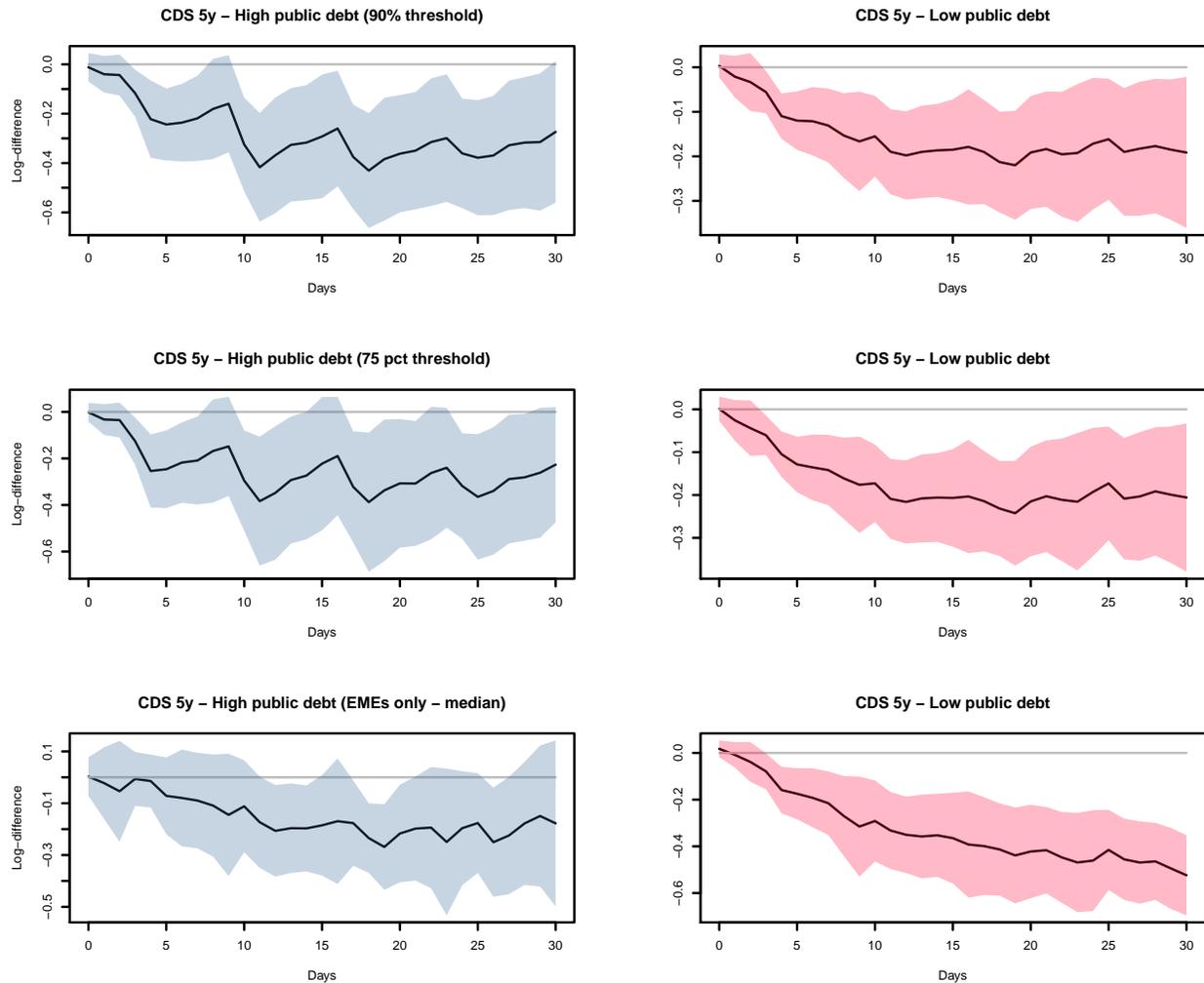
Notes: LHS (RHS) plots IRFs under high (low) public debt whose confidence intervals are shaded in blue (red). Median IRFs are the black solid lines. Responses are reported in log-deviations from the dependent variable's past value.

Sources: Authors' calculations.

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 5, 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 4 weeks

after the shock.[33] 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.

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

---

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

FIGURE 7. Large/low fiscal announcements
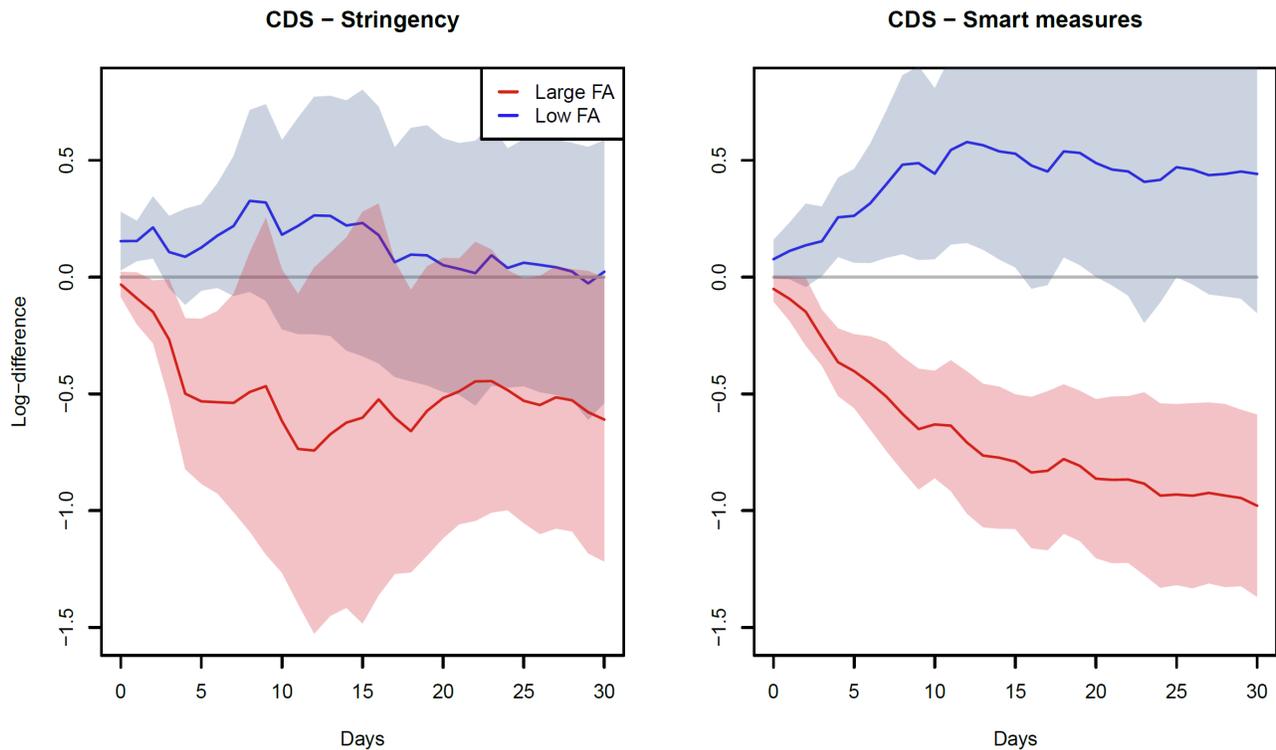
Notes: This figure shows the dynamic responses to a physical (LHS) and smart measures index shock (RHS) of 5-year maturity CDS spreads under large (low) fiscal announcements states whose median IRFs and 90 percent confidence intervals are shaded in red (blue). Responses are reported in log-deviations from the dependent variable's past value.

Sources: Authors' calculations.

6. 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 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,a), 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.

REFERENCES

Acemoglu, D., V. Chernozhukov, I. Werning, and M. D. Whinston (2020). Optimal targeted lockdowns in a multi-group SIR model. Technical report, National Bureau of Economic Research.

Adda, J. (2016). Economic activity and the spread of viral diseases: Evidence from high frequency data. *The Quarterly Journal of Economics 131*(2), 891–941.

Andries, A. M., S. Ongena, and N. Sprincean (2021). The COVID-19 pandemic and sovereign bond risk. *The North American Journal of Economics and Finance 58*, 101527.

Augustin, P., V. Sokolovski, M. G. Subrahmanyam, and D. Tomio (2021). In sickness and in debt: The COVID-19 impact on sovereign credit risk. *Journal of Financial Economics*.

Bi, H. (2012). Sovereign Default Risk Premia, Fiscal Limits, and Fiscal Policy. *European Economic Review 56*(3), 389–410.

Bi, H. and E. M. Leeper (2013). Analyzing Fiscal Sustainability. Staff working papers, Bank of Canada.

Bi, H. and N. Traum (2012). Estimating Sovereign Default Risk. *American Economic Review, Papers & Proceedings 102*(3), 161–166.

Bi, H. and N. Traum (2014). Estimating Fiscal Limits: The Case of Greece. *Journal of Applied Econometrics 29*(7), 1053–1072.

Bognanni, M., D. Hanley, D. Kolliner, and K. Mitman (2020). Economics and Epidemics: Evidence from an Estimated Spatial Econ-SIR Model. Technical report, Bonn: Institute of Labor Economics (IZA).

