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The Economic Effects of COVID-19 Containment Measures*

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Abstract

Containment measures are crucial to halt the spread of the 2019 COVID-19 pandemic but entail large short-term economic costs. This paper tries to quantify these effects using daily global data on real-time containment measures and indicators of economic activity such as Nitrogen Dioxide (NO_2) emissions, flights, energy consumption, maritime trade, and mobility indices. Results suggest that containment measures have had, on average, a very large impact on economic activity—equivalent to a loss of about 15 percent in industrial production over a 30-day period following their implementation. Using novel data on fiscal and monetary policy measures used in response to the crisis, we find that these policy measures were effective in mitigating some of these economic costs. We also find that while workplace closures and stay-at-home orders are more effective in curbing infections, they are associated with the largest economic costs. Finally, while easing of containment measures has led to a pickup in economic activity, the effect has been lower (in absolute value) than that from the tightening of measures.

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Table of Contents

I. INTRODUCTION

Many countries around the world have enacted stringent containment measures and non-pharmaceutical interventions (NPIs) to halt the spread of the coronavirus (COVID-19) and limit the number of fatalities, in a bid to avoid overwhelming the medical system and to buy time while effective treatments and vaccines are developed. Interventions have ranged from improved diagnostic testing and contact tracing, isolation and quarantine for infected people, and 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" and significantly reducing the number of fatalities. In particular, they find that countries that have put in place stringent measures, for example those implemented in countries such as China and Italy, as well as early intervention, such as in New Zealand and Vietnam, may have reduced the number of confirmed cases and deaths 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, and have therefore provided the foundation for a stronger medium-term growth (see Barro, Ursua and Weng, (2020)), they have led to unprecedented economic losses in the short term. Quantifying these short-term economic effects and whether they vary across types of containment measure is of paramount importance for many policymakers around the world facing a painful short-term tradeoff between normalizing economic activity and minimizing health risks.

This paper tries to address these issues empirically. In particular, the paper has four main goals. The first is 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 around the world as well as a unique database containing daily data on several indicators of economic activity: 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 retail 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 address 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. Indeed, 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. To further account for expectations about the country-specific evolution of the pandemic, we also control for country-specific linear, quadratic, and cubic time trends time trends.

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 an upward bias in the estimates. We show that controlling for mobility does not quantitatively change the results.

Further, as an additional reassurance, we include an analysis of the effect international travel restrictions on COVID-19 infections, which were implemented across countries in response to outbreaks in other countries—and before changes in mobility.

The results of this analysis suggest that containment measures have had, on average, a very large impact on economic activity—equivalent to a loss of about 15 percent in industrial production over the 30-day period following the implementation of the containment measure.

The second goal of the paper is to examine whether fiscal and monetary measures implemented by many governments and central banks around the world have been effective so far in mitigating the negative effects of containment measures. To answer this question, we use data provided by the *IMF Policy Tracker* which compiles discretionary fiscal and monetary measures implemented in response to COVID-19. The results suggest that macroeconomic stimulus deployed so far has been effective, with the negative effect of containment measures being much larger—equivalent to a loss in industrial production of about 22 percent—in countries that have provided limited fiscal and monetary policy stimulus.

The third goal of the paper is to examine which types of containment measure 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 part of the country's response to limit the spread of the virus, preliminary evidence suggest that workplace closures, cancellations of events, and stay-at-home requirements, the containment measures which are most effective in curbing infections, are also the costliest in economic terms. In contrast, restrictions on international travel are the least costly but still successful in lowering COVID-19 infections.

The fourth goal of this paper is to assess the effects of re-openings—i.e. exiting the lockdown phase of the COVID-19 pandemic by easing containment measures. For this, we use recent data for countries where containment measures are being loosened after having peaked in stringency. The results suggest that while the loosening of containment measures has sizeable effects on economic activity —equivalent to about a 7 percent increase in industrial production, its effect on economic activity is much smaller (in absolute value) than that of the tightening of containment measures.

This paper contributes to two strands of literature. The first is on the use high-frequency daily economic indicators to monitor economic activity. 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. Marjanovic et al. (2016) uses Extreme Machine Learning (EML) and Genetic Programming (GP) to predict GDP based on CO_2 emissions. Other notable empirical approaches using novel high-frequency indicators include Small et al. (2010), who show that stable night lights data can act as a proxy for urban development. Cerdeiro, Komaromi, Lui and Saeed (2020) use raw Automatic Identification System (AIS) signals emitted by global vessel fleets to create real-time indicators of world seaborne trade.

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, possibly because they were not enforced for long enough. 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 et al. (2020) draw lessons for the COVID-19 pandemic from examining the immediate and bounce-back effects of six past health crises: the 1968 Flu (also referred to as the Hong Kong 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, with the negative impact on GDP being reduced in countries that deployed large first-year responses in government spending and health care. Coibion et al. (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 stylized facts, data and econometric methodology. Section III presents our results on the effect of

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

containment measures, and how these effects vary across countries, depending on fiscal and monetary measures deployed since the pandemic outbreak, by type of containment measure, and the effects of easing containment measures. The last section concludes.

II. STYLIZED FACTS, DATA AND METHODOLOGY

A. Data

We assemble a comprehensive daily database of economic indicators, containment measures and COVID-19 infections and deaths. Table 1 provides the country coverage of each variable and key summary statistics.

Economic data

Nitrogen Dioxide ($\boldsymbol{NO_2}$) 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 (EPA). The database for NO_2 levels covers 62 countries in total, 57 of which are used for our analysis, with coverage beginning from January 1, 2020.[2] The data is based on the median 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).

We use NO_2 emissions as our main variable of interest for the empirical work in this paper, for three reasons: (i) NO_2 emissions are strongly correlated to lower-frequency

[2] *COVID-19 Worldwide Air Quality Data*. Accessed May 7, 2020. https://aqicn.org/data-platform/COVID-19/report/

economic variables which are used in macro-economic analysis, such as industrial production (see next section); (ii) emission levels can be directly linked to overall economic activity, and are not indicative of activity for specific sectors only (as flights would be for tourism, for instance); (iii) data are available on a daily frequency, covering a relatively large sample of 57 countries. That said, we present the effect of containment measures on the following set of daily indicators:

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.[3] 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 35 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.

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

[3] https://www.flightradar24.com/how-it-works

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.

Retail and transit-station mobility. 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 73 countries in our dataset, with coverage beginning from February 15, 2020.

Containment measures

We use data from Oxford's COVID-19 Government Response Tracker4 (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

[4] "Coronavirus Government Response Tracker." Blavatnik School of Government. Accessed May 7, 2020. https://www.bsg.ox.ac.uk/research/research-projects/coronavirus-government-response-tracker.

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 151 countries/regions.

Fiscal and monetary policy measures

Data on fiscal stimulus (announced and implemented fiscal packages in percent of GDP) and monetary policy actions (change in policy rates) implemented 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 195 IMF member countries.

COVID-19 infections and deaths

Data on infections and deaths are collected from the COVID-19 Dashboard from the Coronavirus Resource Center of Johns Hopkins University.[5] Coverage begins from January 22, 2020. It provides the location and number of confirmed cases, deaths, and recoveries for 208 affected countries and regions.

B. Stylized Facts

[5] COVID-19 Map, JHU Coronavirus Resource Center, Accessed May 7, 2020 https://coronavirus.jhu.edu/map.html.

In order to curb COVID-19 infection and fatality rates, governments worldwide put in place containment measures which have ranged from school closures and cancellations of public gatherings, 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 many 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. To do so, we examine the levels of NO_2 emissions in four cities before and after the implementation of (national) containment measures to fight the COVID-19 outbreak: Wuhan (China), Rome (Italy), New York (United States), and Stockholm (Sweden).

Figure 1 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 these four cities after containment measures have been 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 the stringent containment measures in the days that followed. Measures which were put in place within a week of the cordon sanitaire included restrictions on internal movements and gatherings, stay-at-home orders, closures of public transport, and cancellations of public events. By the end of March, emissions were back on the rise, as public transport areas reopened, and restrictions on internal movement and stay-at-home requirements were relaxed but have fallen again since as containment measures were tightened again in early May (Figure 1A).

In Rome, the pace of decline in NO_2 emissions picked up significantly towards end-February (Figure 1B) as a result of containment measures introduced on February 23, 2020.

Measures implemented were highly restrictive of internal movement, and, as in Wuhan, included school and workplace closures, cancellation of public gatherings, restrictions on internal movements and gatherings, and stay-at-home orders. NO_2 levels fell even further following the official lockdown of Italy on March 9, and closures of public transport. There is a noticeable uptick in NO_2 emissions since early May, after four containment measures were relaxed (workplace closures, stay-at-home orders, and restrictions on internal movement and international travel), and one was lifted (closures of public transport).

In New York, containment measures were only 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 movements and the size of gatherings were put in place. Closure of workplaces was the last type of containment measure to be enforced. Consequently, NO_2 emissions fell at a gradual pace and have since plateaued around their lowest levels only after all measures were enforced and have not yet been relaxed (Figure 1C).

Sweden's unique response to the COVID-19 pandemic has entailed limited containment measures. To-date, five containment measures have been implemented in the following order: restrictions on gatherings; school closures; restrictions on international travel; workplace closures; and restrictions on internal movement. However, 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, cafes and pubs remain operational, but must enforce social distancing. Because of less stringent containment measures, it is perhaps unsurprising that NO_2 emissions have not declined significantly in Stockholm (Figure 1D). Summarizing, preliminary evidence seems to suggest 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. 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.

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. 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 the virus. To further account for expectations about the country-specific evolution of the pandemic, we also control for country-specific time trends.

