The Economic Effects of COVID-19 Containment Measures*

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Abstract

This paper examines the economic effects of COVID-19 containment measures using daily global data on containment measures, infections, and economic activity indicators, such as Nitrogen Dioxide (NO_2) emissions, international and domestic flights, energy consumption, maritime trade, and mobility indices. Results suggest that containment measures had a significant impact on economic activity—equivalent to about a 10 percent loss in industrial production over 30 days following their implementation. Fiscal measures used to mitigate the crisis were effective in partly offsetting these costs. We also find that school closures and cancellation of public events are among the most effective measures in curbing infections and are associated with low economic costs. Other highly-effective measures like workplace closures and international travel restrictions are among the costliest in economic terms.

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I. Introduction

Countries worldwide have enacted stringent containment measures and non-pharmaceutical interventions (NPIs) to halt the spread of the coronavirus (COVID-19) pandemic, in a bid to avoid overwhelming the medical system while effective treatments and vaccines are developed. Interventions have ranged from diagnostic testing, contact tracing, isolation and quarantine for infected people, to, importantly, measures aimed at reducing mobility and creating social distancing (containment measures, hereafter).

Empirical evidence from China and few selected economies (Kraemer et al. 2020; Chinazzi et al. 2020; H. Tian et al. 2020, Hsiang S. et al. 2020) as well as for other countries in the world (Deb et al. 2020) suggest that these measures have been effective in flattening the pandemic "curve". In particular, they find that countries that have put in place stringent measures, for example, like in China and Italy, as well as early intervention, such as in New Zealand and Vietnam, may have reduced the number of confirmed cases by more than 90 percent relative to the underlying country-specific path in the absence of interventions.

However, while these measures have contributed to saving lives, therefore providing the foundation for a stronger medium-term growth (see Barro, Ursua and Weng 2020), they have led to unprecedented short-term economic losses. Quantifying these economic effects and whether they vary across types of containment measure is of paramount importance for many policymakers around the world facing a painful tradeoff between normalizing economic activity and minimizing health risks.

This paper tries to address these issues empirically. In particular, the paper has three main goals. The first is to quantify the average economic effect—across countries and measures—of containment measures. For this purpose, we assemble daily data on real-time containment measures implemented by countries worldwide as well as a unique database containing daily data on several economic activity indicators: Nitrogen Dioxide (NO_2) emissions—as explained in the next section, our main variable of interest; international and domestic flights; energy consumption; maritime trade; and mobility indices.

Establishing the causal effect on economic activity is difficult. While containment measures have not been introduced to affect economic activity, the decision of implementing them crucially depends on the evolution of the virus, which in turns may affect mobility and economic activity (Maloney and Taskin, 2020). This implies that addressing causality requires the researcher to effectively control for this endogenous response which would otherwise bias estimates of the effect of containment measures. The use of daily data allows us to tackle this issue by controlling for the change in the number of infected cases and deaths occurring a day before the implementation of containment measures, as well as for lagged changes in daily economic indicators. We also control for a set of variables which may affect future infections such as daily temperature and humidity levels, other non-pharmaceutical interventions (NPIs)—including enhanced testing, contact tracing and public information campaigns aimed at increasing social awareness, and country-specific time trends. Given lags in the implementation of interventions at daily frequency, this approach effectively controls for the endogenous response of containment measures to the spread of the virus.

Another concern is that containment measures were announced before being implemented and, therefore, were anticipated. This may have resulted in reduced mobility ahead of the implementation of some containment measures and to a bias in the estimates (Figure 1). We control for changes in mobility to address this concern. Further, as an additional reassurance, we include an analysis of the effect international travel restrictions, which were implemented across countries in response to outbreaks in other countries, before changes in mobility and exogenous to domestic conditions.

Our results suggest that containment measures have had, on average, a very large impact on economic activity—equivalent to a loss of about 10 percent in industrial production over the 30-day period following the implementation of full lockdown.

The second goal of the paper is to examine whether fiscal measures announced and implemented by governments around the world have been effective in mitigating the negative effects of containment measures. To answer this question, we use data from the *IMF Policy Tracker*, which compiles discretionary fiscal measures in response to COVID-19. The results suggest that macroeconomic stimulus has been effective, with the negative effect of containment measures being much larger—equivalent to a loss in industrial production of about 29 percent—in countries that have provided little or limited fiscal policy stimulus.

The third and final goal of the paper is to examine which types of containment measures have resulted in larger economic costs and short-term tradeoffs between minimizing health risks and economic losses. For this purpose, we analyze the economic and virus transmission effects of the following containment measures: (i) school closures; (ii) workplace closures; (iii) cancellation of public events; (iv) restrictions on size of gatherings ; (v) closures of public transport; (vi) stay-at-home orders; (vii) restrictions on internal movement; (viii) restrictions on international travel. While the results should be treated with caution since many of these measures were often introduced simultaneously as a part of the country's response to limit the spread of the virus, evidence suggests that school closures and cancellations of public events are the most effective measures in curbing infections, but also among the least costly in economic terms. On the other hand, while international travel restrictions and workplace closures are also very effective in curbing infections, they are associated with the largest economic costs.

This paper contributes to two main strands of literature. The first is on the use high-frequency daily indicators to monitor economic activity. For example, Lin and McElroy (2011) show that variation in NO_2 emissions in China resemble its GDP growth during and after the GFC. Kumar and Muhuri (2019) employ a transfer learning-based approach to predict per capita GDP of a country using CO_2 emissions. The second strand of literature this paper contributes to is on the potential economic effect of COVID-19 and containment measures, including based on past pandemic episodes. Barro, Ursua and Weng (2020) studied the effects of non-pharmaceutical interventions (NPIs) such as school closings, prohibition on public gathering and quarantine/isolation on death rates in the United States during the 1919 pandemic. They find that while NPIs have a significant effect on peak death rates, they had a more limited impact on the cumulative number of deaths. They also find that the macroeconomic effects of the pandemic were quite large, with the economy of a typical state contracting by around 6 percent. Ma, Rogers and Zhou. (2020) draw lessons for the COVID-19 pandemic from examining the immediate and bounce-back effects of six past health crises: the 1968 Flu, SARS (2003), H1N1 (2009), MERS (2012), Ebola (2014), and Zika (2016). They find that real GDP is 2.4 percent lower the year of the outbreak in countries affected relative to those unaffected, and that it remains below its pre-shock levels for five years after the crisis despite bouncing back. They also find that fiscal policy plays an important role in mitigating the impact of a health crisis. Coibion, Gorodnichenko and Weber (2020) use data from customized surveys from over 10,000 respondents to estimate the impact of COVID-19 on households' spending and macroeconomic expectations in the United States. They find that aggregate consumer spending has declined substantially so far, especially in travel and clothing. They also find that households living in countries which enforced lockdowns earlier expect a higher unemployment rate over the next three to five years.[1]

The remainder of the paper is structured as follows. Section II describes data, stylized facts on NO_2 emissions and their association with economic activity, and econometric methodology. Section III presents our results on the effect of containment measures, and how these effects vary across countries depending on fiscal measures deployed since the pandemic outbreak, and by type of containment measure. The last section concludes.

II. Data, Stylized facts, NO_2 Emissions and Economic Activity, and Methodology

A. Data

We assemble a comprehensive daily database of economic indicators—of which NO_2 emissions takes central focus—as well as containment measures and COVID-19 infections and deaths. Table A1 of the Appendix provides additional details on sources and descriptive statistics.[2]

Economic data

Nitrogen Dioxide (NO_2) emissions. We use daily data on Nitrogen Dioxide (NO_2) emissions from the Air Quality Open Data Platform of the World Air Quality Index (WAQI). Data available on WAQI is collected from countries' respective Environmental Protection Agencies

[1] For theoretical studies examining the effect of containment measures on economic activity see, for example, Eichenbaum, Rebelo and Trabandt (2020) and references therein.

[2] A comprehensive description of all the indicators of economic activity is included in the appendix.

(EPA). The database for NO_2 levels covers 62 countries in total, 50 of which are used for our analysis, with coverage beginning from January 1, 2020. The data is based on the median level of emissions reported by city-specific stations which are updated three times a day. Data on NO_2 pollution is provided in US EPA standards, which mandates that units of measure for NO_2 emissions be parts per billion (ppb). Further, to test the association between the level of NO_2 emissions and economic activity, we use OECD data on total man-made emissions of nitrogen oxides for 37 countries, from 1990 to 2018.

Containment measures data

We use data from the Oxford's COVID-19 Government Response Tracker (OxCGRT) for containment measures. OxCGRT collects information on government policy responses across eight dimensions, namely: (i) school closures; (ii) workplace closures; (iii) public event cancellations; (iv) gathering restrictions; (v) public transportation closures; (vi) stay-at-home orders; (vii) restrictions on internal movement; and (viii) international travel bans. The database scores the stringency of each measure ordinally, for example, depending on whether the measure is a recommendation or a requirement and whether it is targeted or nation-wide. We normalize each measure to range between 0 and 1 to make them comparable. In addition, we compute and aggregate a Stringency Index as the average of the sub-indices, again normalized to range between 0 and 1. The data start on January 1, 2020 and cover 176 countries/regions.