Botev, J., J.-M. Fournier, and A. Mourougane (2016). A re-assessment of fiscal space in oecd countries. *OECD Economics Department Working Papers, No. 1352*.

Caselli, F., F. Grigoli, L. Weicheng, and D. Sandri (2018). Assessing Fiscal Space: An Update and Stocktaking. *IMF Policy Paper*.

Caselli, F., F. Grigoli, L. Weicheng, and D. Sandri (2020). Protecting lives and livelihoods with early and tight lockdowns. *IMF Working Paper No. 20/234*.

Cevik, S. and B. Ozturkkal (2020). Contagion of Fear: Is the Impact of COVID-19 on Sovereign Risk Really Indiscriminate?

Chen, S., D. O. Igan, N. Pierri, A. F. Presbitero, M. Soledad, and M. Peria (2020). Tracking the economic impact of COVID-19 and mitigation policies in Europe and the United States. *IMF Working Papers No. 20/125*.

Chinazzi, M., J. T. Davis, M. Ajelli, C. Gioannini, M. Litvinova, S. Merler, A. P. y Piontti, K. Mu, L. Rossi, K. Sun, et al. (2020). The effect of travel restrictions on the spread of the 2019 novel coronavirus (COVID-19) outbreak. *Science 368*(6489), 395–400.

Coibion, O., Y. Gorodnichenko, and M. Weber (2020). The cost of the covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending. Technical report, National Bureau of Economic Research.

Collard, F., M. Habib, and J.-C. Rochet (2015). Sovereign Debt Sustainability In Advanced Economies. *Journal of the European Economic Association 13*(3), 381–420.

Deb, P., D. Furceri, D. Jimenez, S. Kothari, J. D. Ostry, and N. Tawk (2021a). Determinants of COVID-19 Vaccine Rollouts and Their Effects on Health Outcomes. *IMF Working Paper No. 21/247*.

Deb, P., D. Furceri, D. Jimenez, S. Kothari, J. D. Ostry, and N. Tawk (2021b). The Effects of COVID-19 Vaccines on Economic Activity. *IMF Working Paper No. 21/248*.

Deb, P., D. Furceri, J. D. Ostry, and N. Tawk (2020a). The economic effects of Covid-19 containment measures. *IMF Working Paper No. 20/158*.

Deb, P., D. Furceri, J. D. Ostry, and N. Tawk (2020b). The economic effects of Covid-19 containment measures. *IMF Working Paper No. 20/158*.

Deb, P., D. Furceri, J. D. Ostry, and N. Tawk (2020c). The effect of containment measures on the COVID-19 pandemic. *IMF Working Paper No. 20/159*.

Deb, P., D. Furceri, J. D. Ostry, N. Tawk, and N. Yang (2021). The Effects of Fiscal Measures During COVID-19. *IMF Working Papers 2021*(262).

Demirgüç-Kunt, A., M. Lokshin, and I. Torre (2021). The sooner, the better: The economic impact of non-pharmaceutical interventions during the early stage of the covid-19 pandemic. *Economics of Transition and Institutional Change*.

Esteves, R. P. and N. Sussman (2020). Corona spreads to emerging markets. Technical report.

Ettmeier, S., C. H. Kim, and A. Kriwoluzky (2020). Financial market participants expect the coronavirus pandemic to have long-lasting economic impact in europe. *DIW Weekly Report 10*(19/20), 243–250.

Fotiou, A. and A. Lagerborg (2021). Smart containment: Lessons from countries with past experience. *IMF Working Papers No. 21/99*.

Garibaldi, P., E. R. Moen, and C. A. Pissarides (2020). Modelling contacts and transitions in the sir epidemics model. *Covid Economics 5*(16.04).

Ghosh, A., J. I. Kim, E. Mendoza, J. Ostry, and M. Qureshi (2013). Fiscal Fatigue, Fiscal Space and Debt Sustainability in Advanced Economies. *Economic Journal*, F4–F30.

Granger, C. and T. Terasvirta (1993). *Modelling Nonlinear Economic Relationships*. Advanced texts in econometrics. Oxford [u.a.]: Oxford Univ. Press.

Hosny, A. (2021). The Sooner (and the Smarter), the Better: COVID-19 Containment Measures and Fiscal Responses.

Hsiang, S., D. Allen, S. Annan-Phan, K. Bell, I. Bolliger, T. Chong, H. Druckenmiller, L. Y. Huang, A. Hultgren, E. Krasovich, et al. (2020). The effect of large-scale anti-contagion policies on the covid-19 pandemic. *Nature 584*(7820), 262–267.

Islamaj, E., D. T. Le, and A. Mattoo (2021). Lives versus Livelihoods during the COVID-19 Pandemic. *WB Policy Research Working Paper No. 9696*.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Kermack, W. O. and A. G. McKendrick (1927). A contribution to the mathematical theory of epidemics. *Proceedings of the royal society of london. Series A, Containing papers of a mathematical and physical character 115*(772), 700–721.

Kose, M. A., S. Kurlat, F. Ohnsorge, and N. Sugawara (2017). A cross-country database of fiscal space.

Kraemer, M. U., C.-H. Yang, B. Gutierrez, C.-H. Wu, B. Klein, D. M. Pigott, O. C.-. D. W. Group, L. du Plessis, N. R. Faria, R. Li, et al. (2020). The effect of human mobility and control measures on the covid-19 epidemic in china. *Science 368*(6490), 493–497.

Leeper, E. M. (2013). Fiscal Limits and Monetary Policy. NBER Working Papers 18877, National Bureau of Economic Research, Inc.

Maloney, W. F. and T. Taskin (2020). Determinants of social distancing and economic activity during covid-19: A global view. *World Bank Policy Research Working Paper* (9242).

Metelli, L. and K. Pallara (2020). *Fiscal space and the size of the fiscal multiplier*. Banca d'Italia Eurosistema.

Ostry, J. D., A. R. Ghosh, and R. A. Espinoza (2015). When Should Public Debt Be Reduced? IMF Staff Discussion Notes, International Monetary Fund.

Ostry, J. D., A. R. Ghosh, J. I. Kim, and M. S. Qureshi (2010). Fiscal space. *IMF Staff Position Notes 2010*(011).

Pallara, K. and J.-P. Renne (2021). Fiscal limits and the pricing of eurobonds. *Available at SSRN 3891358*.

Plagborg-Møller, M. and C. K. Wolf (2021). Local projections and vars estimate the same impulse responses. *Econometrica 89*(2), 955–980.

Ramey, V. A. (2011a). Can government purchases stimulate the economy? *Journal of Economic Literature 49*(3), 673–85.

Ramey, V. A. (2011b). Identifying government spending shocks: It's all in the timing. *The Quarterly Journal of Economics 126*(1), 1–50.

Ramey, V. A. and S. Zubairy (2018). Government spending multipliers in good times and in bad: evidence from us historical data. *Journal of Political Economy 126*(2), 850–901.

Tenreyro, S. and G. Thwaites (2016). Pushing on a string: Us monetary policy is less powerful in recessions. *American Economic Journal: Macroeconomics 8*(4), 43–74.

Teräsvirta, T. (1994). Specification, estimation, and evaluation of smooth transition autoregressive models. *Journal of the american Statistical association 89*(425), 208–218.

Tian, H., Y. Liu, Y. Li, C.-H. Wu, B. Chen, M. U. Kraemer, B. Li, J. Cai, B. Xu, Q. Yang, et al. (2020). An investigation of transmission control measures during the first 50 days of the covid-19 epidemic in china. *Science 368*(6491), 638–642.

WEO, I. (10/2020). World economic outlook, october. *International Monetary Fund*.

APPENDIX A. 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.[34]

- 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 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,a). In Figure 10, we report the (static average) divisions across categories of the fiscal announcements. In Figure 11, we show the set of policy instruments under the demand support category as an illustration.

---

[34]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

FIGURE 8. Original dataset for fiscal announcements in Austria

Date	Country	Country Other	Implementing Institution	Implementing Institution Other	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

FIGURE 9. Newly constructed dataset for fiscal announcements in Austria

FIGURE 10.