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 and monetary policy 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:

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

where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ is the logarithm of the daily economic indicator (NO_2 emissions in the baseline) in country i observed at date t.[6] $c_{i,t}$ denotes the OxCGRT Stringency Index. u_i are country-fixed effects to account for time-invariant country-specific characteristics. X is a vector of control variables which includes the amount of number of COVID-19 infections and deaths in country i observed at date t, daily temperature and humidity levels, and country-specific linear, cubic and quadratic time trends.[7]

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

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

[6] Given the large volatility in the daily economic indicators, we smooth their time series using a 5-day moving average. However, the results are very similar when using non-smoothed series (see Appendix Figure A2 for NO_2 emissions).

[7] Since emissions are affected by climatic conditions, in the analysis using NO_2 as a dependent variable 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, based on the median of several stations, from January 1, 2020.

with $F(z_{it}) = exp^{-\gamma z_{it}}/(1 - exp^{-\gamma z_{it}}), \quad \gamma > 0$ (2)

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 state of the economy. The coefficients θ_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, for example, 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 (1 and 2) are estimated for each day h=0,..,30. Impulse response functions are computed using the estimated coefficients θ_h, and the 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 57 economies with at least 30 observation days after a significant outbreak (100 cases). The data cut-off date is June 15, 2020.

III. RESULTS

A. Baseline

Figure 2 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 the containment measure, together with the 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. They suggest that in countries where stringent containment measures have been implemented, these may have reduced the amount of NO_2 emissions cumulatively by almost 99 percent 30 days after the implementation, relative to the underlying country-specific path in the absence of intervention.

B. NO_2 emissions and Industrial Production

In order to translate the drop in NO_2 emissions to losses in economic activity, 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 April 2020. The panel regression is estimated as follows:

$$\Delta IP_{i,t} = \alpha + \beta \Delta NO_2 + \mu_i + \varepsilon_{i,t} \qquad (3)$$

where $\Delta IP_{i,t}$ is the monthly growth rate of industrial production, and ΔNO_2 is the monthly growth rate of NO_2 emissions. The results show that a one percent drop in NO_2 emissions is associated with a 0.015 percent decline in industrial production.[8] Translating the estimated effect on NO_2 presented before, this implies that containment measures may have led to a 15 percent decline (month-on-month) of industrial production.

C. Robustness checks

We conducted several robustness checks of our main finding. First, we included additional controls in the regressions such as daily time fixed effects. Second, we repeated the analysis adding retail or transit mobility as controls to account for the fact that in many cases, containment measures were anticipated and often announced before implementation. This may

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[8] $\underset{(0.035)}{\Delta IP_{i,t} = 0.357} + \underset{(0.006)}{0.015} * \Delta NO_2$, with parenthesis denoting standard errors clustered at the country level.
The results is consistent with previous studies highlighting a strong positive correlation between industrialization and emissions of pollutants, including NO_2 emissions (see, for example, Akimoto 2003; Cherniwchan 2012).

have reduced mobility ahead of the enforcement of containment measures (Figure A1), thus biasing the baseline estimates.[9] Third, we follow Teulings and Zubanov (2014) and include leads of the stringency index— $\sum_{k=1}^{h}\left(\varphi_k R_{j,t+k}\right)$, 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 3)[10].

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 estimate the relationship between NO_2 emissions and monthly fixed effects using a monthly database of 38 countries from January 2019 to June 2020. The results, not reported, show that (with the exception of July and October) monthly fixed effects are typically not statistically significant, suggesting that seasonality is not an important empirical issue in our analysis.

D. Impact of containment on other indicators of economic activity

In this section, we examine whether containment measures have had an impact on other indicators of economic activity. Namely, we focus on the impact of stringency measures on: (i) total flights; (ii) energy consumption; (iii) maritime import indices; (iv) maritime export

[9] We also tested the robustness of these results by including contemporaneous mobility controls, and different lags to mobility, and found the results very robust.

[10] We also repeated the analysis excluding China from the sample. This is due to the fact that containment measures were introduced first in China, therefore creating a risk that the longer-term (30 days) results may simply reflect the decline in economic activity in China. The results (not reported) are very similar to the baseline.

indices; (v) retail mobility indices; and (vi) transit indices. These variables can shed lights on the effect of containment measure on different sectors of the economy, such as tourism, trade, and retail consumption.

Results for equation (1) for each indicator are reported in Figure 4. 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.[11] [12]

E. Role of macro policy responses in mitigating the fallout in economic activity

Governments and central banks around the world have implemented unprecedented economic measures in response to the COVID-19 pandemic. This section examines whether such measures have been effective in mitigating the negative effects of containment measures, using data on discretionary fiscal and monetary measures implemented in response to COVID-

[11] As for NO2, 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.

[12] Data for mobility indices are provided initially as percent deviation from the baseline. The results presented are therefore cumulative percentage points.

19 provided by the *IMF Policy Tracker*. We explore whether the average effect of containment measures varies depending on the magnitude of country policy responses deployed.

Fiscal stimulus

As of June 15, 2020, more than 90 countries worldwide had deployed (or announced) fiscal measures to mitigate the impact of the pandemic. Fiscal packages have been heterogeneous in size, ranging from less than 1 percent of GDP, to as much 12 percent of GDP for economies such as El Salvador, Japan, Luxembourg, and Macao SAR (Figure 5, Panel A). On average, fiscal stimulus used in Advanced Economies (AEs) averaged at 5 percent of GDP, compared to 2.3 percent in Emerging Market and Developing Economies (EMDEs).

To examine the role of fiscal stimulus in mitigating the decline in NO_2 emissions, we estimate equation (2) with an interaction term which measures the amount of fiscal stimulus (as a percent of GDP) deployed since the beginning of the pandemic. The results in Figure 6 (top panel) show that containment measures have had a much larger adverse impact on economic activity in countries with relatively small fiscal packages—equivalent to a 22 percent decline in industrial production. In contrast, the impact is not statistically different from zero in countries that deployed large fiscal stimulus packages.[13] Consistent with the evidence of Ma et al. (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.

[13] The impulse responses under the two regimes are statistically different from each other.

Policy interest rate cuts

Policy rates have been reduced in 97 countries from January 2019 to-date (Figure 5B). With policy rates closer to zero-lower-bound in AEs, policy rate cuts were much larger in EMDEs: more than 10 EMDEs lowered their policy rates by over 200 bps, with Ukraine cutting its policy rate by 400 bps.

The results in Figure 6 (bottom panel) are obtained by estimating equation (2) using the cumulative policy rate cut as an interaction term. They suggest that in countries where central banks lowered policy rates more aggressively, the adverse impact of containment measures was mitigated to a greater extent. We find that the economic impact of containment measures is much more adverse in countries where monetary policy was not eased. In contrast, the impact of containment measures in countries with large cuts in policy rates is not statistically significant.[14] The results suggest that monetary policy plays a significant role and may have helped in offsetting the economic fallout from the COVID-19 pandemic.

F. 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 measure resulted in larger short-term tradeoffs between minimizing health risks and economic losses. This can inform the discussion of how countries should open-up their economies as well as how best they can respond to any second wave of infections.

[14] The impulse responses under the two regimes are statistically different from each other.

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 size of gatherings; (v) closures of public transport; (vi) stay-at-home orders; (vii) restrictions on internal movement; and (viii) restrictions on international travel.

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:

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

where $\Delta d_{i,t+h} = d_{i,t+h} - d_{i,t+h-1}$ 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, average temperature, etc.). X is a vector of control variables which includes daily temperature and humidity levels, in addition to country-specific linear, cubic and quadratic time trends.[15]

As noted earlier, estimating the overall effect of each measure is challenging, because many of the measures were introduced simultaneously. Examining the effect of international travel restrictions however provides further 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

[15] As a robustness check, we used a dummy variable to identify the start and end of different containment and mitigation measures—this is similar to treating the containment measures as a shock. The results in Appendix Figure A5 are very similar to, and not statistically different, from the baseline.

conditions. 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 (1) 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.

The results for the effects of different containment measures on economic activity and infections are summarized in Table 2 and reported in Appendix Figures A3-A4—we report results for the second approach in Appendix Figures A6-A7. They suggest that workplace closures, cancellations of events, and stay-at-home orders are among the most effective measures in curbing infections; however, those measures are also associated with the largest economic losses. The results suggest that closures of public transport and restrictions on internal movement, though costly in economic terms, are not as effective in curbing infections. Finally, less costly containment measures, such as restrictions on international travel, are nonetheless successful in lowering COVID-19 infections.

G. Re-openings (easing of containment measures)

Many countries have started to exit the lockdown phase of the COVID-19 pandemic and are beginning to ease and lift some containment measures. In this section, we use more recent data for those countries abovementioned to assess the impact of re-openings (easing of containment measures) on economic activity.

To do so, we first identify countries which have entered the re-opening phase by restricting the data to after the stringency index $c_{i,t}$ has reached its peak value and then was lowered for the remaining time frame. The sample consists of a balanced panel of 54 countries. The effect of easing containment measures is then obtained using equation (1).

Figure 7 shows the estimated dynamic response of NO_2 emissions to a unitary decline in the aggregate containment stringency index over the 20-day period following relaxation of containment measures, together with 90 and 95 percent confidence intervals around the point estimate.[16] The results suggest that the easing of containment measures have significant effects on economic activity, leading to an average rise in NO_2 emissions by more than 500 log percentage points in 20 days, relative to a baseline of stringent containment measures. This pick-up in emissions is almost equivalent to an increase in industrial production of around 7 percent, which, though sizeable, is much lower (in absolute terms) than the impact of tightening containment measures on economic activity.