Fiscal measures data

Data on fiscal stimulus (announced and implemented fiscal packages in percent of 2019 GDP) in response to the COVID-19 pandemic are sourced from the IMF policy tracker. The survey is distributed to country authorities to provide information on policy measures implemented since the beginning of the pandemic, ranging from external, financial, fiscal, monetary, and other policy streams. Responses are collected and updated on a weekly basis. The coverage includes 97 IMF member countries.

COVID-19 infections and deaths data

Data on infections and deaths are collected from the COVID-19 Dashboard from the Coronavirus Resource Center of Johns Hopkins University. Coverage begins from January 22, 2020. It provides the location and number of confirmed cases, deaths, and recoveries for 211 affected countries and regions.

Additional controls data

Additional non-pharmaceutical interventions. We include daily data for the following non-pharmaceutical interventions: testing policies, contacting tracing policies, and public information campaigns. The data are collected from OxCGRT and are available for 176 countries from January 1, 2020.

Temperature and humidity. We include daily data on mean temperature and humidity for 95 countries. The data are collected from the Air Quality Open Data Platform and include humidity and temperature for each major city, based on the median of several stations, in 95 countries from January 1, 2020.

Mobility Trends. We collect data on retail and transit-station mobility from Google Mobility Reports. The reports provide daily data by country and highlight the percent change in visits to places related to retail activity (restaurants, cafes, shopping centers, movie theaters, museums, and libraries), or public transport (subways, buses, train stations etc.). The data for each day is reported as the change relative to a baseline value for that corresponding day of the week, and the baseline is calculated as the median value for that corresponding day of the week, during the 5-week period between January 3rd and February 6th, 2020. Daily data are available for over 130 countries, with coverage beginning from February 15, 2020.

B. Stylized Facts

To curb COVID-19 infections and fatalities, governments worldwide put in place containment measures which have ranged from school closures to restrictions on internal movement and stay-at-home orders. The stringency of such measures effectively led to shutdowns of production, manufacturing and transportation sectors, and to lockdowns of cities for prolonged periods of time. This section provides a first look at the data to examine whether containment measures have played a role in the observed decline in economic activity, proxied by NO_2 emissions. We therefore examine NO_2 emissions in four cities before and after the implementation of (national) COVID-19 containment measures: Wuhan (China), Rome (Italy), New York (United States), and Stockholm (Sweden).

Figure 2 presents the pattern of NO_2 emission (left scale) together with the evolution of the stringency indicator (right scale). It shows that emissions significantly declined in three of these four cities after containment measures were put in place. In Wuhan, a dramatic fall in NO_2 levels coincided with the enforcement of the cordon sanitaire on January 22, 2020, and the implementation of containment measures in the days that followed. Measures put in place included restrictions on internal movements and gatherings, stay-at-home orders, closures of public transport, and cancellations of public events. By end-March, emissions were back on the rise, as public transport reopened, and restrictions on internal movement and stay-at-home requirements were relaxed (Figure 2, panel A).

In Rome, the pace of decline in NO_2 emissions quickened (Figure 2, panel B) after containment measures were introduced on February 23, 2020. Measures implemented were restrictive of internal movement, and included school and workplace closures, public gatherings bans, and stay-at-home orders. NO_2 levels fell further following the official lockdown of Italy on March 9, and closures of public transport. Since early May, there is a noticeable uptick in NO_2 emissions, after four containment measures were relaxed (workplace closures, stay-at-home orders, restrictions on internal movement and international travel), and one was lifted (closures of public transport).

In New York, containment measures were tightened drastically by end-March. Initially, containment measures entailed restrictions on international travel, school closures and cancellations of public events. As the outbreak evolved, restrictions on internal movement and on sizes of gatherings, and closure of workplaces were put in place. Consequently, NO_2 emissions fell at a gradual pace and plateaued around their lowest levels after all measures were enforced (Figure 2, Panel C).

Sweden's response to the COVID-19 pandemic has entailed limited containment measures. To-date, five containment measures have been implemented: restrictions on gatherings; school closures; restrictions on international travel; workplace closures; and restrictions on internal movement. With the exception of international travel restrictions, the other four containment measures implemented rank lowest in stringency: schools for younger children are open, bans on public gatherings are for crowds of over fifty people, and restaurants and pubs remained operational. Consequently, NO_2 emissions have not declined significantly in Stockholm (Figure 2, Panel D). Summarizing, preliminary evidence suggests that containment measures have led to a decline in economic activity, as reflected in lower emissions. The next section checks whether this descriptive evidence holds up to more formal tests.

C. NO2 Emissions and Economic Activity

Akin to the literature on the use of lights data to predict economic activity (see Henderson, Storeygard and Weil, 2011, 2012), we establish that NO_2 emissions are strongly associated with the level of economic activity. Using data available from the OECD database for total man-made emissions of nitrogen oxides from 1990-2018, we test the sensitivity of such emissions to conventional measures of economic activity such as GDP growth, growth in manufacturing value added and growth in measures of industrial production. Table 1 shows a robust relationship between these economic variables and NO_2 emissions. The results, available upon request, suggest an even stronger long-run relation between the level of NO_2 emissions and the level of economic activity.

To further validate these results, including for the time-period covered in the analysis of the effect of containment measures, we estimate the relationship between NO_2 emissions and industrial production indices using a monthly database of industrial production indices for 38 countries and monthly levels of NO_2 emissions from January 2019 to July 2020. The results, reported in Table 2, confirm a statistically significant relationship between NO_2 emissions and industrial production at the monthly frequency.[3]

These results help to validate our choice of NO_2 emissions as the main variable of interest for the empirical work in this paper. To summarize: (i) emission levels are directly linked to overall economic activity, and are not indicative of activity for specific sectors only (as flights would be for tourism, for instance); (ii) data are available on a daily frequency, covering a relatively large sample of 50 countries; and (iii) most important, NO_2 emissions are strongly correlated to lower-frequency economic variables which are used in macro-economic analysis, such as GDP growth and industrial production.

D. Methodology

This section describes the empirical methodology used to examine the causal effect of containment measures on economic activity. Establishing causality is difficult in this context because the decision of countries to implement containment measures crucially depends on the evolution of the virus, which in turn may affect mobility and economic activity (Maloney and Taskin 2020). This implies that addressing causality requires the researcher to effectively control for this endogenous response. Failure to control for possible reverse causality would result in biased estimates of the effect of containment measures.

[3] In Table 2, we also present the relationship between NO_2 and industrial production using NO_2 as the explanatory variable to directly translate the effect of containment measures on NO_2 into the effects on industrial production.

We address this issue by controlling for the change in the number of infected cases and deaths the day before implementation of containment measures, as well as for lagged changes in daily economic indicators and in mobility trends. To further account for expectations about the country-specific evolution of the pandemic, we also control for a set of variables which may affect future infections such as daily temperature and humidity levels, other non-pharmaceutical interventions (NPIs)—including enhanced testing, contact tracing and public information campaigns aimed at increasing social awareness, and country-specific time trends. Given lags in the implementation of interventions at daily frequency, this allows one to effectively control for the endogenous response of containment measures to the spread of COVID-19.

Another concern is that containment measures were announced before being implemented and, therefore, were anticipated. This may have resulted in reduced mobility ahead of the implementation of some containment measures and to a bias in the estimates. We control for changes in mobility to address this concern. Further, as an additional reassurance, we include an analysis of the effect international travel restrictions, which were implemented across countries in response to outbreaks in other countries, before changes in mobility and exogenous to domestic conditions.

Two econometric specifications are used to estimate the effect of containment measures on economic activity. The first establishes whether containment measures had, on average, significant effects. The second assesses whether these effects vary across countries depending on country-specific policy responses, such as the magnitude of the fiscal support.

We follow the approach proposed by Jordà (2005) to assess the dynamic cumulative effect of containment measures on economic activity, a methodology used also by Auerbach and Gorodnichenko (2013), Ramey and Zubairy (2018), and Alesina et al. (2019) among others. This procedure does not impose the dynamic restrictions embedded in vector autoregressions and is particularly suited to estimating nonlinearities in the dynamic response. The first regression we estimate is:

$$n_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} c_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h} \tag{2}$$

where $n_{i,t+h}$ represents the logarithm of the daily economic indicator (the level of NO_2 emissions) in country i observed at date t; $c_{i,t}$ is the OxCGRT Stringency Index ($c_{i,t}$); u_i are country-fixed effects to account for time-invariant country-specific characteristics; X is a vector of control variables which includes lags of the containment measures, the amount of number of COVID-19 infections and deaths in country i observed at date t, lagged changes in mobility, and a set of variable which may affect future infections such as daily temperature and humidity levels, other non-pharmaceutical interventions (NPIs)—including enhanced testing, contact tracing and public information campaigns aimed at increasing social awareness, and country-specific time trends.[4]

The second specification allows the response to vary with countries characteristics. It is estimated as follows:

$$n_{i,t+h} = u_i + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} F(z_{i,t}) \Gamma_h{}^L + X'_{i,t} (1 -$$

$$F(z_{i,t}) \Gamma_h{}^H + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta n_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$$

$$\text{with } F(z_{it}) = exp^{-\gamma z_{it}} / (1 - exp^{-\gamma z_{it}}), \quad \gamma > 0 \tag{3}$$

[4] Since emissions are affected by climatic conditions, we include temperature and humidity levels as controls—the results, however, are almost identical excluding these variables. Data are collected from the Air Quality Open Data Platform and include humidity and temperature for each major city, from January 1, 2020.

where z is a country-specific characteristic normalized to have zero mean and a unit variance.