Fiscal announcement by macro-category - Eurozone averages

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 Neherlands.
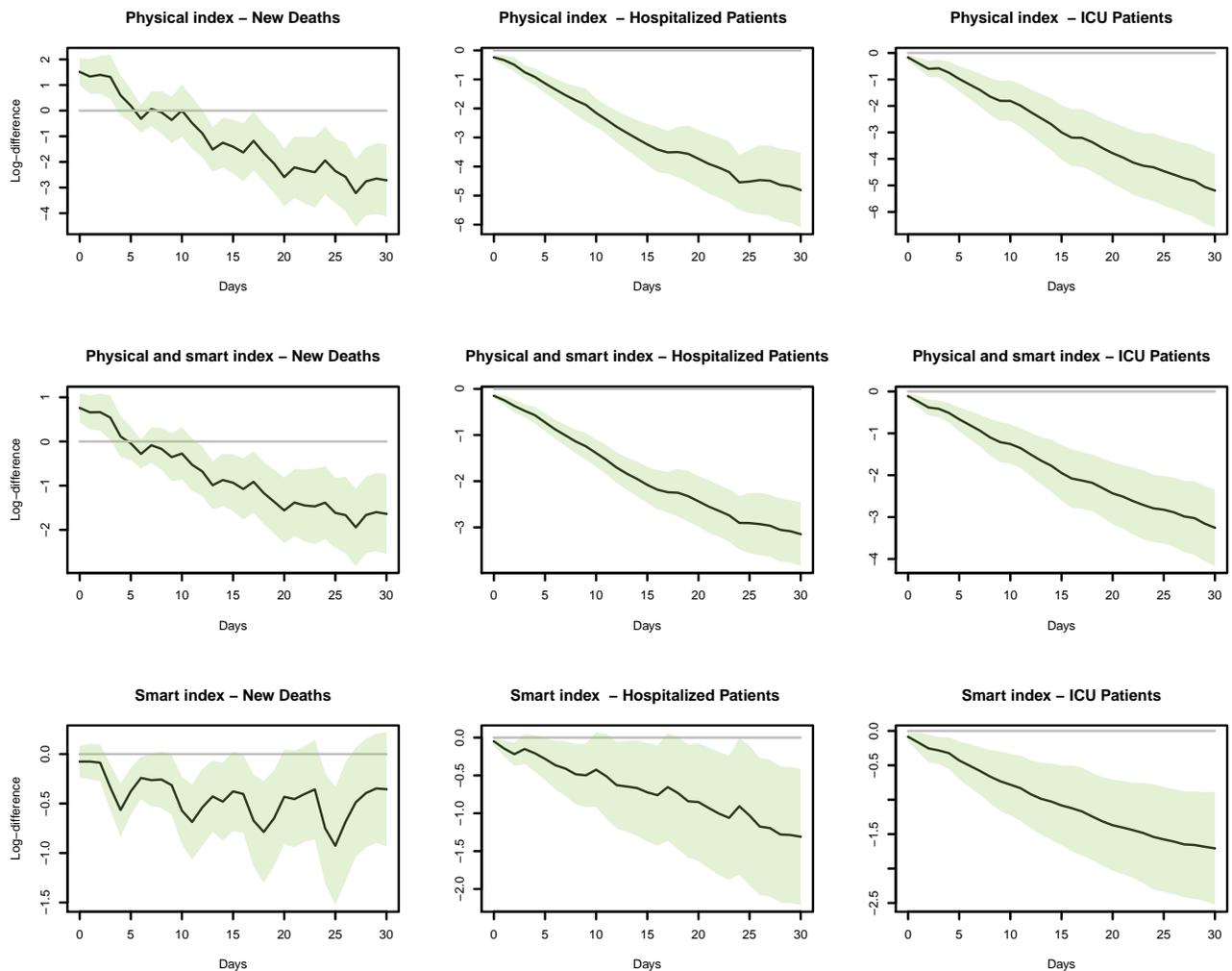
FIGURE 11.

DEMAND SUPPORT: FISCAL POLICY INSTRUMENTS BREAKDOWN

- Wage supplements 8%
- Cash transfers 0.1%
- Unemployment benefits 1%
- Tax relief 14%
- Healthcare spending 38%
- Targeted transfers 16%
- Infrastructure spending 3%
- Payment forbearance 3%
- Reduction of social security contributions 0.1%
- Support to SMEs 6%
- Sector support 11%
- Salary compensation 0.2%
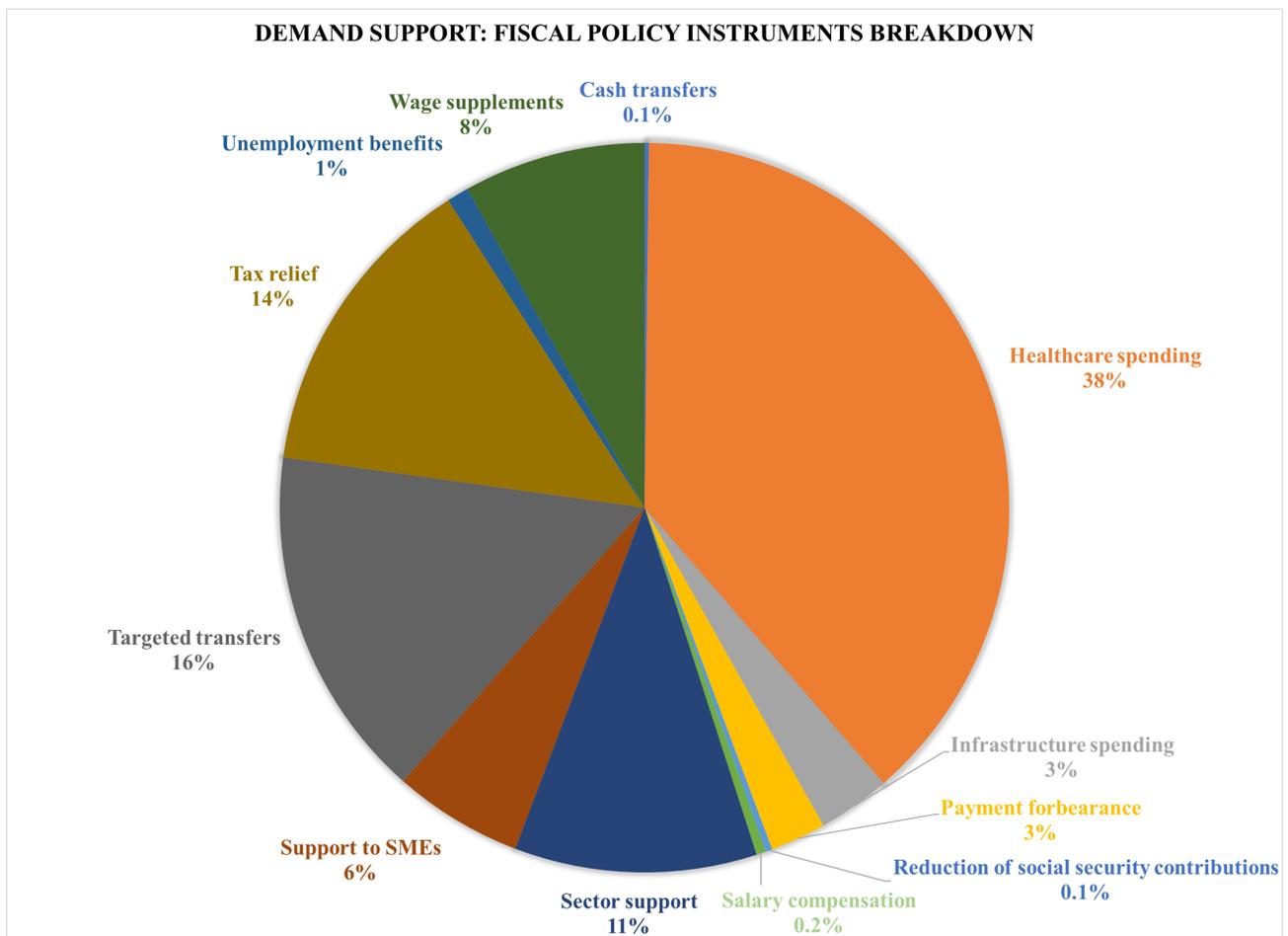
This figure reports the break-down of policy instruments contained within the demand support category of the fiscal announcements dataset.

APPENDIX B. ADDITIONAL RESULTS (FIGURES AND TABLES)

FIGURE 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 90% confidence intervals, while the black solid lines represent the median IRFs.