IV. CONCLUSIONS

Containment measures, though crucial to halting the spread of COVID-19 and limiting the number of fatalities in the absence of effective therapies and vaccines, 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 high-frequency indicators of economic activity, including Nitrogen Dioxide (NO_2) emissions, international and domestic flights, energy consumption, maritime trade, and retail mobility indices.

[16] In this analysis we consider a 20-day horizon, given that to-date, only a few countries have lifted restrictions for a longer period.

Results suggest that containment measures have had, on average, very large impacts on NO_2 emissions, with the decline in emissions levels equivalent to a loss of about 15 percent in industrial production over the 30-day period following the implementation of the containment measure. Results for other indicators of economic activity suggest that containment measures have had a very large adverse impact on flights worldwide, energy consumption, maritime trade, and retail and transit mobility.

Fiscal and monetary policies deployed during the COVID-19 crisis have 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, and where monetary policy easing was more limited.

Among different types of containment measures, workplace closures, stay-at-home orders, and cancellations of events are of the more effective in flattening COVID-19 related infections but are the costliest in terms of their impact on economic activity. Less costly containment measures, such as restrictions on international travel, are nonetheless successful in reducing COVID-19 infections.

In countries that have exited the lockdown phase of the pandemic and are re-opening their economies and easing of containment measures, this has resulted in a pickup in economic activity. However, this effect is considerably lower (in absolute value) to that from the tightening of containment measures.

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Tables

Table 1. Summary Statistics

	Obs.	Mean	Min	Max	Std. Dev.	Source	Starting Date	N. of countries
NO_2 emissions (log)	9,170	2.0	-0.9	4.4	0.7	Air Quality Open Data Platform	1-Jan-20	62
Total Flights (log)	29,997	3.4	0.0	10.8	2.1	FlightRadar24	1-Jan-20	217
Retail Mobility (%)	13,456	-11.7	-58.6	2.6	13.3	Google Mobility Index	15-Feb-20	132
Transit Station Mobility (%)	13,350	-12.2	-57.8	3.3	13.5	Google Mobility Index	15-Feb-20	131
Maritime Import Index (log)	2,420	4.6	3.83	4.9	0.12	Cerdeiro, Komaromi, Lui and Saeed (2020)	1-Jan-20	22
Maritime Export Index (log)	2,310	4.6	4.21	5.1	0.12	Cerdeiro, Komaromi, Lui and Saeed (2020)	1-Jan-20	22
Energy Consumption (log)	4,785	12.1	3.62	15.6	1.5	ENTSO-E	1-Jan-20	35
Confirmed Cases (log)	16,996	5.3	-0.9	14.3	3.0	Coronavirus Resource Center of JHU	21-Jan-20	208
Confirmed Deaths (log)	11,379	3.2	-1.9	11.5	2.5	Coronavirus Resource Center of JHU	22-Jan-20	176
Stringency of Measures Index (%)	24,626	0.4	0	1	0.4	OxCGRT.	1-Jan-20	158
Fiscal Stimulus (% of GDP)	14,290	3.3	0	12.1	3.1	IMF Policy Tracker	1-Jan-20	97
Policy rate cuts (bps)	25,377	76.2	0	1000	118.8	IMF Policy Tracker	1-Jan-20	172

Table 2. Cumulative effect of containment measure, 30 days after its introduction (log percentage points)

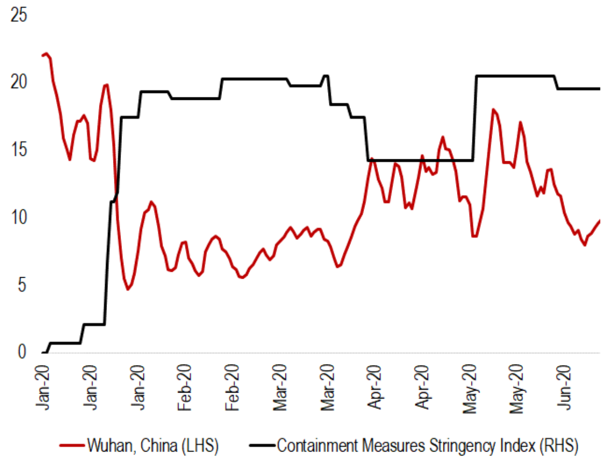
	NO_2 emissions	Confirmed Cases
Workplace closures	-580	-101
Closures of public transport	-437	-64
Cancellation of events	-413	-149
School closures	-368	-88
Restrictions on internal movement	-296	-75
Stay-at-home requirements	-296	-100
Restrictions on size of gathering	-293	-107
International travel restrictions	-162	-111

Note: the results reported in Table 2 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 30 days after the introduction of containment measures. Estimates based on $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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 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. Results are based on June 15 data.

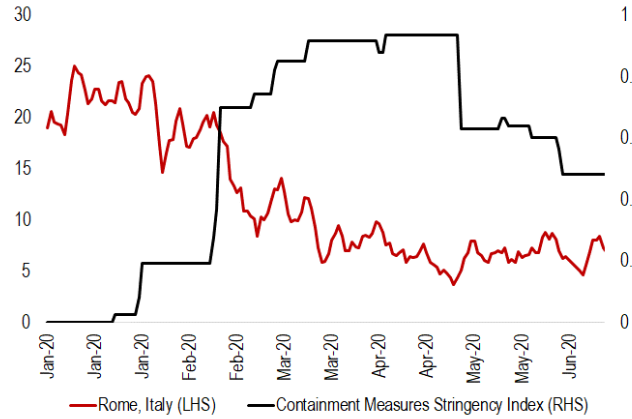
Figures

Figure 1: Evolution of NO_2 emissions, selected cities

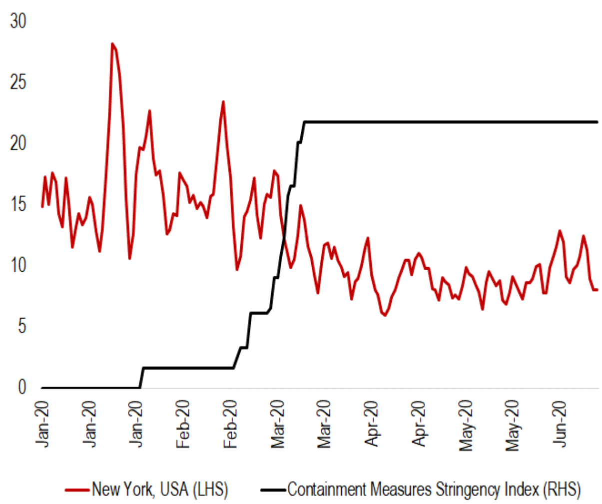
Panel A. NO_2 emissions, Wuhan (parts per billion (ppb))



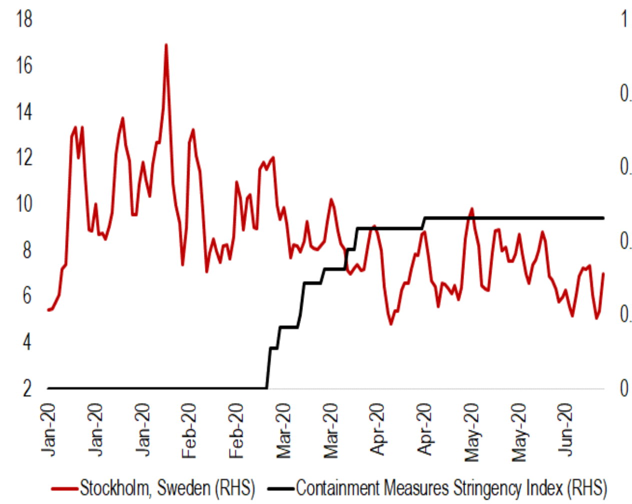
Panel B. NO_2 emissions, Rome (parts per billion (ppb))



Panel C. NO_2 emissions, New York (parts per billion (ppb))

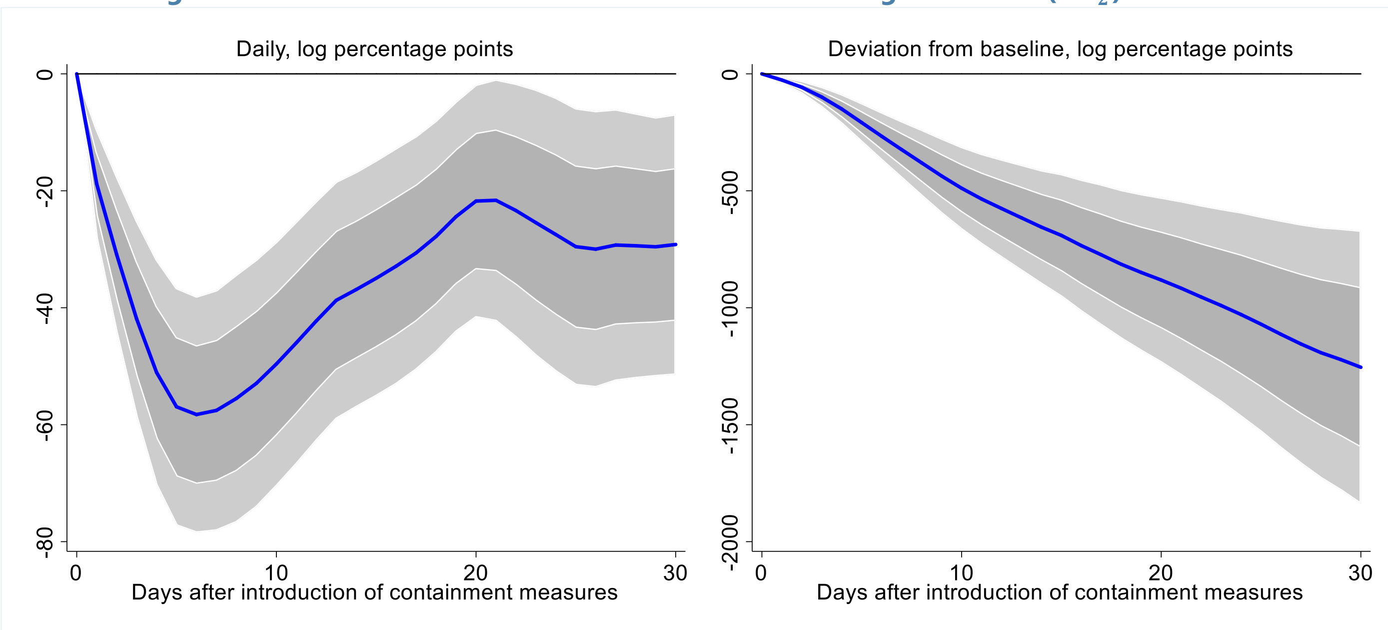


Panel C. NO_2 emissions, Stockholm (parts per billion (ppb))