The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given regime. The coefficients $\theta_h^L$and θ_h^H capture the impact of containment measures at each horizon h in cases of very low levels of z $(F(z_{it}) \approx 1$ when z goes to minus infinity) and very high levels of z $(1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively. $F(z_{it})$=0.5 is the cutoff between low and high country-specific policy responses—that is, low and high fiscal stimulus.

This approach is equivalent to the smooth transition autoregressive model developed by Granger and Terävistra (1993). The advantage of this approach is twofold. First, compared with a model in which each dependent variable would be interacted with a measure of country-specific characteristics, it permits a direct test of whether the effect of containment measures varies across different country-specific "regimes". Second, compared with estimating structural vector autoregressions for each regime, it allows the effect of containment measures to vary smoothly across regimes by considering a continuum of states to compute impulse responses, thus making the functions more stable and precise.

Equations (2) and (3) are estimated for each day h=0,..,30. Impulse response functions are computed using the estimated coefficients θ_h, and the 90 and 95 percent confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients θ_h, based on robust standard errors clustered at the country level. Our sample consists of a balanced sample of 50 economies. The data cut-off date is September 18, 2020.

III. Results

A. Impact of Containment on NO_2 Emissions

Figure 3 shows the estimated dynamic response of NO_2 emissions to a unitary change in the aggregate containment stringency index over the 30-day period following the implementation of containment measures, together with the 90 and 95 percent confidence interval around the point estimates. The left-hand panel shows the responses of daily change of NO_2 emissions while the right-hand panel shows the cumulative response (which can be thought of as a proxy for lost output).

The results provide evidence that containment measures have significantly reduced the amount of NO_2 emissions: in countries where stringent containment measures were implemented, these may have reduced the amount of NO_2 emissions cumulatively by almost 99 percent 30 days after their implementation[5], relative to the underlying country-specific path in the absence of intervention. Translating the estimated effect on NO_2 emissions from the results in Table 2, this implies that containment measures may have led to an approximate decline of 10 percent (month-on-month) in industrial production.

We conducted several robustness checks of our main finding. First, we included daily time fixed effects as additional controls. Second, we restrict the data to end on June 1, 2020 so as to exclude data which may capture the relaxing of containment measures and so are able to focus on the lockdown phase of the pandemic exclusively, given that containment measures began to be eased in most countries beyond June. Third, we follow Teulings and Zubanov

[5] As for NO_2, the percent effects are computed as $(e^{\theta_h}-1)*100$. We also find that energy consumption as well as flights are positively correlated with industrial production growth—both correlations are statistically significant at 5 percent.

(2014) and include leads of the stringency index— $\sum_{k=1}^{h}(\varphi_k R_{j,t+k})$, which control for containment measures introduced within the response horizon $t+h$ (for $h>1$). Fourth, to further mitigate reverse causality, we use the contemporaneous change in NO_2 emissions as a control and estimate the impact only after one day of the implementation of containment measures. In all cases, the results are very similar to, and not statistically different from, the baseline (Figure 4). Finally, another concern is related to the potential seasonality of NO_2 emissions. In particular, it could be the case that the level of emissions tends to systematically decline during the first months of the year—the main sample of our analysis. To check for this possibility, we re-estimate the relationship between NO_2 emissions and monthly fixed effects using equation (3), relying on the monthly database of 38 countries from January 2019 to April 2020. The results, not reported, show that, with the exception of October, monthly fixed effects are typically not statistically significant, suggesting that seasonality is not an important empirical issue in our analysis.

B. Role of Fiscal Policy

Governments around the world announced and implemented unprecedented economic measures in response to the COVID-19 pandemic. As of September 18, 2020, more than 90 countries worldwide had deployed (or announced) fiscal measures to mitigate the impact of the pandemic. Fiscal packages were heterogeneous in size, ranging from less than 1 percent of GDP, to as much 12 percent of GDP for Japan and Luxembourg. This section examines whether such measures have been effective in mitigating the negative effects of containment measures, using data on discretionary fiscal measures implemented in response to COVID-19 provided by the *IMF Policy Tracker*. We explore whether the average effect of containment measures varies depending on the magnitude of policy responses deployed.

To examine the role of fiscal stimulus in mitigating the decline in NO_2 emissions, we estimate equation (3) with an interaction term which measures the amount of fiscal stimulus (as a percent of 2019 GDP) deployed since the beginning of the pandemic. The results in Figure 5 show that containment measures have had a larger adverse impact on economic activity in economies with relatively small fiscal packages—equivalent to a 29 percent decline in industrial production. In contrast, the impact is much lower (7 percent) and not statistically different from zero in countries that deployed large fiscal stimulus packages.[6] Consistent with the evidence of Ma, Rogers and Zhou (2020) on previous pandemics, this suggests that fiscal stimulus measures can play a crucial role during the COVID-19 pandemic to mitigate the economic fallout of the crisis.

C. Cost-effectiveness of different containment measures

In this section, we explore how different containment measures compare in terms of economic cost—through their impact on economic activity and effectiveness. Our purpose is to examine which types of containment measures resulted in larger short-term tradeoffs between minimizing health risks and economic losses. This can inform the discussion of how countries should re-open their economies as well as how they can respond to a second wave of infections. For this purpose, we analyze the effects on economic activity and infections, of the following containment measures: (i) school closures; (ii) workplace closures; (iii) cancellation of public events; (iv) restrictions on gatherings sizes ; (v) closures of public transport; (vi) stay-at-home orders; (vii) restrictions on internal movement; and (viii) restrictions on international travel. Moreover, examining the effect of international travel restrictions provides further

[6] The impulse responses under the two regimes are statistically different from each other at 5 percent.

reassurance on the causal effect of containment measures, given that travel restrictions were mostly implemented in response to outbreaks in other countries and ahead of declining mobility, and are therefore exogenous to domestic conditions.

To estimate the effects of different containment measures on infections, we follow the approach used by Deb et al. (2020), and adapt equation (1) to the following:

$$d_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta d_{i,t-\ell} + \varepsilon_{i,t+h} \qquad (4)$$

where $d_{i,t+h}$ and $d_{i,t}$ is the logarithm of the number of infections, in country i observed at date t. $c_{i,t}$ denotes the OxCGRT Stringency Index. u_i are country-fixed effects to account for time-invariant country-specific characteristics (for example, population density, age profile of the population, health capacity, etc.). X is a vector of control variables which includes daily temperature and humidity levels, NPIs, lagged changes in mobility, and country-specific linear, cubic and quadratic time trends[7].

Estimating the overall effect of each measure is challenging, because many of the measures were introduced simultaneously. Following Deb et al. (2020), we use two alternative approaches to gauge the potential magnitude of the effect of each of measure. In the first, we introduce each measure one at a time in equations (2) and (4), respectively. Clearly, the problem with this approach is that the estimates suffer from omitted variable bias. In the second approach, we include them all together. While this approach addresses omitted variable bias, the estimates are likely to be less precise due to multicollinearity.

[7] Lags for each measure are not included here as these were typically one-off and not serially correlated.

The results for the first approach—the effects of each containment measure on economic activity and infections are summarized in Table 3. Figures are reported in Figures 6-7 for the first approach and Figure A1-2 for the second.[8] They suggest that school closures and cancellation of public events are the most effective measures in curbing infections; but also, they are also associated with lower economic costs. The results also suggest that while workplace closures are very effective in curbing infections, they are among the costliest measures. Meanwhile, closures of public transport, though costly in economic terms, do not appear to be as effective in curbing infections. Finally, less costly containment measures, such as restrictions on gathering size, are also not as successful in lowering COVID-19 infections.

IV. Conclusions

Containment measures, though crucial for halting the COVID-19 pandemic, have resulted in large short-term economic losses. In this paper, we provide a first empirical assessment on the impact of COVID-19 containment measures on economic activity, through the use of a novel daily database of economic activity indicators, including Nitrogen Dioxide (NO_2) emissions, international and domestic flights, energy consumption, maritime trade, and mobility indices.

Results suggest that containment measures have had, on average, very large impacts on NO_2 emissions, equivalent to a loss of about 10 percent in industrial production over the 30-day period following the implementation of containment measures. Results for other economic

[8] The results for NO2 are less precisely estimated when including all containment measures together. Reassuringly, however, the effects of international travel restrictions—which are exogenous to domestic conditions—remain statistically significant.

activity indicators suggest that containment measures have had adverse impacts on flights, energy consumption, maritime trade, and retail and transit mobility.

Fiscal measures used during the COVID-19 crisis played an important role in mitigating the impact of containment measures on economic activity: results suggest that short-term economic losses are greater in countries where less fiscal stimulus was deployed.