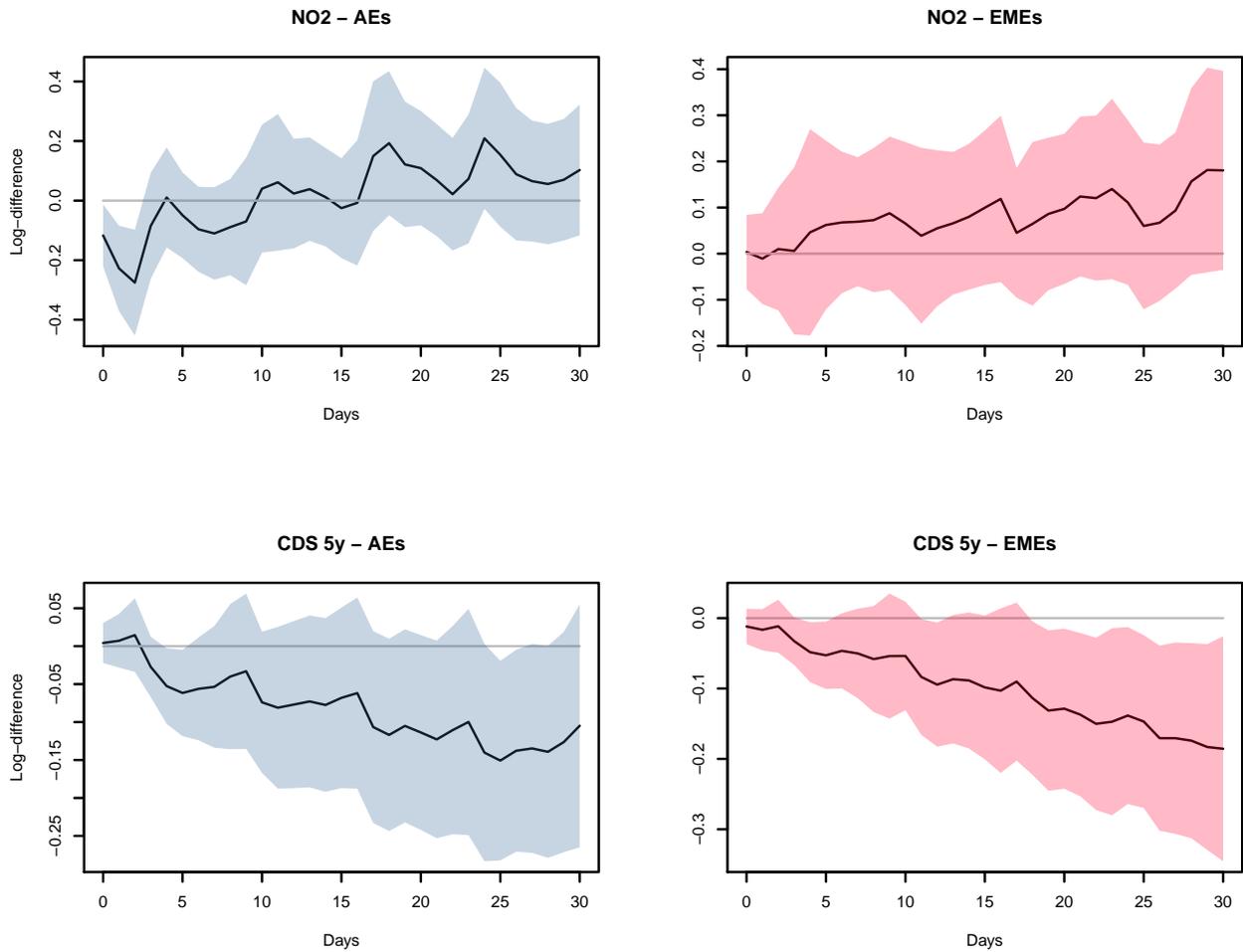FIGURE 13. IRFs of NO_2 emissions and CDS spreads - Stingency index: sub-indices
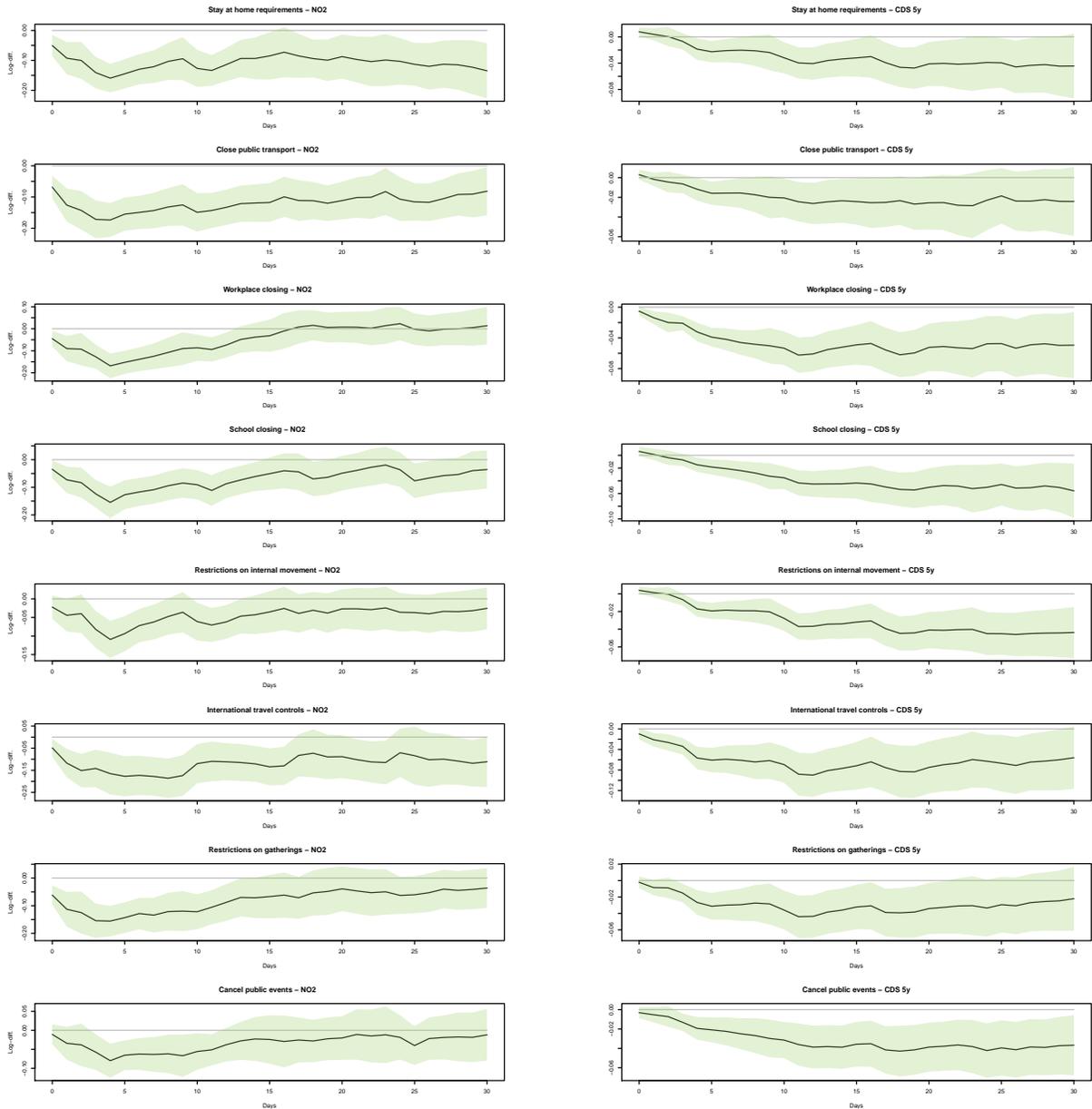
This figure reports the impulse response functions from linear local projection (eq. 1) of NO_2 emissions (economic activity indicator) and 5-year CDS spreads (fiscal space indicator) by using, in turn, the sub-indices contained in the stringency index (physical closures) as shock variable. The response of our variables of interest are reported in log-deviations from their past values. The shaded green areas stand for the 90% confidence intervals, while the black solid lines represent the median IRFs.