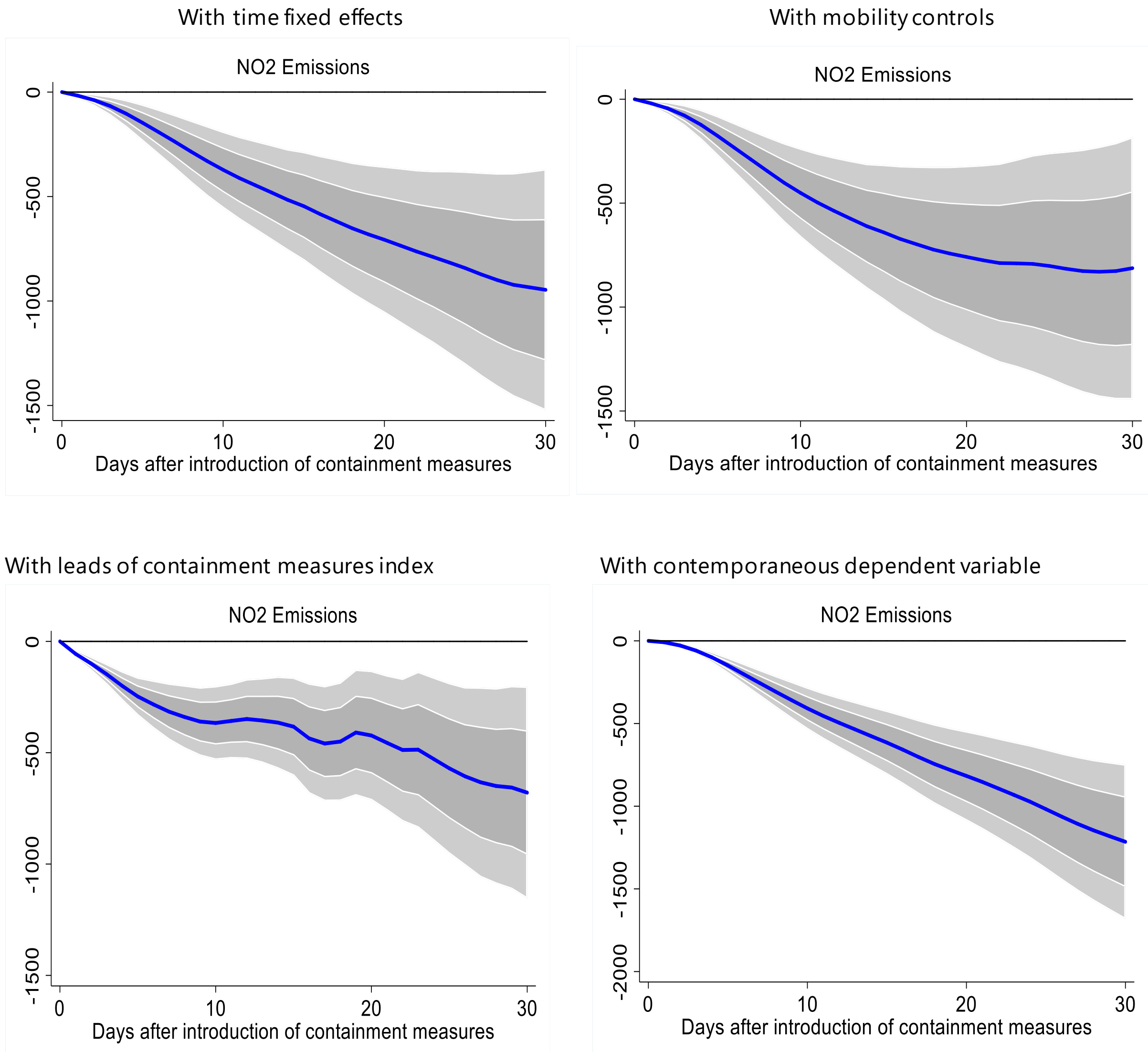
Source: Air Quality Open Data Platform, OxCGRT Stringency Index and IMF Staff calculations.
Note: levels of emissions are smoothed with a five-day moving average to remove excess volatility.

Figure 2: Effect of Containment Measures on Total Nitrogen Dioxide (NO_2) Emissions



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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 $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends. Results are based on June 15 data. The figure displays log-difference changes whereas the text translates these into percent changes.

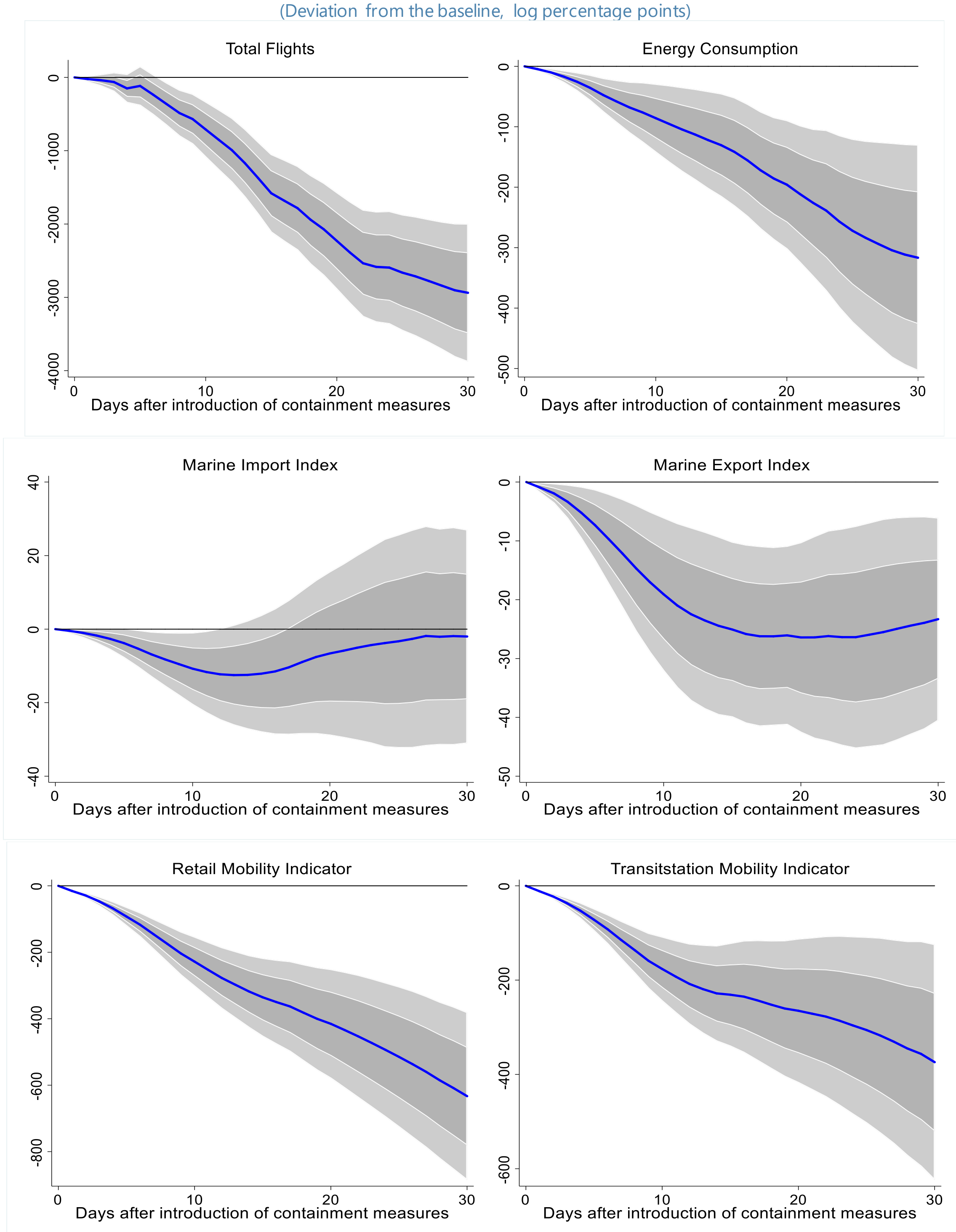
Figure 3: Robustness checks: effect of Containment Measures on NO_2 Emissions (deviation from the baseline, log percentage points)



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta d_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ is the logarithm of the level 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 the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends. Results are based on June 15 data.