Among types of containment measure, school closures and cancellation of public events are the most effective in curbing COVID-19 infections and are less costly in terms of their impact on economic activity. However, other highly effective containment measures, such as workplace closures and restrictions on international travel, are among the costliest measures in economic terms.

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Table 1. NO_2 emissions and economic activity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDP growth	0.341**	0.326*	0.307*						
	(2.147)	(1.942)	(1.865)						
Manufacturing VA growth				0.130***	0.134***	0.135***			
				(3.347)	(3.426)	(3.334)			
IP growth							0.203*	0.201**	0.206**
							(2.028)	(2.166)	(2.381)
Time trend	-0.001***	-0.001	0.000	-0.002***	-0.001**	-0.001	-0.002**	0.000	0.001
	(-3.353)	(-1.520)	(0.770)	(-3.352)	(-2.086)	(-1.046)	(-2.348)	(0.638)	(0.919)
Average temperature		-0.012***	-0.011**		-0.011***	-0.011**		-0.010**	-0.012**
		(-3.285)	(-2.521)		(-3.151)	(-2.628)		(-2.214)	(-2.537)
Urban population		-0.004			-0.004			-0.011**	
		(-1.335)			(-1.324)			(-2.088)	
Population Density			-0.001*			-0.001*			-0.002**
			(-1.920)			(-1.896)			(-2.097)
Income per-capita			0.000			0.000			-0.000
			(0.065)			(0.108)			(-1.200)
Log GDP			-0.056						
			(-1.601)						
Log Manufacturing VA						0.005			
						(0.295)			
Log IP									-0.042
									(-1.356)
Constant	-0.005	0.350*	1.763*	0.004	0.380*	0.101	0.006	0.913**	0.558**
	(-0.529)	(1.898)	(1.825)	(0.500)	(1.838)	(0.195)	(0.399)	(2.509)	(2.511)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.061	0.082	0.086	0.051	0.074	0.076	0.058	0.100	0.092
Observations	929	863	828	852	789	775	623	568	566
No. of countries	36	36	36	36	36	36	30	30	30

Standard errors clustered at the country level in parentheses.
*** ρ<0.01, ** ρ<0.05, *** ρ<0.1.

Table 2: NO_2 emissions and Industrial Production

	Industrial Production (percent)	NO_2 emissions (percent)
Variables		
NO_2 emissions (percent)	0.015**	
	(0.006)	
Industrial Production (percent)		0.27*
		(0.151)
Constant	0.004***	0.023***
	(0.0003)	(0.001)
Observations	421	421
R-Squared	0.016	0.005
Number of countries	38	38

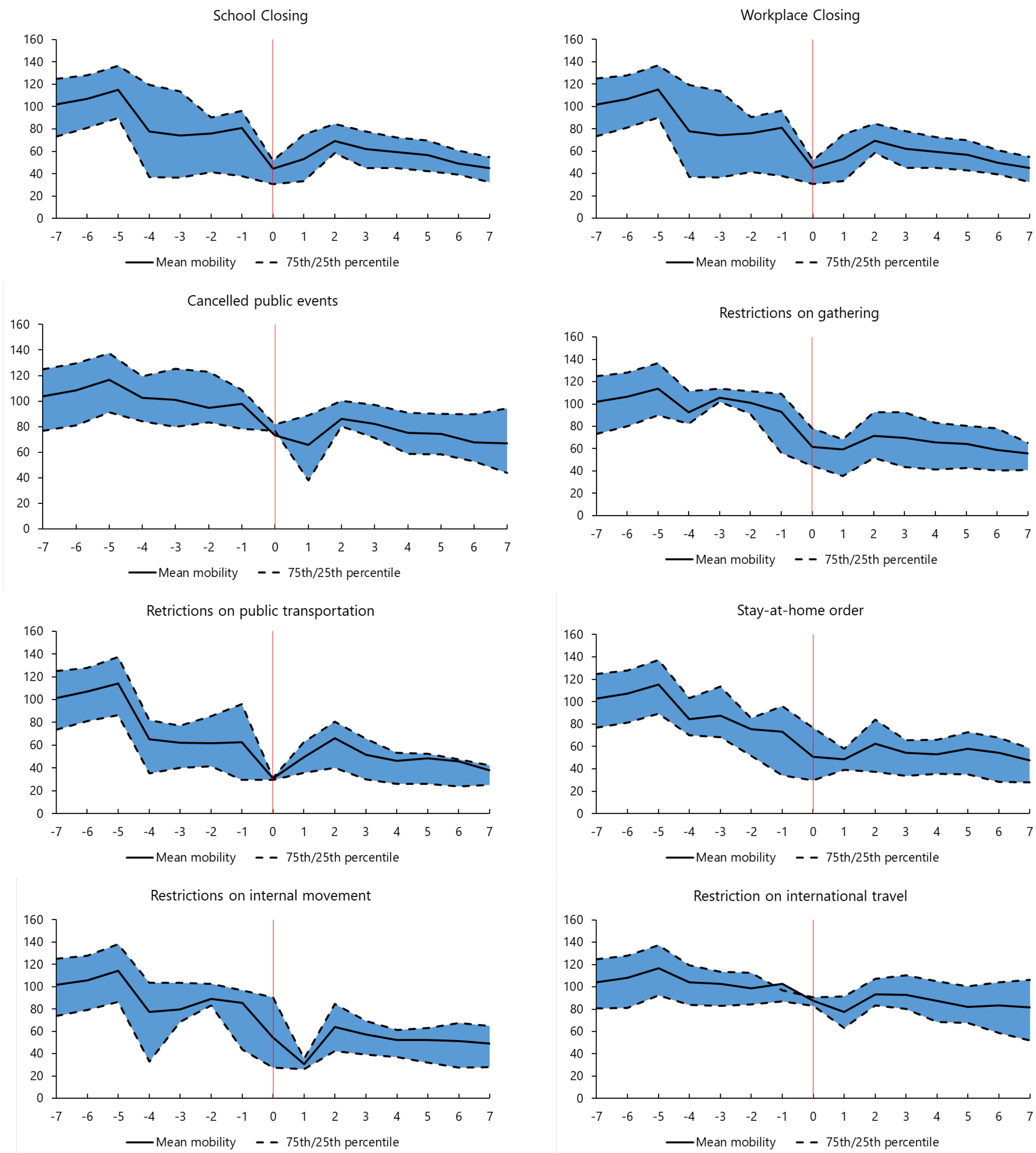
Standard errors clustered at the country level in parentheses.
*** ρ<0.01, ** ρ<0.05, *** ρ<0.1.

Table 3. Cumulative effect of containment measure, 30 days after its introduction (log-percentage points)

	Confirmed Cases	NO_2 emissions
School Closures	-103	-191
Workplace Closures	-81	-256
Cancellation of Events	-77	-1’
International Travel Restrictions	-77	-283
Stay-at-Home Requirements	-74	-286
Bans on Public Gatherings	-56	-128
Restrictions on Internal Movement	-50	-174
Closures of Public Transport	-49	-328

Note: The results denote the cumulative local projection response to NO_2 emissions and confirmed cases to each type of containment measure. ’ denotes that results are **not** significant at the 90 percent level 30 days after the introduction of containment measures. Estimates based on $n_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} c_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ is the logarithm of NO_2 emissions (or infections) in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the index capturing different types containment measures, introduced one at a time; X is a matrix of time varying control variables and country-specific time trends.

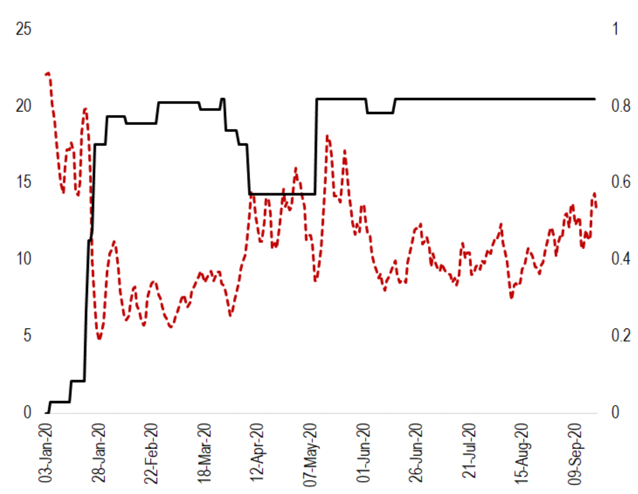
Figure 1. Mobility before and after containment measures (percent deviation from baseline)



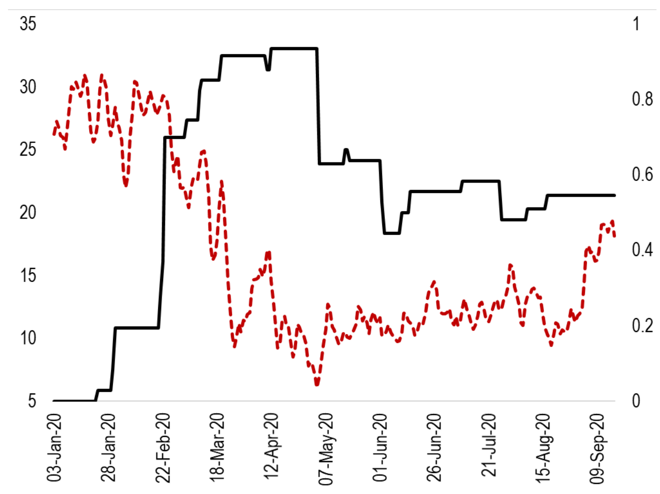
Sources: Apple Mobility Indices, OxCGRT Stringency Index and IMF Staff calculations. An index =100 suggest no decline in mobility compared to trend.