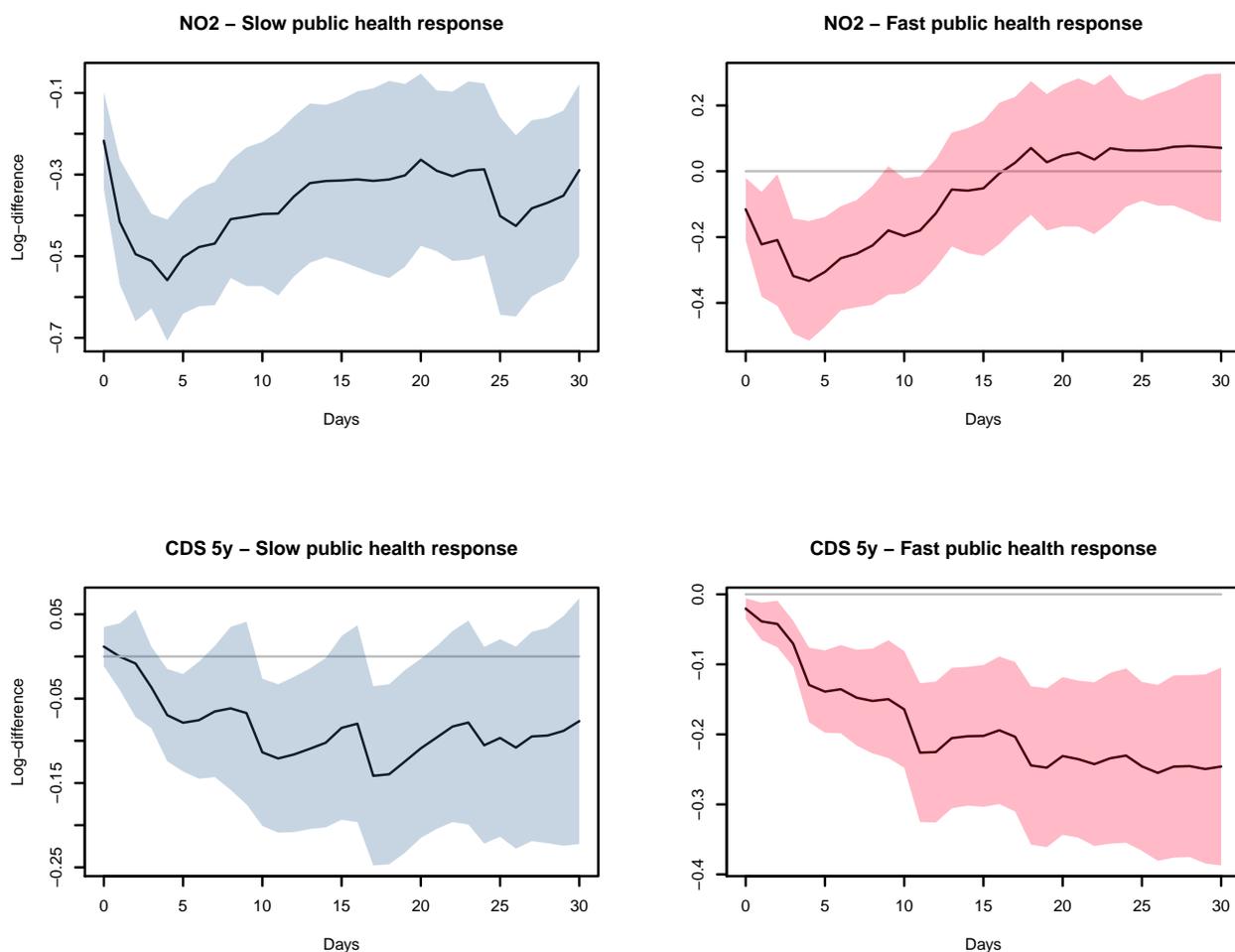FIGURE 14. Advanced/emerging economies - Physical and smart index
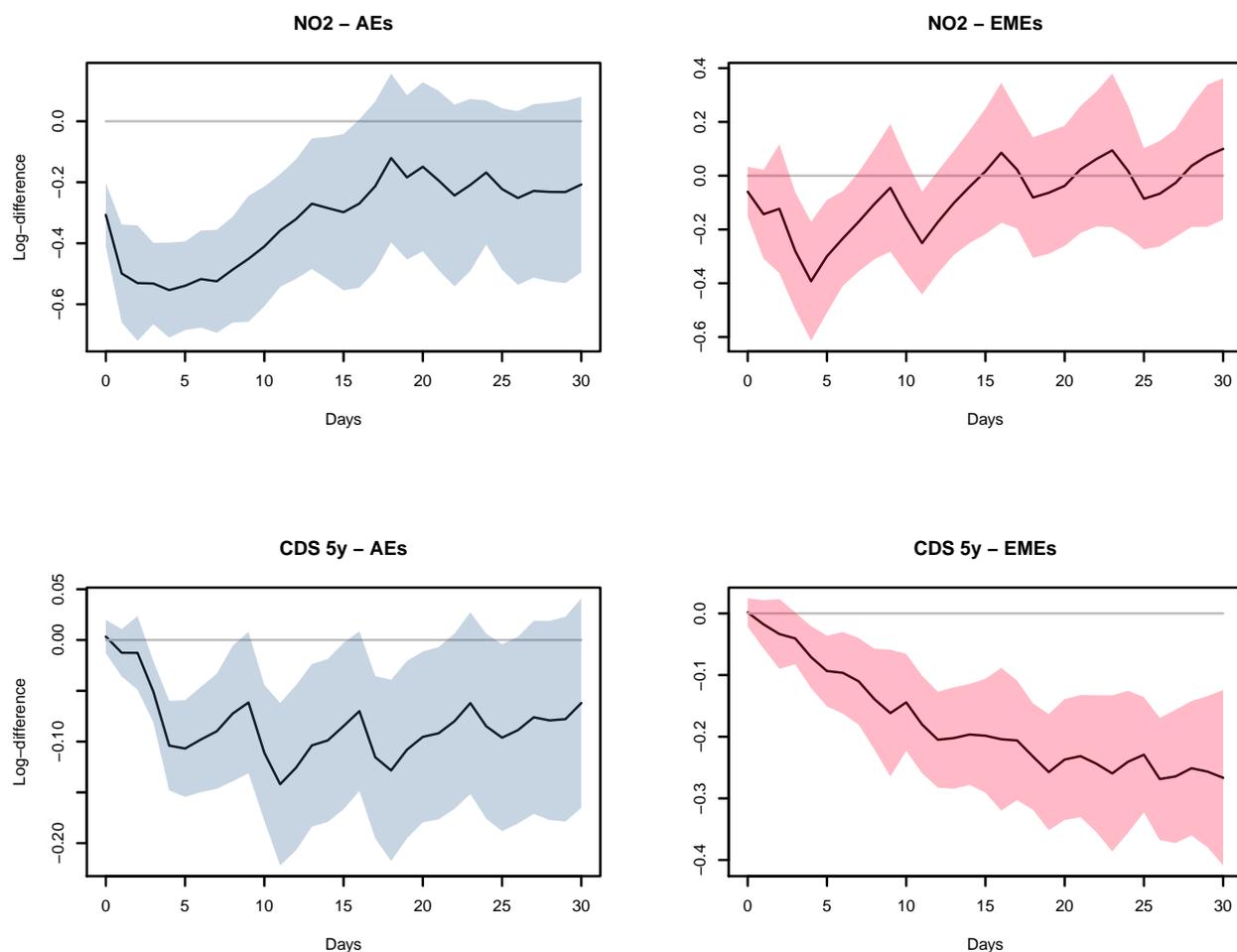
This figure shows on the left hand side plots the dynamic responses to a containment health index shock of both NO_2 emissions and CDS spreads under the advanced economy state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of both 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.

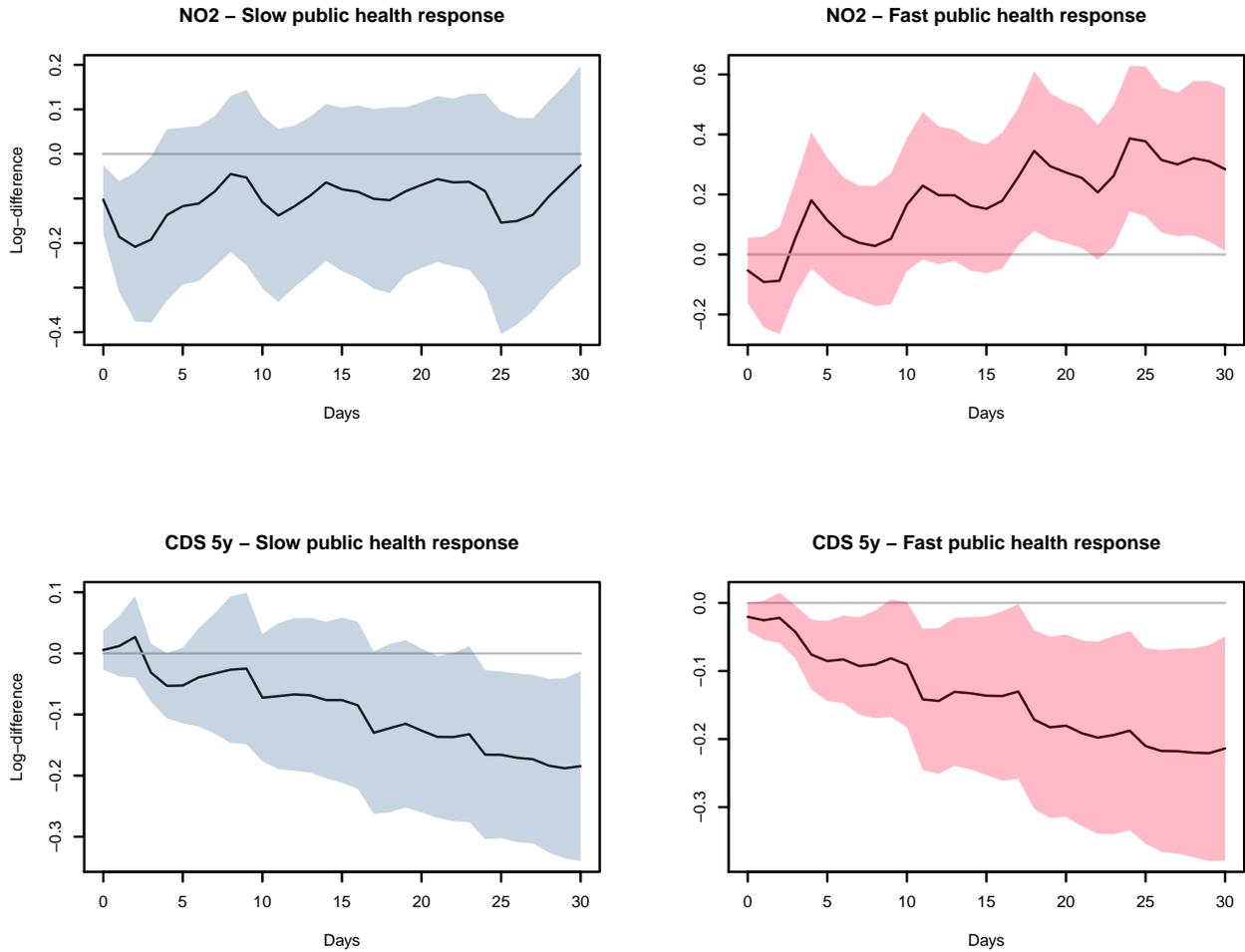FIGURE 15. Advanced/emerging economies - Smart index

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.