Figure 4: Local projection response to indicators of economic activity

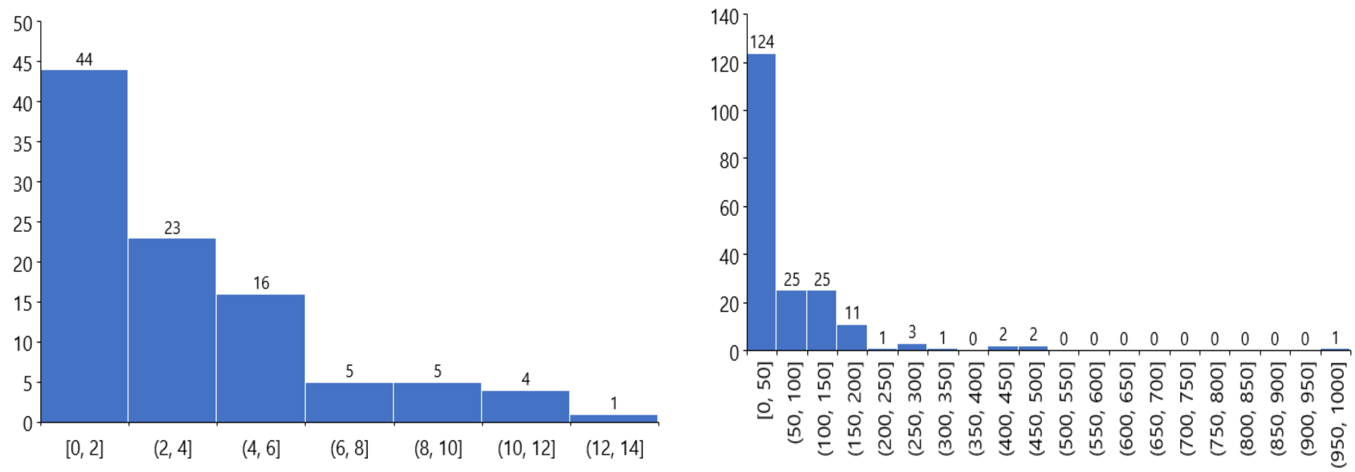
(Deviation from the baseline, log percentage points)



Note: Impulse response functions are estimated using a sample of 119 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. The graph shows the response and confidence bands at 95 percent. The horizon tal axis shows the response x days after the containment measures. Estimates based on $\Delta e_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta e_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta e_{i,t+h} = e_{i,t+h} - e_{i,t+h-1}$ and $e_{i,t}$ is the logarithm of the economy activity indicator (depending on specification) 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. Results are based on June 15 data. Energy consumption results are based on May 26 data.

Figure 5: Policy Responses to the COVID-19 Pandemic

Panel A. Fiscal Stimulus (in percent of GDP) **Panel B**. Policy Rate Cuts (in basis points)

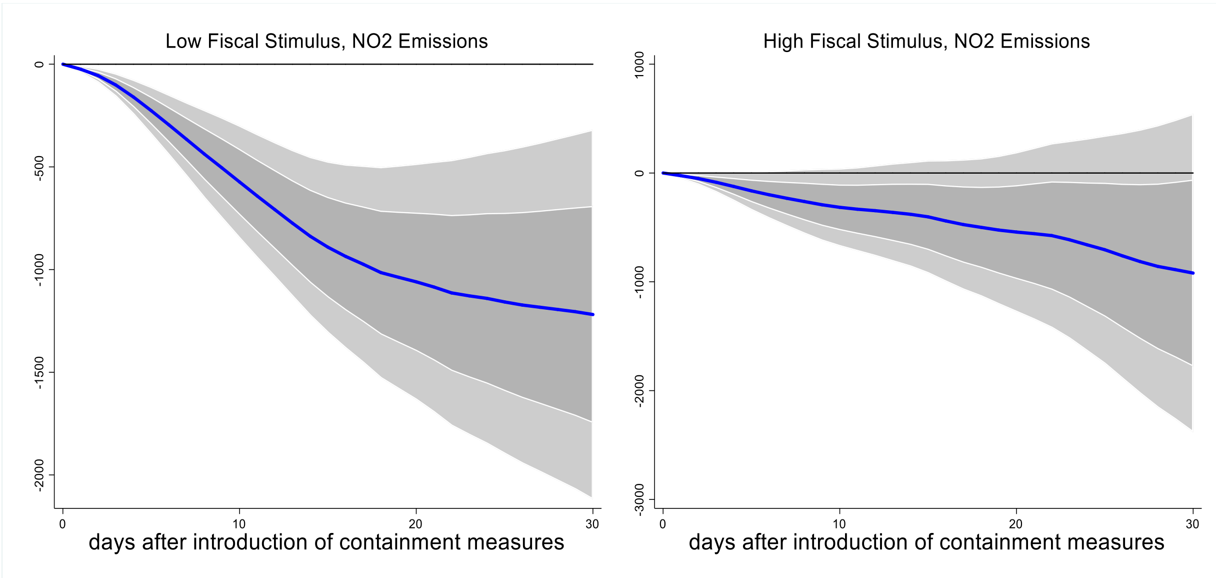


Source: IMF Policy Tracker.

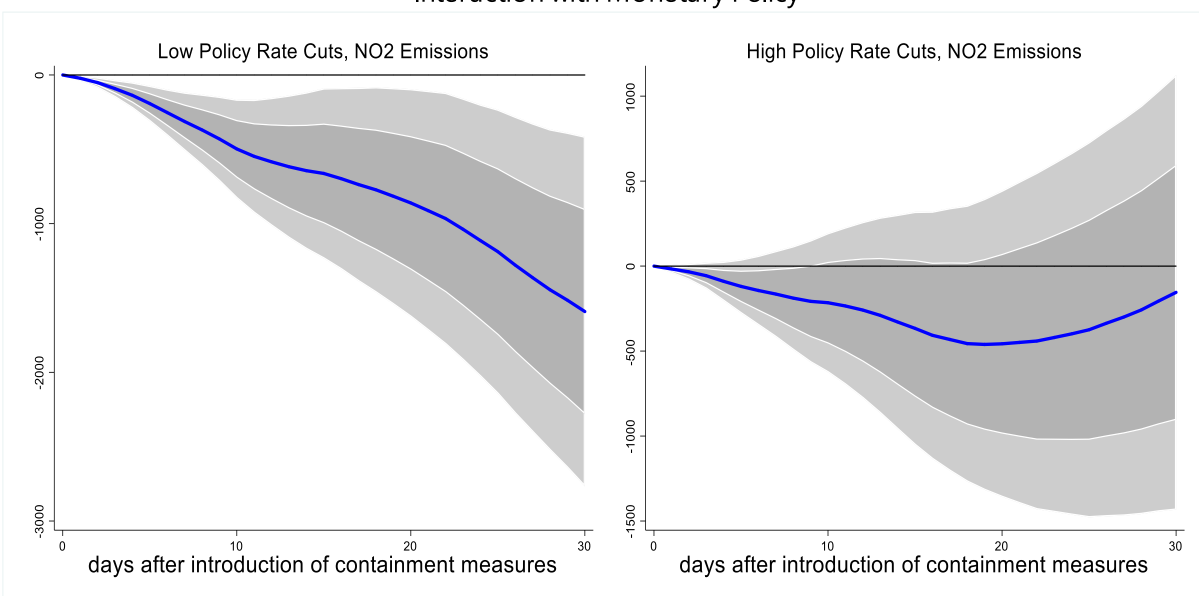
Figure 6: Interaction with Fiscal and Monetary Policy

(log-differences * 100)

Interaction with Fiscal Policy

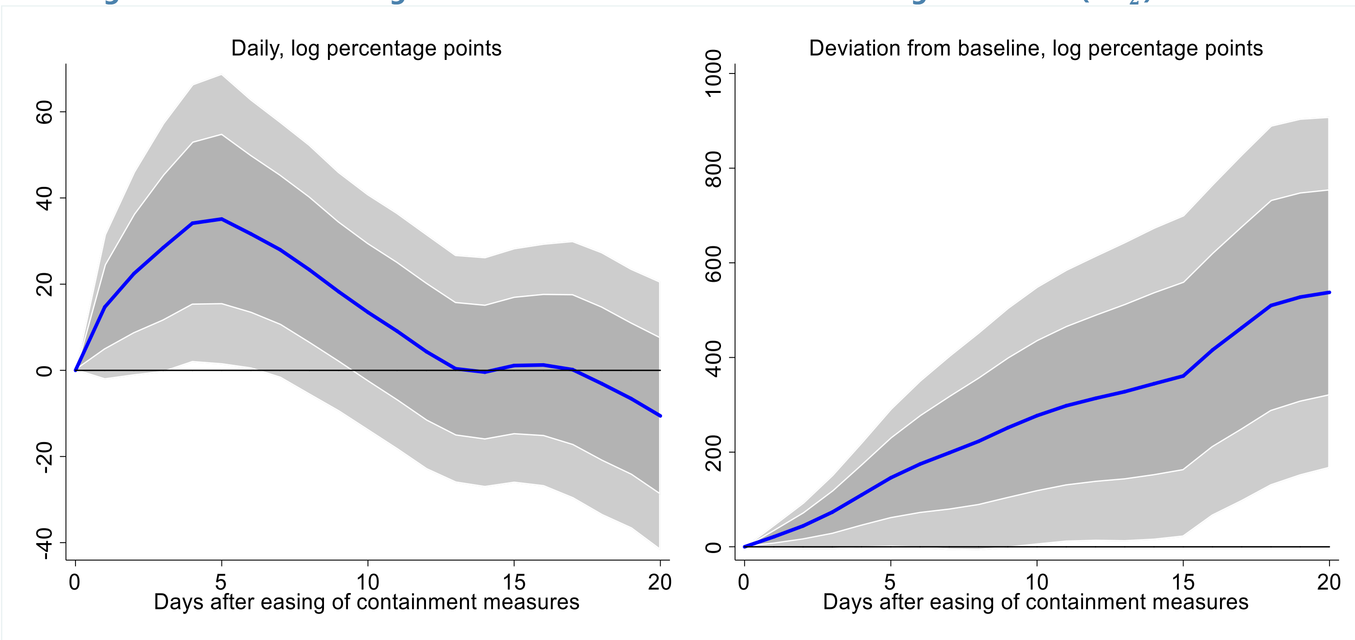


Interaction with Monetary Policy



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. 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 $\Delta n_{i,t+h} = u_i + u_t + \theta_h^L F(z_{i,t}) c_{i,t} + \theta_h^H (1 - F(z_{i,t})) c_{i,t} + X'_{i,t} \Gamma_h + \sum_{\ell=1}^{\mathcal{L}} F(z_{i,t})\, \psi_{h,\ell} \Delta n_{i,t-\ell} + \sum_{\ell=1}^{\mathcal{L}} (1 - F(z_{i,t})) \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ with $F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1-exp^{-\gamma z_{it}})}, \gamma > 0$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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. Results are based on June 15 data.