Figure 2. NO_2 Emissions and Containment Measures Stringency Indices, Selected Cities

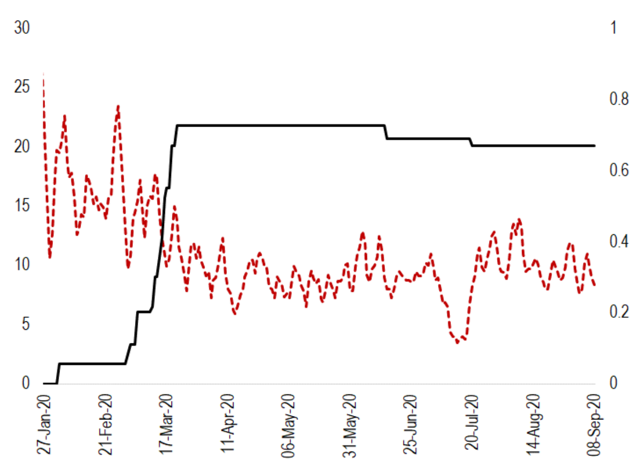
Panel A. Wuhan, China



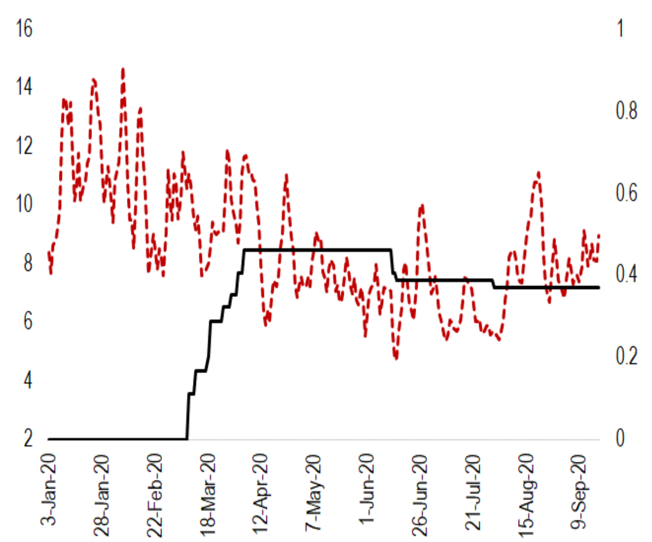
Panel B. Rome, Italy



Panel C. New York, USA



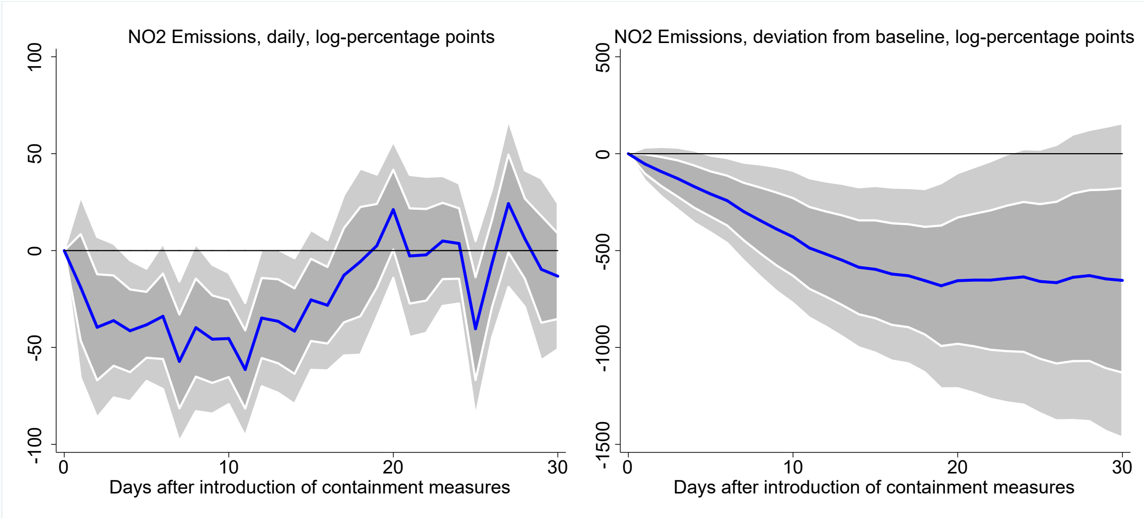
Panel D. Stockholm, Sweden



NO2 Emissions — Containment Measures Stringency Index (RHS Y-Axis)

Note: This figure plots NO_2 emissions (in parts per billion) and containment measures' stringency indices (in levels) per country, from January 3, 2020 to June 15, 2020. Emissions are smoothed with a five-day moving average to remove excess volatility.

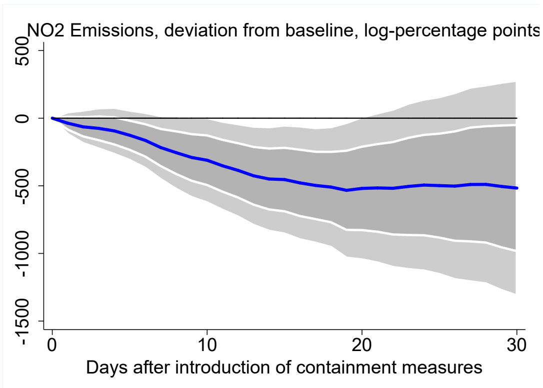
Figure 3. Effect of Containment Measures on Total Nitrogen Dioxide (NO_2) Emissions



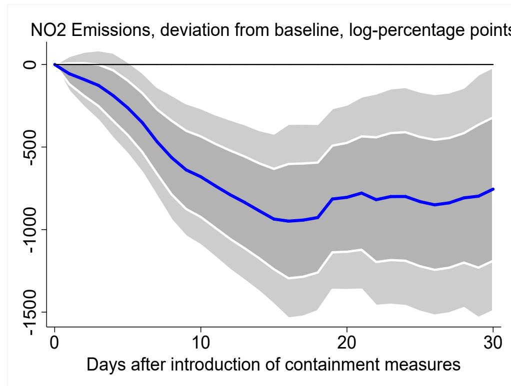
Note. Impulse response functions are estimated for a sample of 50 countries using daily data from January 1, 2020. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $n_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} c_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ is the logarithm of NO_2 emissions in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the index capturing the level of containment measures; X is a matrix of time varying control variables and country specific time trends.

Figure 4. Robustness checks

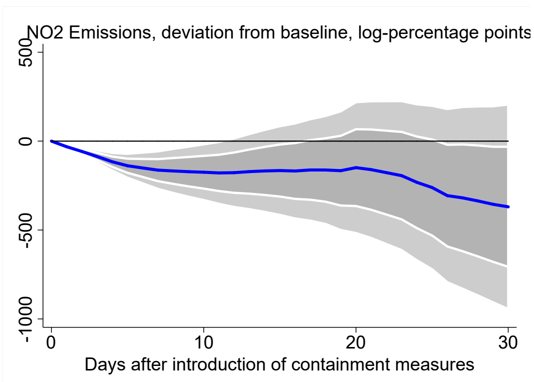
(a): With Time-Fixed Effects



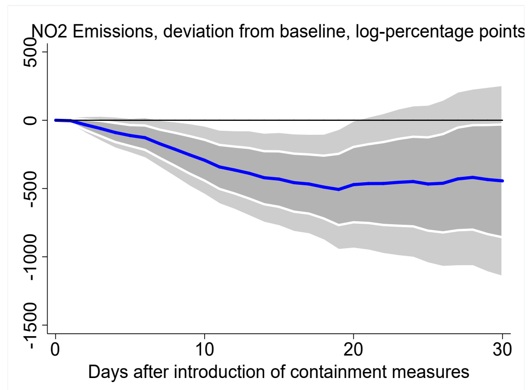
(b): With data restricted to lockdown periods only