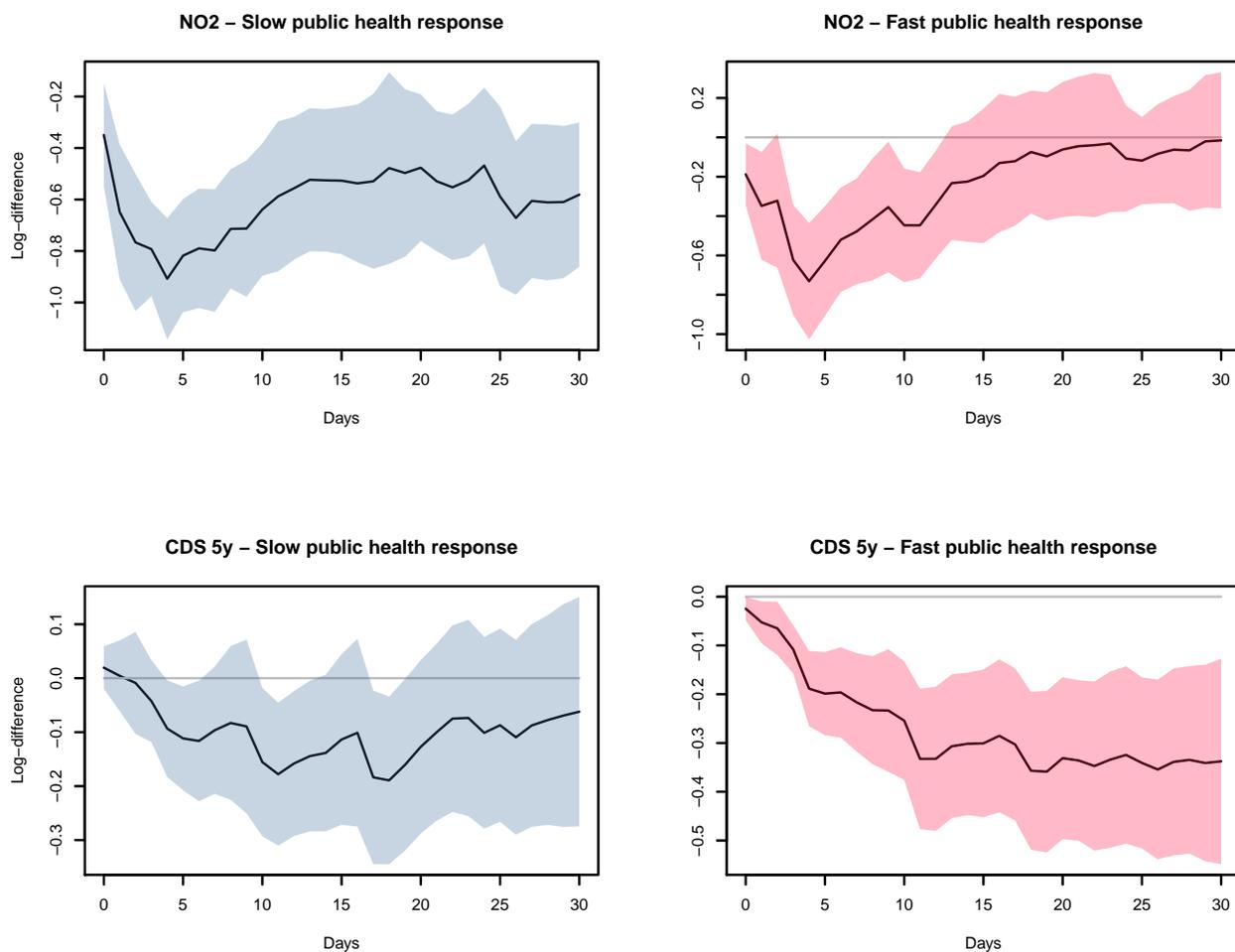FIGURE 16. Fast/slow public health response time - Physical and smart index

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.

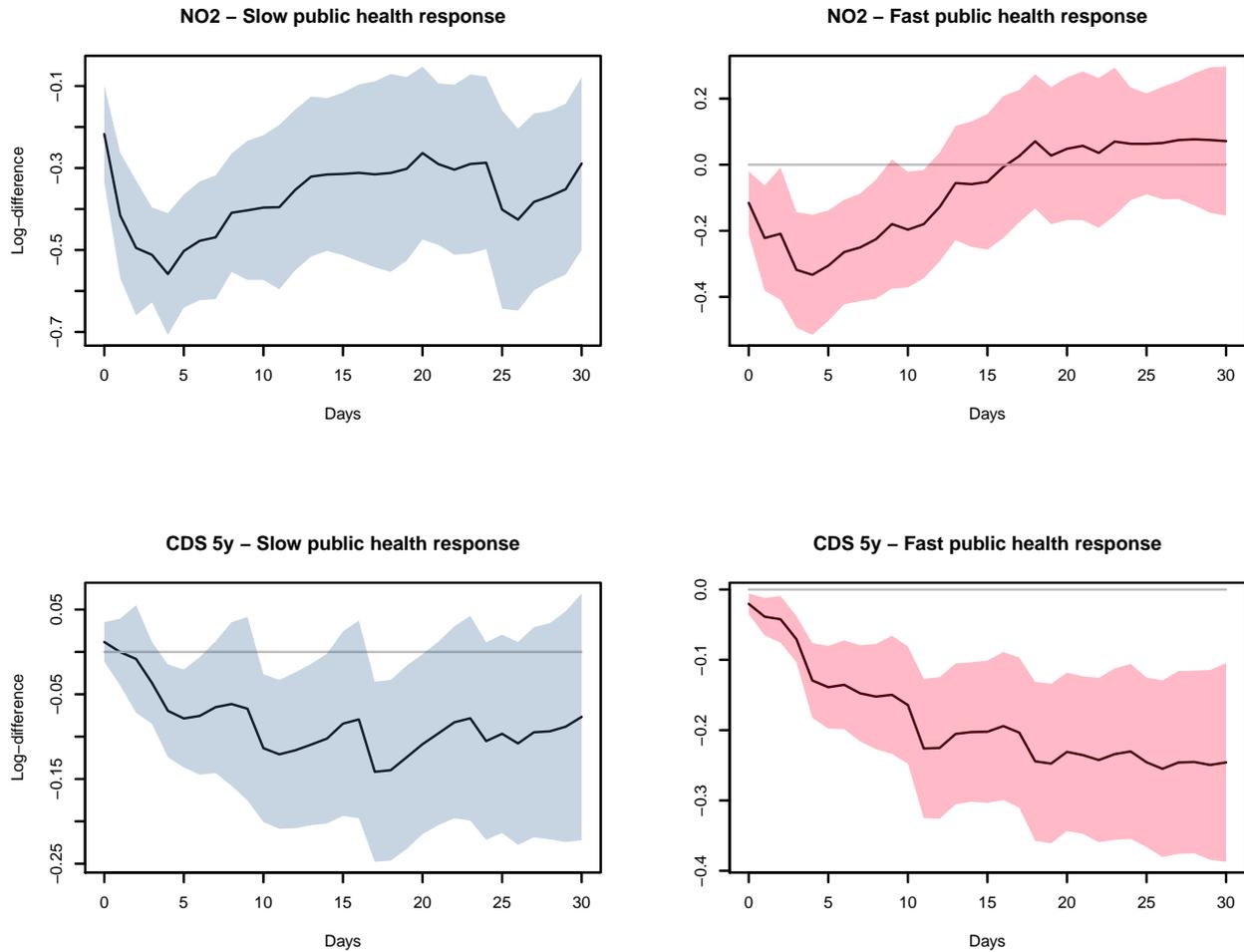FIGURE 17. Fast/slow public health response time - Smart index

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.