Figure 7: Effect of Easing Containment Measures on Total Nitrogen Dioxide (NO_2) Emissions

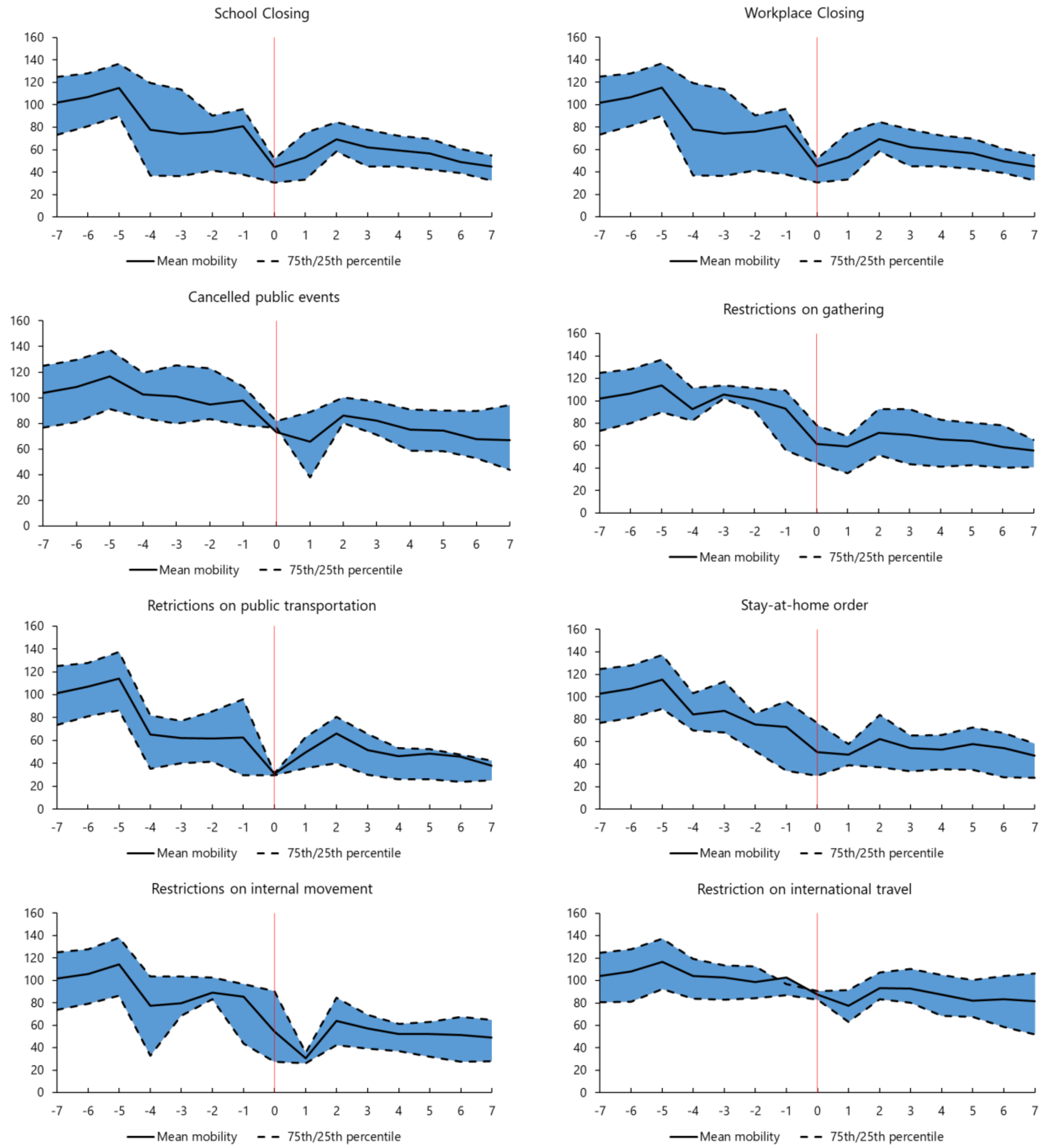


Note: Impulse response functions are estimated using a sample of 54 countries using daily data from the start of easing of containment measures. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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 $\ell = 1, 2 \ldots \mathcal{L}$; $c_{i,t}$ is the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends. Results are based on June 15 data.

Annex

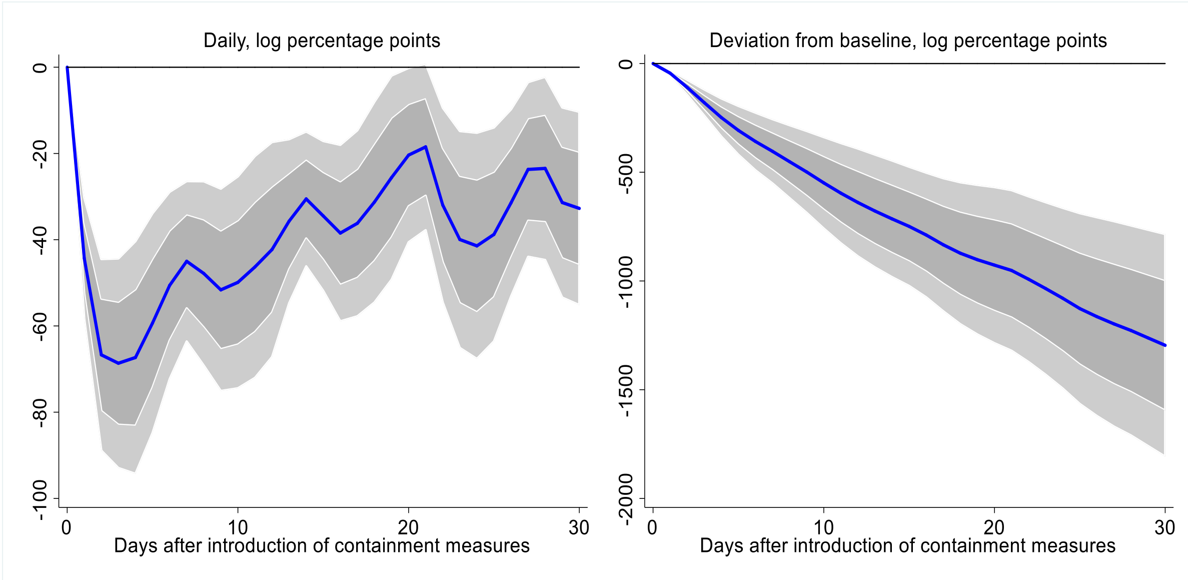
Figure A1. Containment measures and mobility

(mobility index, percent)



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

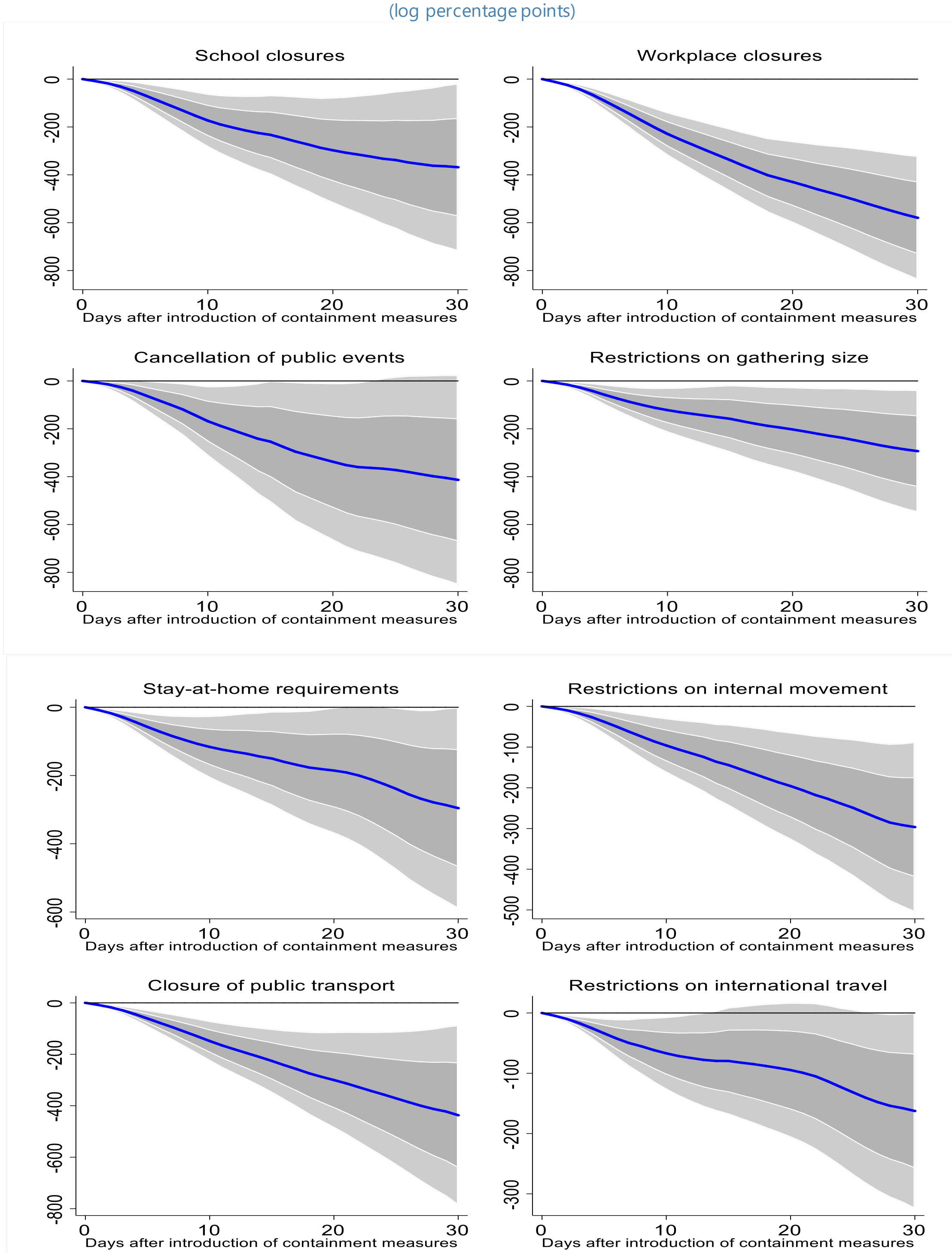
Figure A2: Local projection response of NO_2 emissions (unsmoothed) to containment measures