(c): With leads of Stringency Index

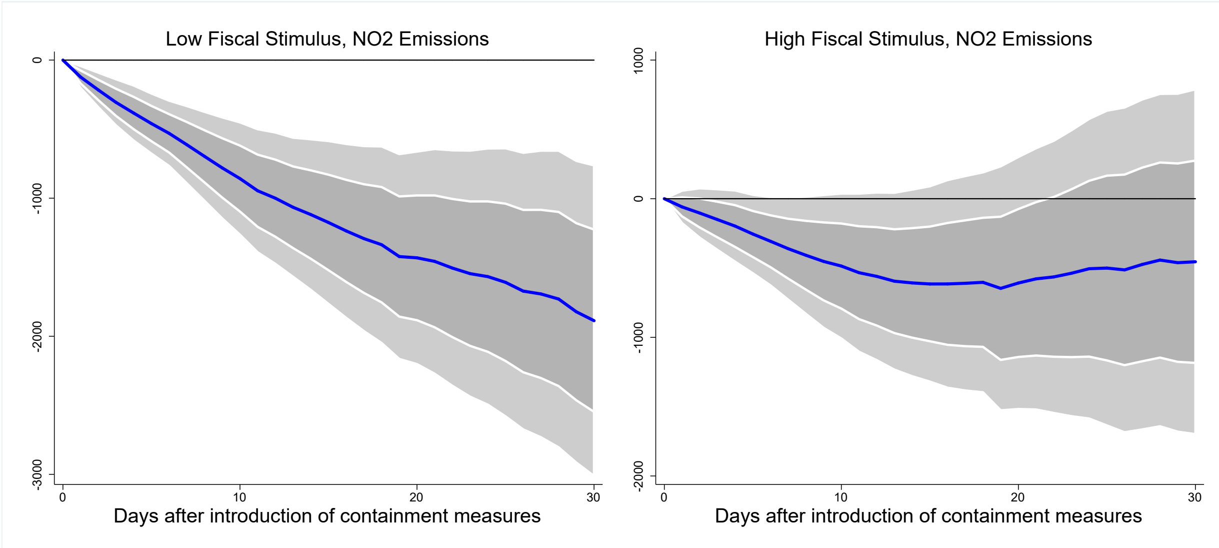


(d): With Contemporaneous NO_2 emissions



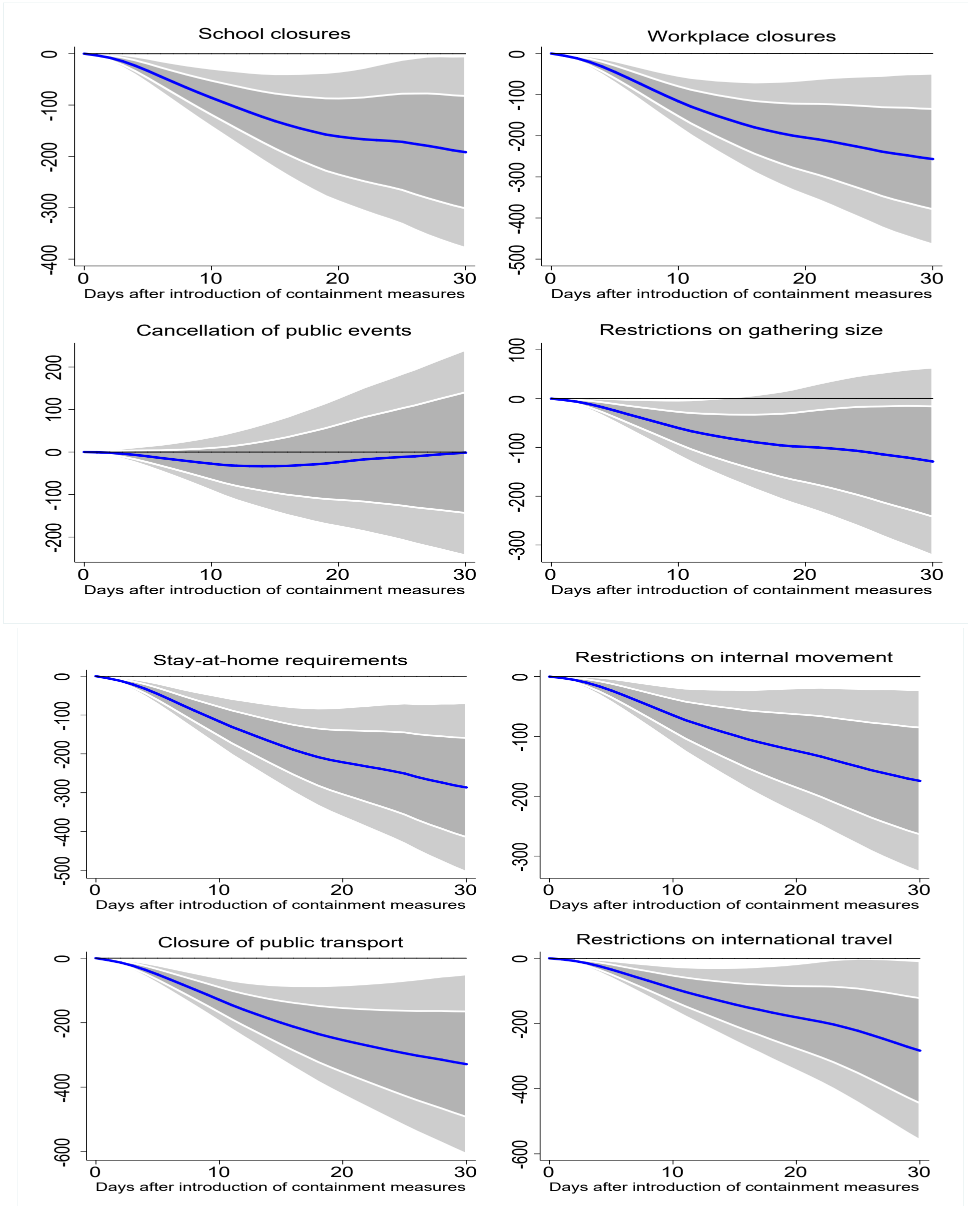
Note: Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $n_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} c_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ is the logarithm of NO_2 emissions in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific time trends.

Figure 5. Effect of Containment Measures on NO_2 Emissions, Interaction with Fiscal Measures



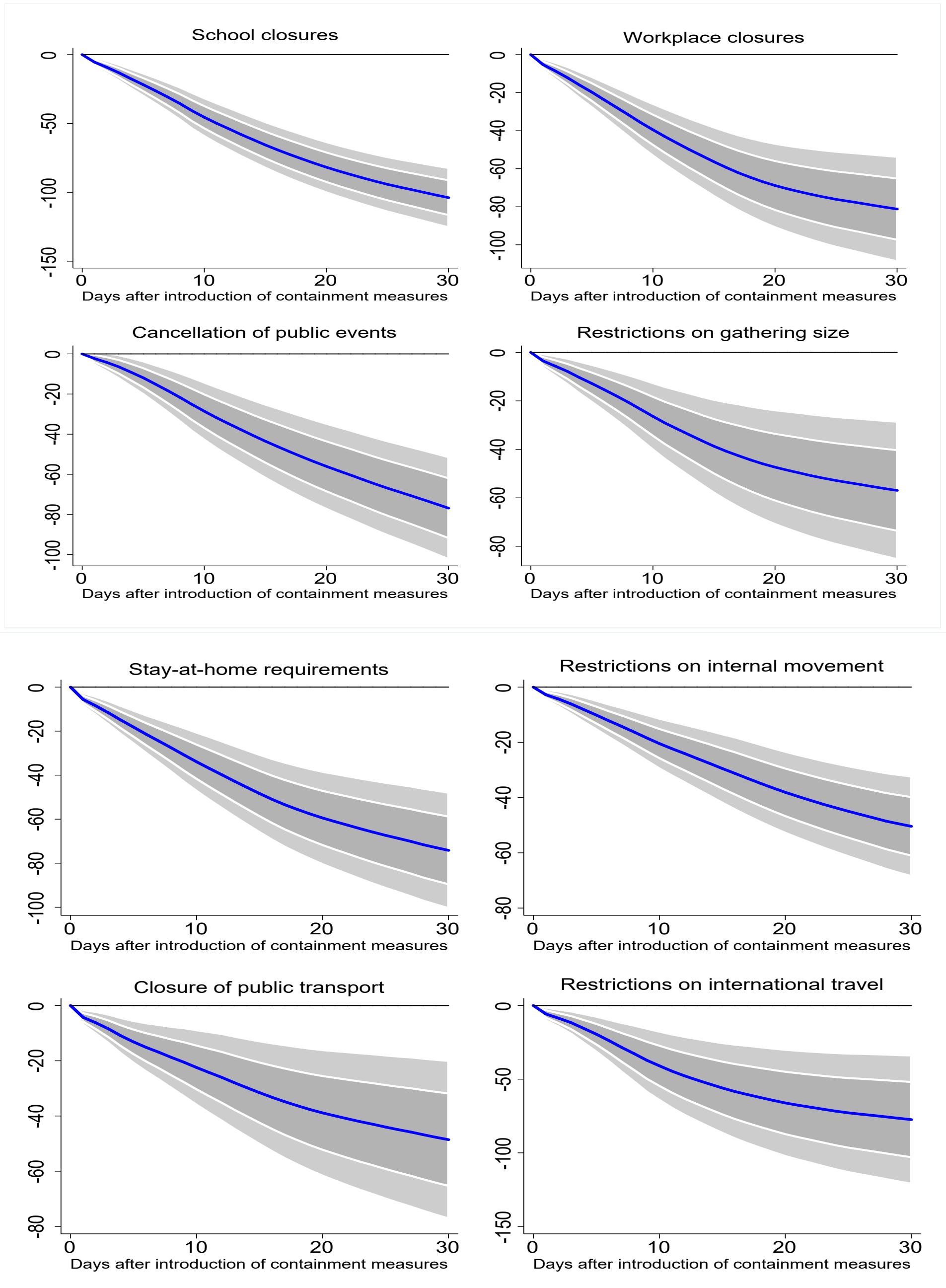
Note. Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $n_{i,t+h} = u_i + u_t + \theta_h^L F(z_{i,t})c_{i,t} + \theta_h^H (1 - F(z_{i,t}))c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell}\Delta n_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}}(1 - F(z_{i,t}))\psi_{h,\ell}\Delta n_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} \Theta_{h,\ell} c_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $n_{i,t}$ is the logarithm of NO_2 emissions in country i observed at date t and z is the country-specific characteristics normalized to have zero mean and a unit variance. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific time trends.