FIGURE 18. Fast/slow public health response time (first alternative definition) - Physical index
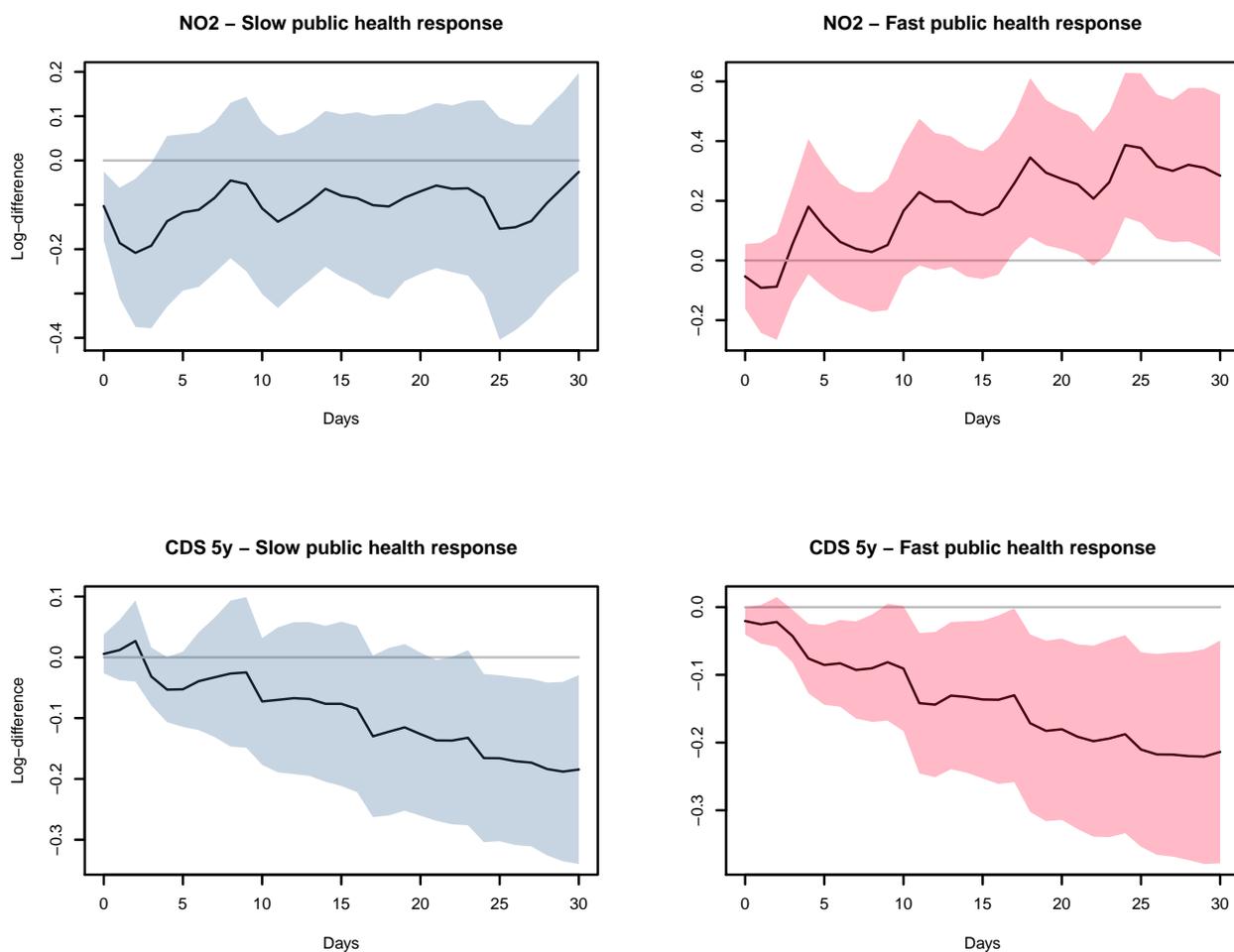

This figure shows on the left hand side plots the dynamic responses to a stringency index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses 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.

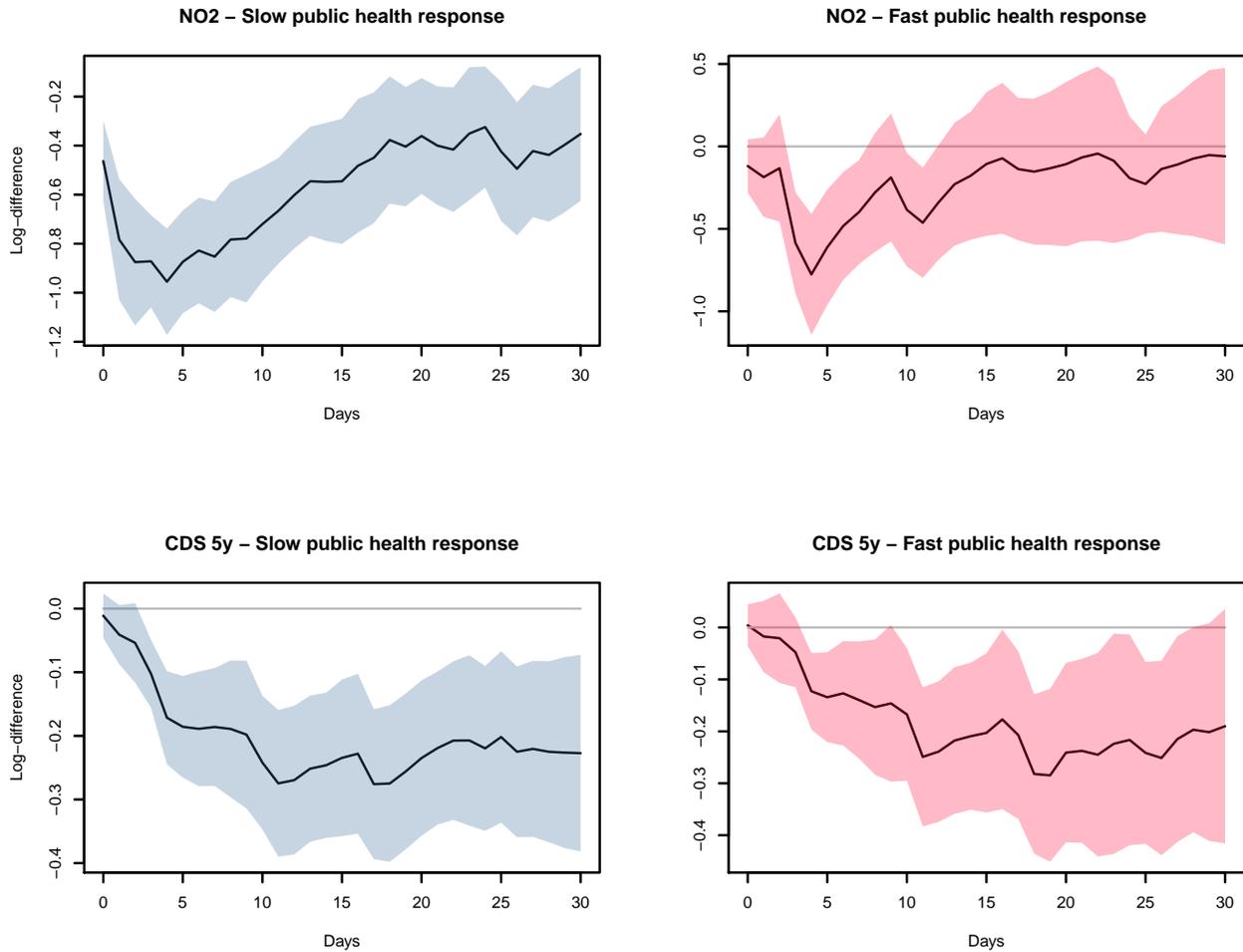FIGURE 19. Fast/slow public health response time (first alternative definition) - Physical and smart index

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.

FIGURE 20. Fast/slow public health response time (first alternative definition) - Smart index
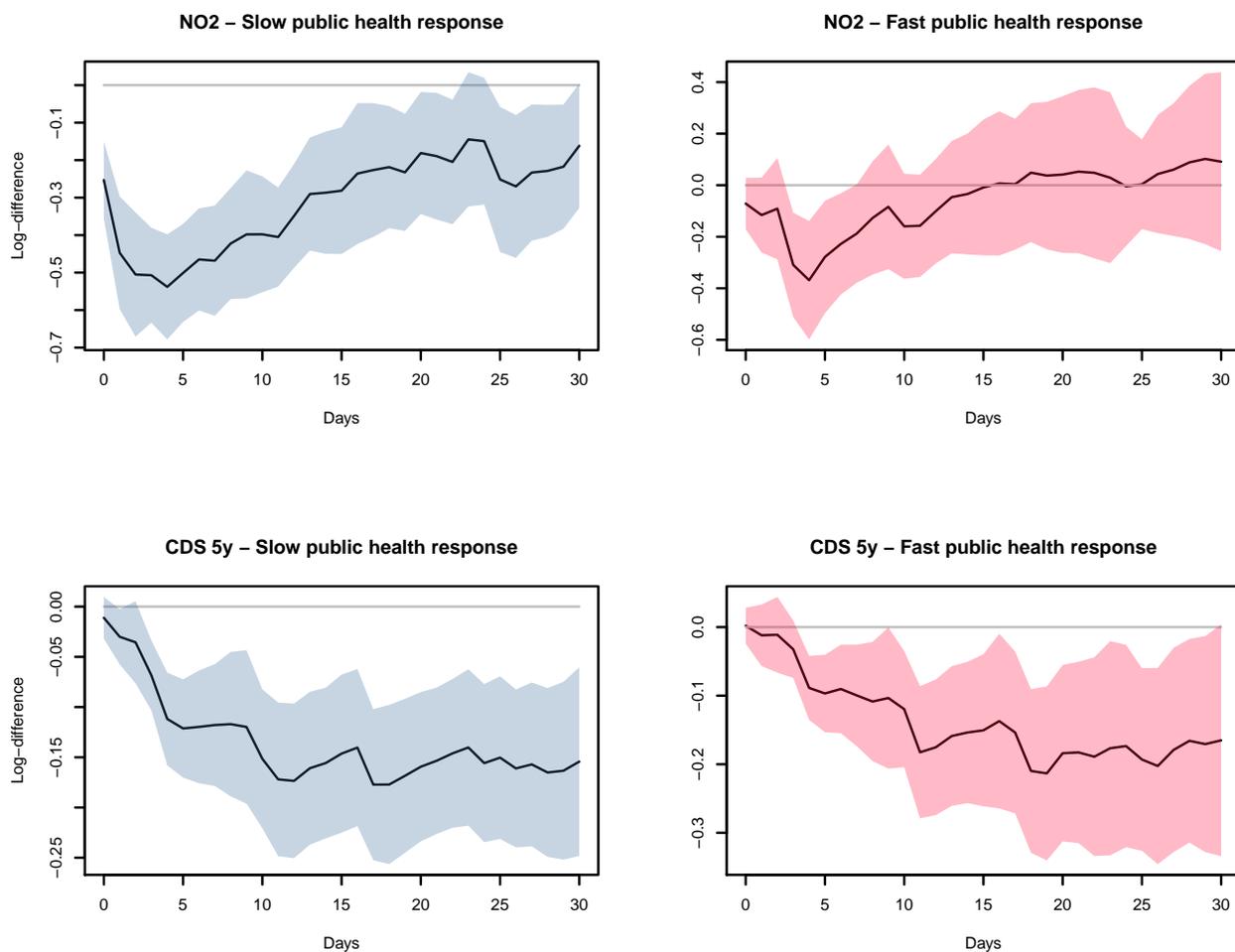

This figure shows on the left hand side plots the dynamic responses to a smart containment measures index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the 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.