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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 $\ell = 1,2 \dots \mathcal{L}$; $c_{i,t}$ the index capturing the level of containment and mitigation measures; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends. Results are based on June 15 data.

Figure A3: Local projection response of NO_2 emissions to different containment measures

(log percentage points)

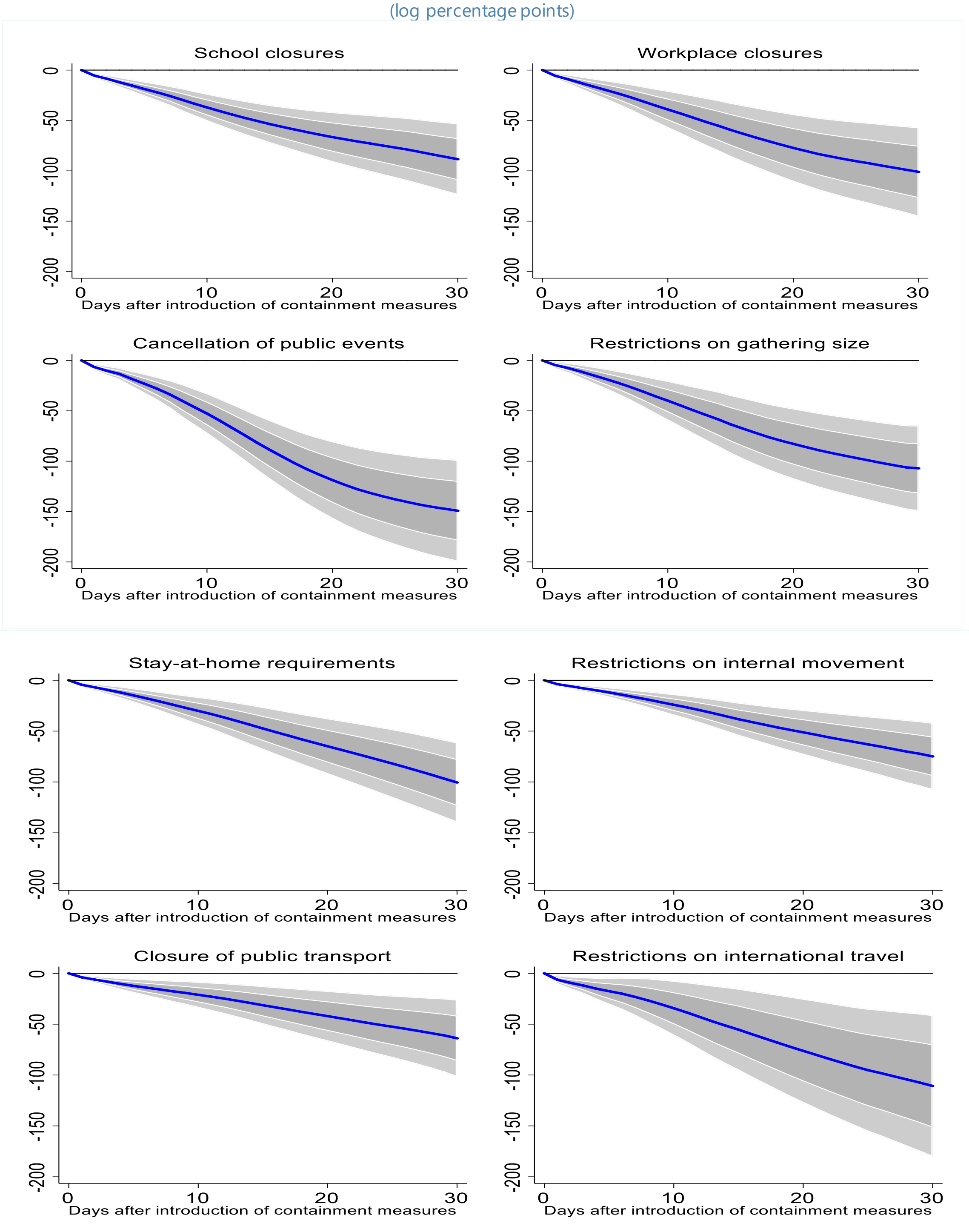


Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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 specific linear, cubic and quadratic time trends. Results are based on June 15 data.

Figure A4: Local projection response of confirmed infections to different containment measures

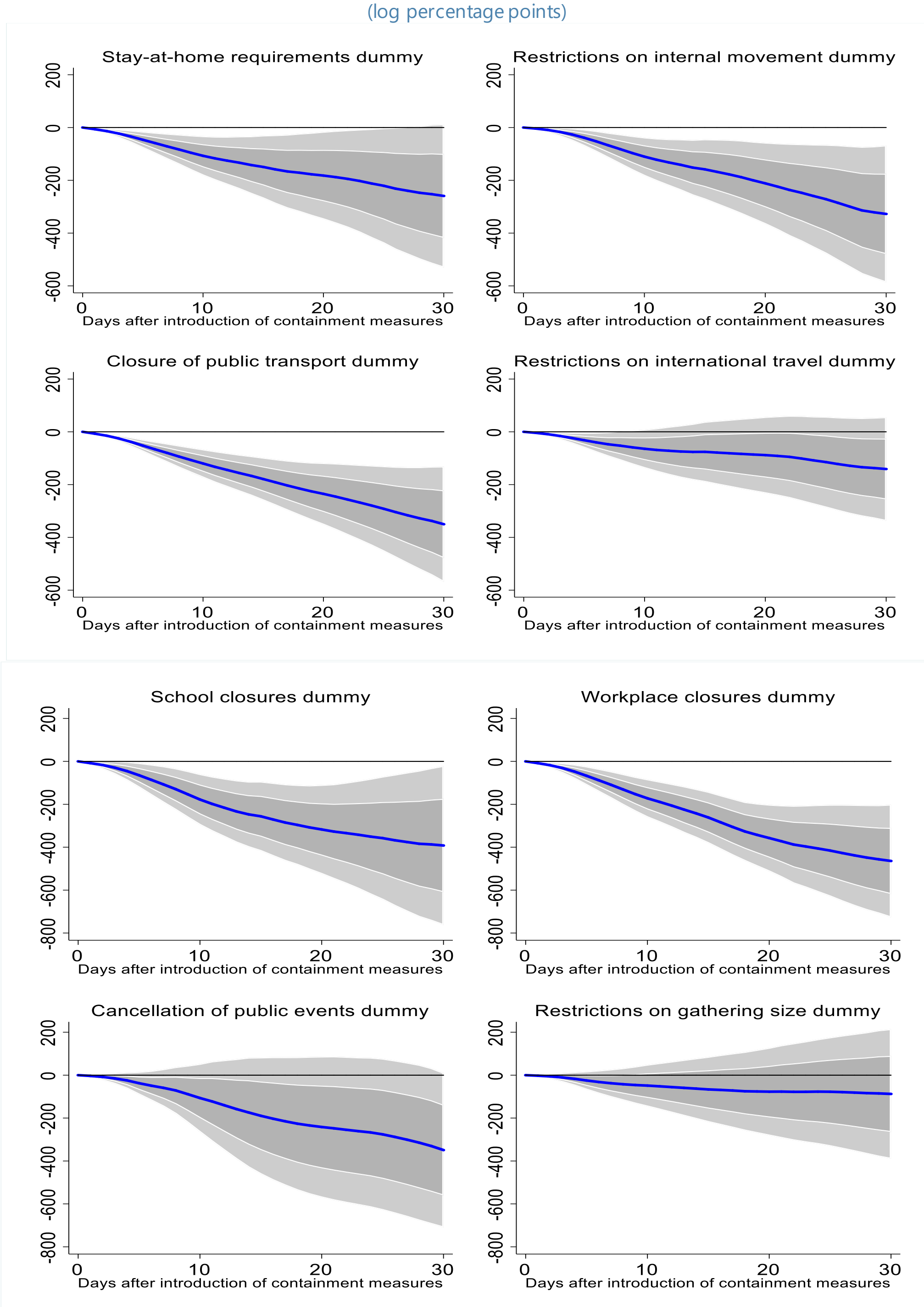
(log percentage points)



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ the logarithm of the number of COVID-19 cases 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 one at a time; X is a matrix of time varying control variables and country specific linear, cubic and quadratic time trends. Results are based on June 15 data.