Figure 6. Local projection response of NO_2 emissions to types of containment measures (one by one)



Note: Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ is the logarithm of NO_2 emissions in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the index capturing different types containment and mitigation measures, introduced one at a time; X is a matrix of time varying control variables and country time trends.

Figure 7. Local projection response of infections to containment measures (one by one)



Note: Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response 30 days after the containment measures. Estimates based on $d_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta d_{i,t-\ell} + \varepsilon_{i,t+h}$and $d_{i,t}$ is the logarithm of COVID-19 infections in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the index capturing different types containment and mitigation measures, introduced one at a time; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends.

Appendix

A. Data

We present here a comprehensive daily database of high-frequency indicators of economic activity.

Flights. Flight data are collected from FlightRadar24, which provides real-time information on worldwide flights from several data sources, including automatic dependent surveillance-broadcast (ADS-B), (Multilateration) MLAT and radar data. The database covers international and domestic inbound and outbound flights data for over 200 countries, 84 of which are used in our analysis. Data coverage is on a daily frequency and begins on January 1, 2020. Data for total flights is calculated by summing daily domestic and international flights.

Energy consumption. We use daily data on energy consumption for 33 countries in Europe from ENTSO-E's transparency platform. The platform provides hourly total load of electricity generated per market time unit by plants covered by Transmission System Operators (TSO) and Distribution System Operators (DSO) networks. Coverage in our sample begins from January 1, 2020 and ends on August 1,2020.

Maritime imports and exports indices. For maritime import and export indices, we use data from Cerdeiro, Komaromi, Lui and Saeed (2020), who build real-time indicators of world seaborne trade using raw Automatic Identification System (AIS) signals emitted by global vessel fleets through their transponders. They use machine-learning techniques to transform AIS data, which contain information on vessels' speed, location, draught, etc., into import and export maritime indices.

Their database produces import and export indices for 22 countries. Data coverage begins on January 1, 2020.

B. Impact of Containment Measures on Other Indicators of Economic Activity

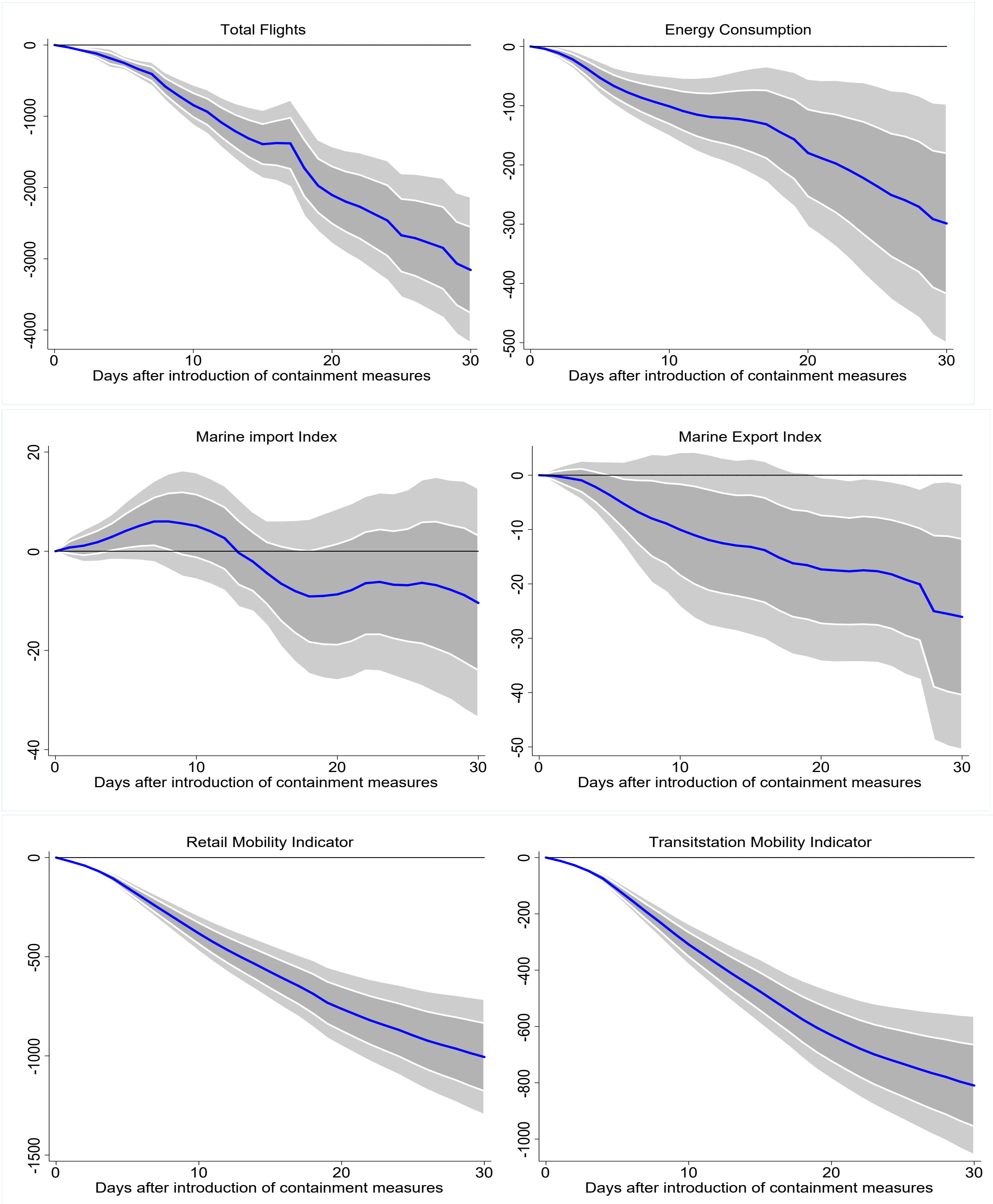
We also examine whether containment measures have had an impact on other indicators of economic activity, namely: (i) flights; (ii) energy consumption; (iii) maritime import and export indices; and (iv) retail and transit mobility indices. These variables can shed light on the effect of containment measures on different sectors of the economy, such as tourism, trade, and retail consumption.

Results for equation (2) for each indicator are reported in Figure A1. They suggest that the impact of containment measures has been overwhelmingly adverse across all sectors, and most importantly tourism. Specifically, the results indicate that containment measures have reduced the total number international and domestic flights by more than 99 percent in the 30-day period following the implementation of containment measures. Total energy consumed has declined by more than 95 percent; maritime imports and exports have been reduced by around 30 percent, though the impact is more pronounced and significant on exports; retail and transit mobility have been reduced by more than 400 percentage points relative to country-specific paths in the absence of intervention.

Table A1. Summary Statistics

	Obs.	Mean	Min	Max	Std. Dev.	Source	Starting Date	N. of countries
NO_2 emissions (log)	15,208	1.8	-0.9	3.7	0.6	Air Quality Open Data Platform	1-Jan-20	62
Total Flights (log)	55,994	3.2	0.0	10.8	2.1	FlightRadar24	1-Jan-20	218
Retail Mobility (%)	28,145	-0.2	-0.9	0.8	0.3	Google Mobility Index	15-Feb-20	135
Transit Station Mobility (%)	28,138	-0.3	-1.0	0.3	1.25	Google Mobility Index	15-Feb-20	134
Maritime Import Index (log)	5,654	4.5	3.6	4.9	0.1	Cerdeiro, Komaromi, Lui and Saeed (2020)	1-Jan-20	22
Maritime Export Index (log)	5,544	4.6	4	5	0.1	Cerdeiro, Komaromi, Lui and Saeed (2020)	1-Jan-20	22
Energy Consumption (log)	8,576	12.1	8.3	15.6	1.5	ENTSO-E	1-Jan-20	33
Confirmed Cases (log)	41,151	6.9	-0.9	15.7	3.2	Coronavirus Resource Center of JHU	21-Jan-20	211
Confirmed Deaths (log)	32,846	4.2	-1.9	12.2	2.7	Coronavirus Resource Center of JHU	22-Jan-20	186
Stringency of Measures Index (%)	47,946	0.4	0	1	0.3	OxCGRT.	1-Jan-20	176
Fiscal Stimulus (% of GDP)	25,509	3.3	0	12.1	3.1	IMF Policy Tracker	1-Jan-20	97
Public Awareness Campaigns (levels)	46,641	1.5	0	2	0.8	OxCGRT.	1-Jan-20	176
Testing Policies (levels)	46,433	1.3	0	3	0.9	OxCGRT.	1-Jan-20	175
Contact Tracing (levels)	46,429	1.1	0	2	0.8	OxCGRT.	1-Jan-20	176
Humidity (levels)	21,603	67.4	7	99	16	Air Quality Open Data Platform	1-Jan-20	95
Temperature (levels)	21.652	18	-30	41	9	Air Quality Open Data Platform	1-Jan-20	95