FIGURE 21. Fast/slow public health response time (second alternative definition) - Physical index
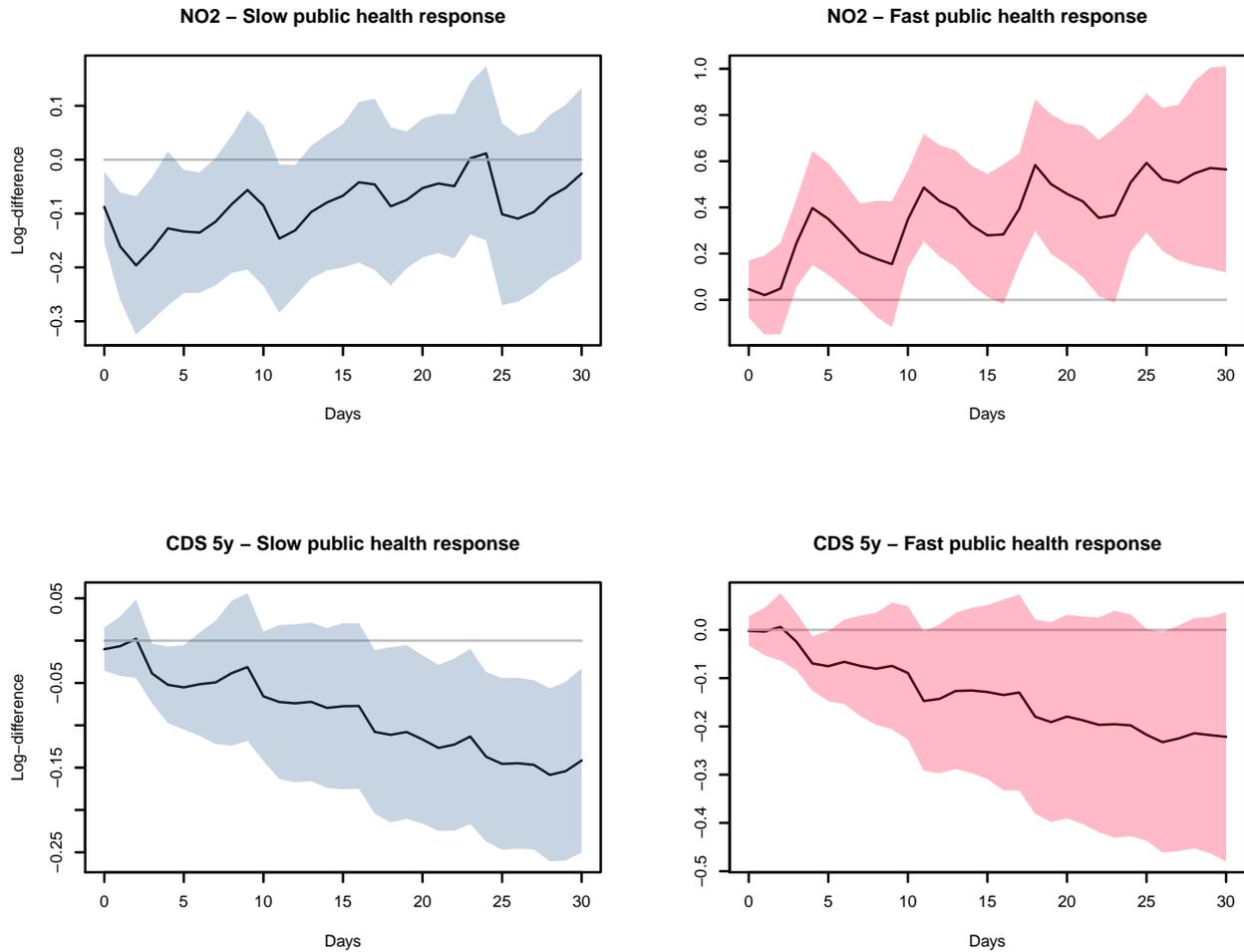

This figure shows on the left hand side plots the dynamic responses to a stringency index shock of both NO_2 emissions and CDS spreads under the slow public health response time state whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses 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.

FIGURE 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.

FIGURE 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.

FIGURE 24. High/low public debt - IRFs of NO_2 emissions - Physical index
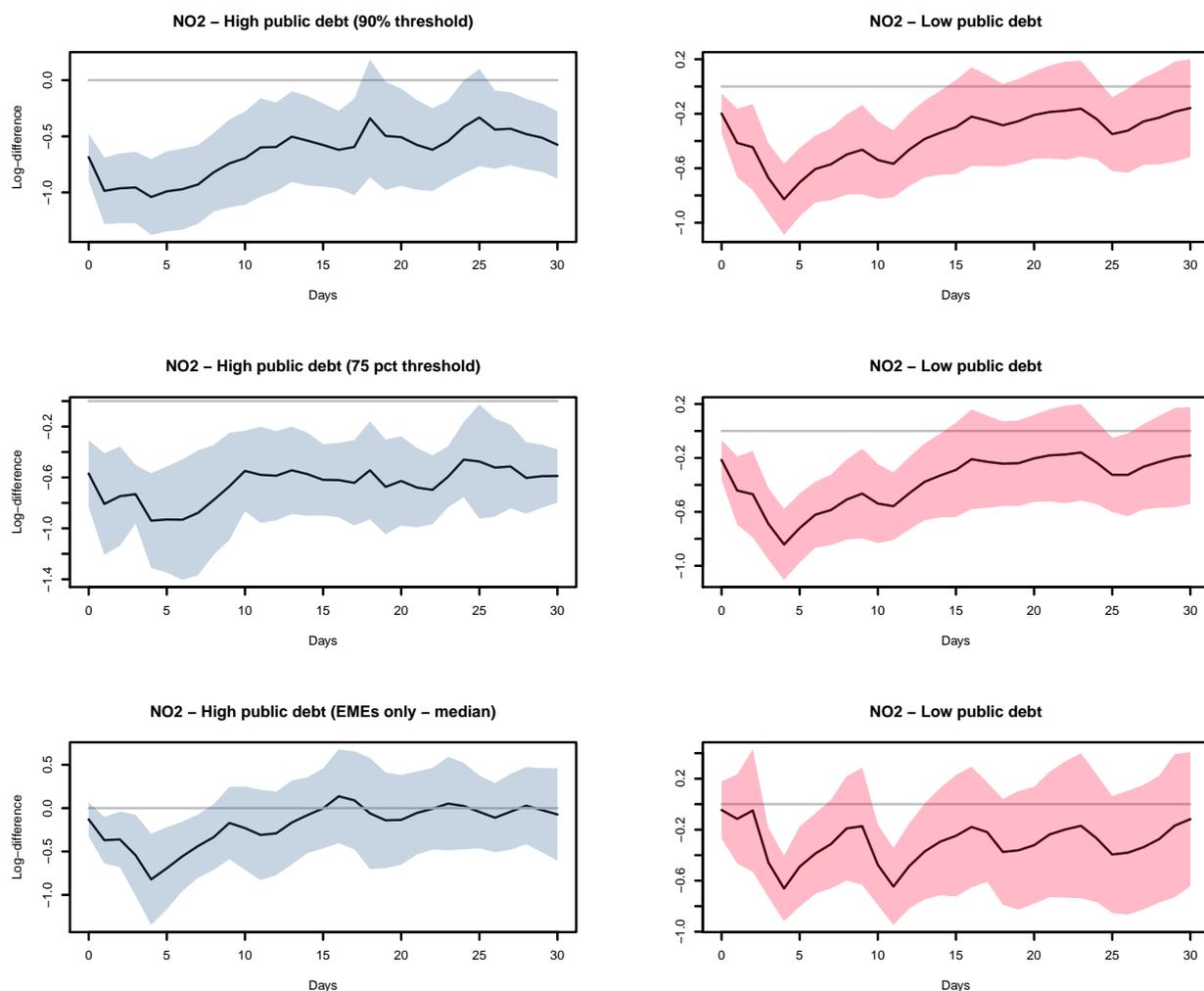
This figure shows on the left hand side plots the dynamic responses to a stingency index shock of NO_2 emissions under high public debt states whose confidence intervals are shaded in blue. While, on the right hand side plots, we report the the dynamic responses of NO_2 emissions under low public debt 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.

PUBLICATIONS