Figure A5: Local projection response of NO_2 emissions to containment measures dummy

(log percentage points)

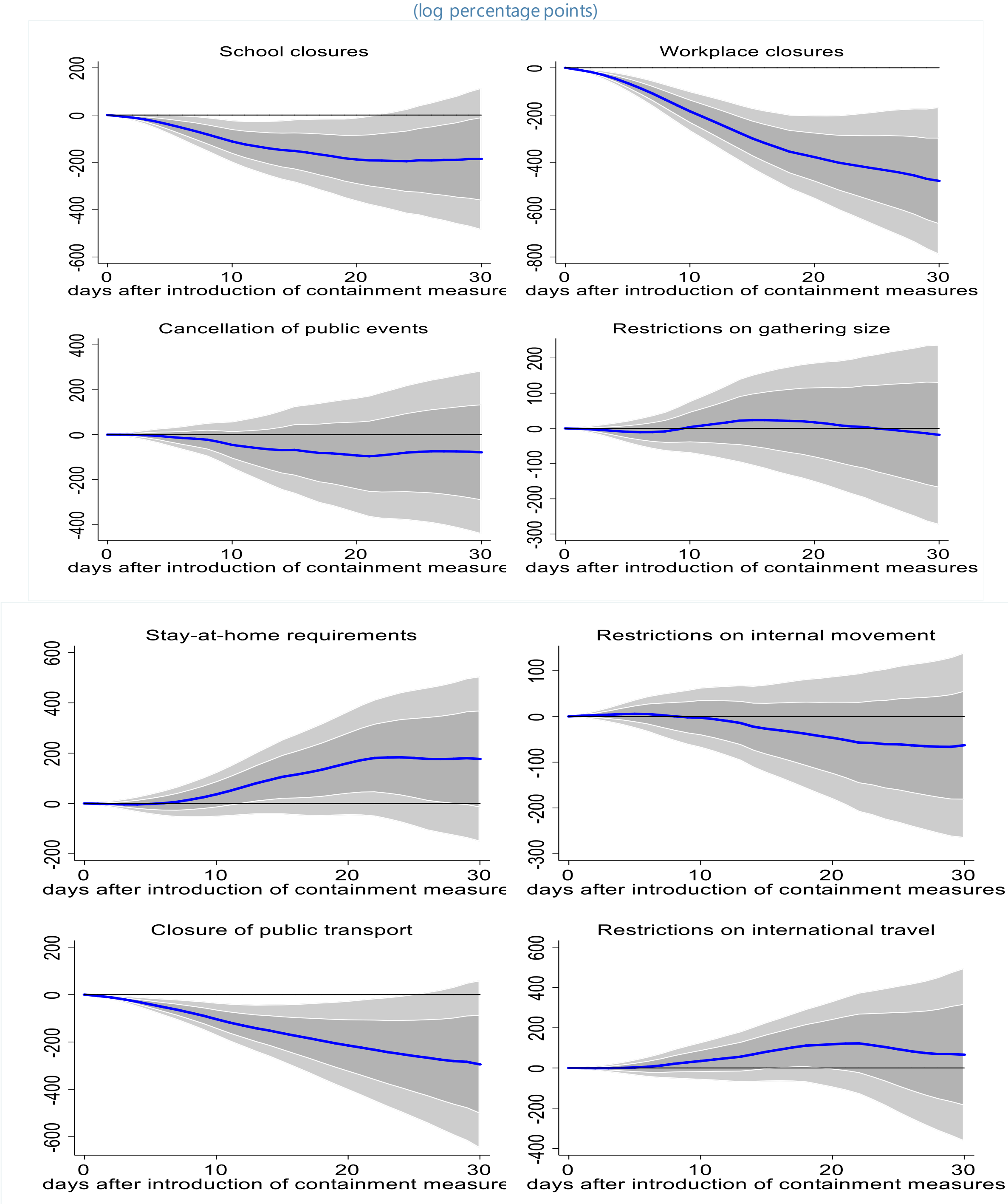


Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. The graph shows the response and confidence bands at 95 percent. The horizon tal axis shows the response x days after the containment measures.

Estimates based on $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell}\Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ 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_{it} is an index dummy 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. Results are based on June 15 data.

Figure A6: Local projection response of NO_2 emissions to different containment measures (together)

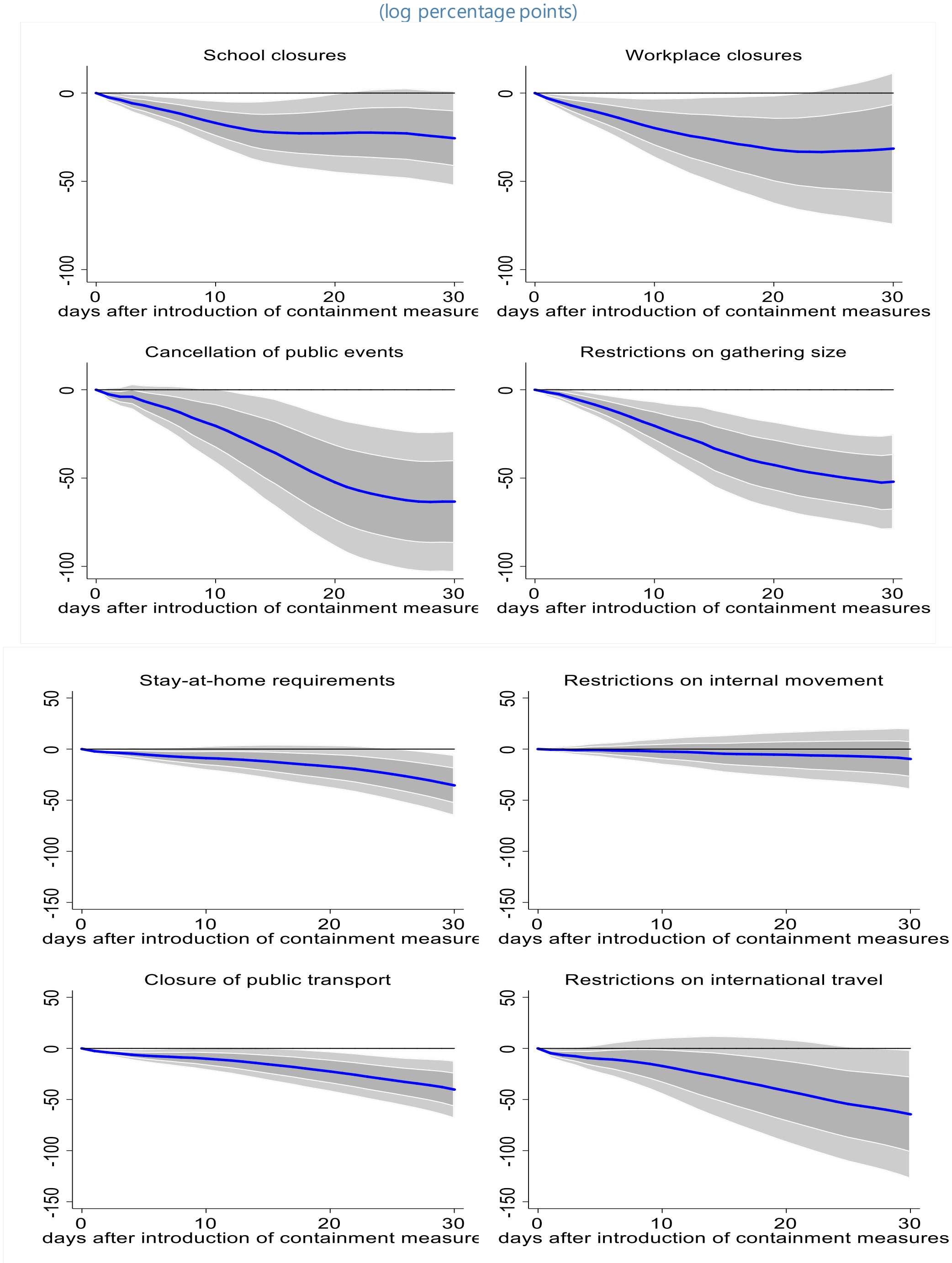
(log percentage points)



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ the logarithm of NO2 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 linear, cubic and quadratic time trends. Results are based on June 15 data.

Figure A7: Local projection response confirmed COVID-19 cases to different containment measures (together)

(log percentage points)



Note: Impulse response functions are estimated using a sample of 57 countries using daily data from the start of the outbreak. The analysis is restricted to countries with a significant outbreak that has lasted at least 30 days. t = 0 is the date when the outbreak becomes significant (100 cases) in each country. 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 $\Delta n_{i,t+h} = u_i + \theta_h c_{i,t} + X'_{i,t}\Gamma_h + \sum_{\ell=1}^{\mathcal{L}} \psi_{h,\ell} \Delta n_{i,t-\ell} + \varepsilon_{i,t+h}$ where $\Delta n_{i,t+h} = n_{i,t+h} - n_{i,t+h-1}$ and $n_{i,t}$ the logarithm of the number of COVID-19 cases 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 linear, cubic and quadratic time trends. Results are based on June 15 data.