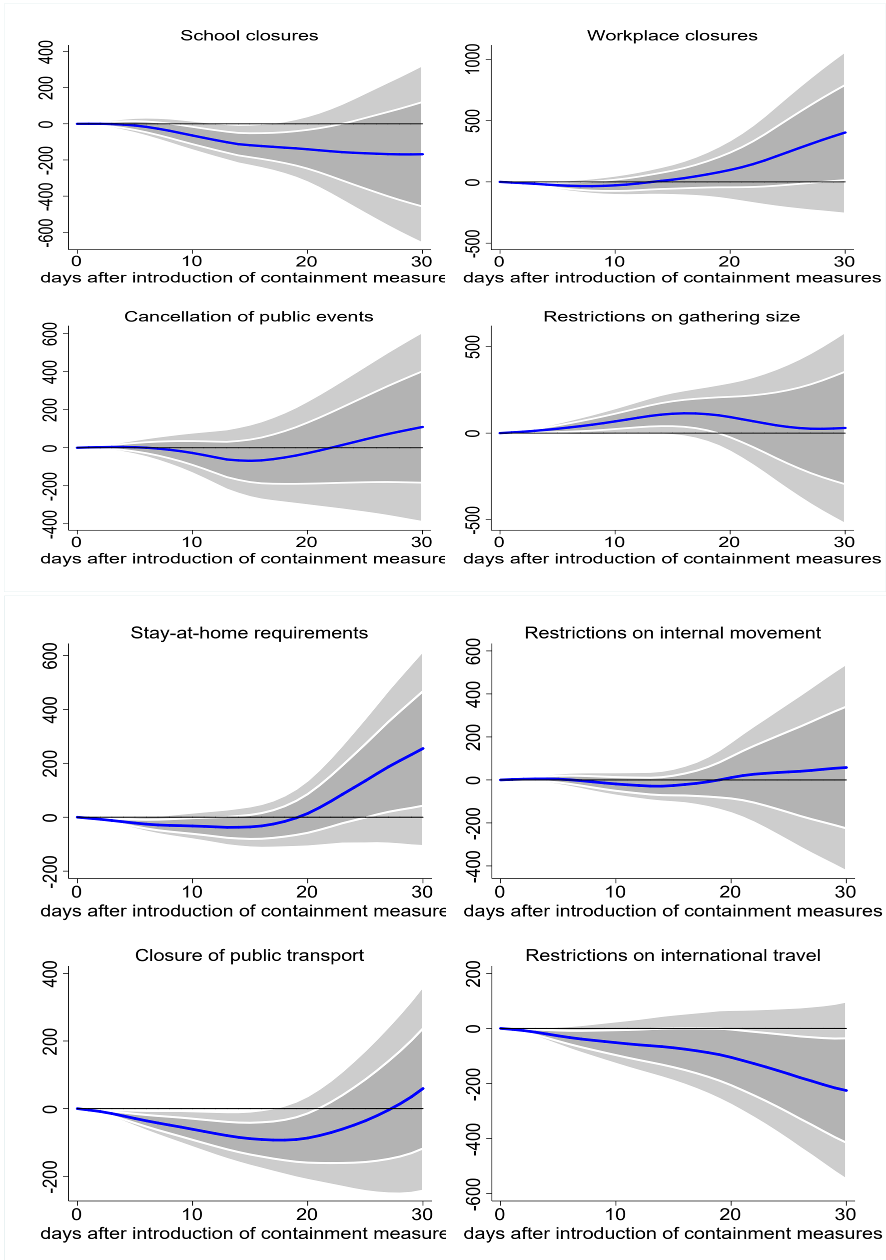
Figure A1. Local projection response of alternative economic indicators



Note: Impulse response functions are estimated using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures.

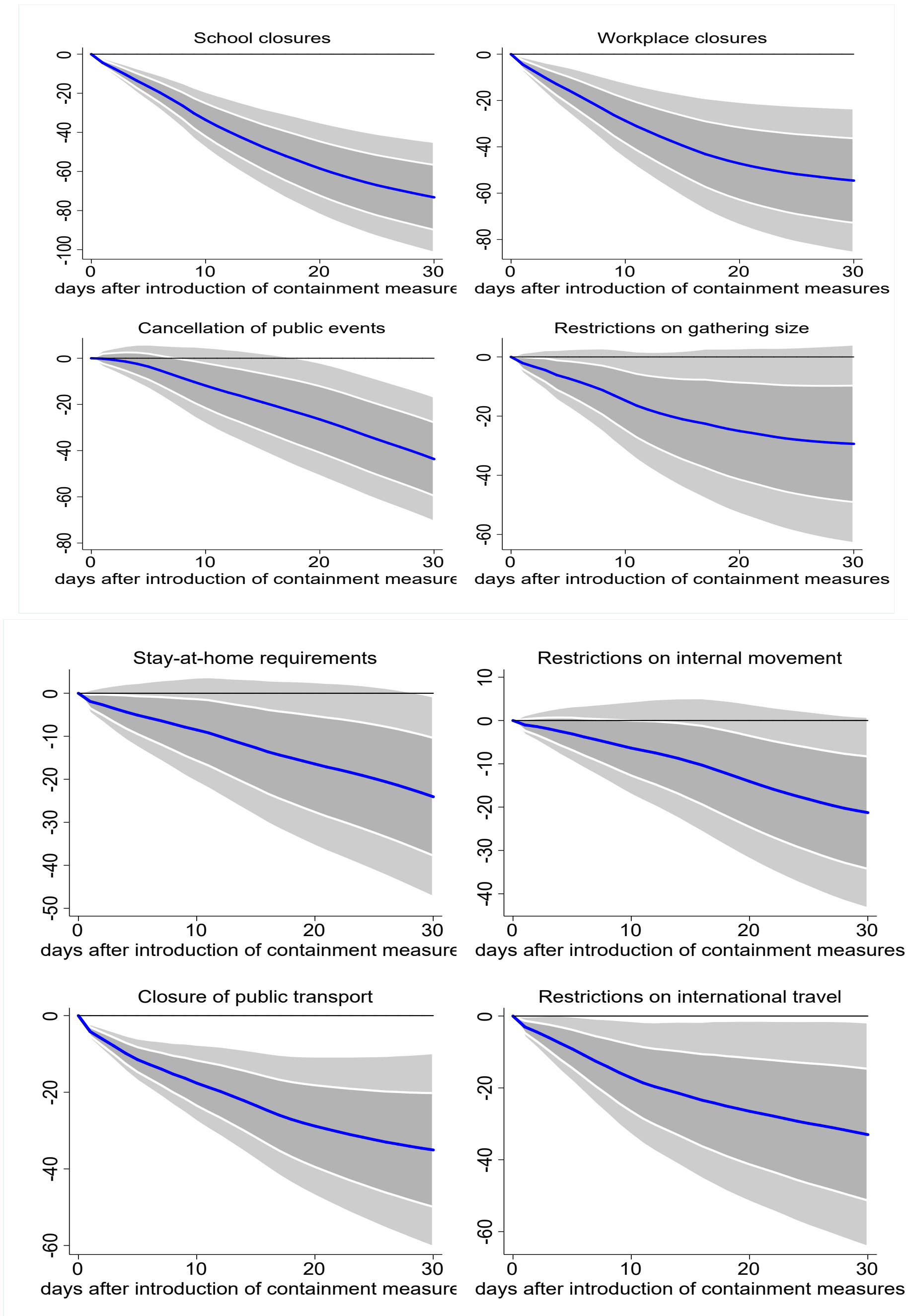
Estimates based on $n_{i,t+h} = u_i + \sum_{\ell=0}^{\mathcal{L}} \theta_{h,\ell} c_{i,t-\ell} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ is the logarithm of NO_2 emissions in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific time trends.

Figure A2. Local projection response of NO_2 emissions to containment measures (all together)



Note: Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $n_{i,t}$ the logarithm of the number of NO_2 emissions in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \ldots H$, with a lag structure $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the index capturing different types containment and mitigation measures, introduced altogether; X is a matrix of time varying control variables and country specific time trends.

Figure A3. Local projection response of infections to containment measures (all together)



Note: Impulse response functions are estimated using a sample of 50 countries using daily data from the start of the outbreak. The graph shows the response and confidence bands at 90 and 95 percent. The horizontal axis shows the response x days after the containment measures. Estimates based on $d_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta d_{i,t-\ell} + \varepsilon_{i,t+h}$ where $d_{i,t}$ the logarithm of the number of COVID-19 infections in country i observed at date t. The model is estimated at each horizon $h = 0, 1, \dots H$, with a lag structure $\ell = 1, 2 \dots \mathcal{L}$; $c_{i,t}$ is the index capturing different types containment and mitigation measures, introduced altogether; X is a matrix of time varying control variables and country specific time trends.