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# The impact of the COVID-19 pandemic on global industrial production

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AEI Economics Working Paper 2021-04

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# The Impact of the COVID-19 Pandemic on Global Industrial Production

Steve Kamin, and John Kearns\*

March 18, 2021

## Abstract

This paper describes one of the first attempts to gauge the effect of the COVID-19 pandemic on the global trajectory of a key measure of economic activity – industrial production – over the course of 2020. It is also among the first efforts to distinguish between the role of domestic variables and global trade in transmitting the economic effects of COVID-19. We estimate panel data regressions of the monthly growth in industrial production (IP) on its determinants for 58 countries over the period March through December of 2020. We find that readings on the number of COVID-19 deaths had a statistically significant but small effect in our aggregate sample. Changes in the stringency of the lockdown measures taken by governments to restrict the spread of the virus were a more important influence on the growth of IP. In addition to these domestic pandemic effects, global trade represented a significant channel through which the economic effects of the pandemic spilled across national borders. The economic effects of the pandemic differed substantially between rich and poor countries: COVID-19 deaths, lockdown restrictions, and trade were all important drivers of production in wealthier countries. In poorer countries, deaths exerted little impact on production, whereas lockdown restrictions and variations in global trade played substantial roles.

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## 1. Introduction

The COVID-19 pandemic has triggered the sharpest downturn in the world economy since the Depression, with global GDP projected in the latest IMF World Economic Outlook to decline 3.5 percent in 2020 compared to a rise of 2.8 percent in 2019. While it is obvious that COVID-19 was the cause of this downturn, there are critical questions about the channels through which the pandemic depressed economic activity: Was it mainly through lockdowns or voluntary social distancing? How did the economic effects of the pandemic differ among different economies? How large a role was played by the collapse in global trade?

As discussed in Section 2, a plethora of studies have emerged to address these questions, using a wide range of different methodologies: production-based or computable general equilibrium (CGE) models, epidemiological models, event studies, and broader panel data analyses. But only a few of these papers (Deb et al. 2020, IMF 2020, Maloney and Taskin 2020, Furceri et al. 2021) draw on the full range of economic experiences around the world, and, aside from Furceri et al. (2021), these focus mainly on daily proxies for economic activity—e.g., atmospheric emissions and cellphone-based mobility data—rather than actual production measures.

By contrast, our paper focuses on how the pandemic has influenced the evolution of an actual measure of economic activity – industrial production (IP). Industrial production refers to output of mining, manufacturing, utilities, and sometimes (though not in our dataset) construction. IP is available on a monthly basis -- with as many as 12 months of data during the pandemic now available for 58 countries, this is sufficient to identify the links between the spread of the virus, lockdown measures, and IP. Moreover, our use of monthly data allows us to distinguish the effects on IP of domestic pandemic variables from those exerted by movements in

global trade also caused by COVID-19. Previous studies have not explored this important distinction.

To be sure, IP was not as hard-hit by the pandemic as production in many service sectors, and thus might be thought to provide a misleading read on the impact of the virus on economic activity. However, as we show in this paper, the evolution of the virus and the efforts to contain it did indeed significantly affect the trajectory of IP around the world.

Moreover, IP is strongly related to broader measures of economic activity. It generally accounts for a substantial share of GDP, ranging from below 20 percent (for example, Greece and Brazil) to highs near 50 percent (Middle Eastern oil exporters); the median share of GDP in our sample is 38.5%. And movements in IP are well-correlated with movements in GDP. Table 1 compares panel-data estimation results for a regression of quarterly GDP growth in 2020 on quarterly averages of the growth of IP and Google workplace mobility data, a popular proxy for economic activity. IP growth explains 81 percent of the variation in GDP growth across countries and time, compared with only 59 percent for the Google mobility data. And when both explanatory variables are placed in the regression, the  $R^2$  rises only a little from that of the equation with IP alone.

In our paper, we estimate panel data regressions of the monthly growth in IP on several measures of the pandemic for 58 countries over the period of March through December of 2020. The domestic pandemic measures include deaths per 1,000 of the population and a measure of the stringency of lockdown restrictions, the Oxford Stringency Index (OSI). All else equal, a rise in pandemic deaths would be expected to lower IP, both by inducing supply shortages and by prompting an increase in social distancing that leads production to be scaled back. Similarly, an increase in lockdown restrictions would also be expected to lower IP. However, both variables

could in principle be subject to reverse causality: a shock to IP that affects the extent of social distancing could lead to changes in COVID-19 cases, deaths, and OSI, biasing the coefficients. Accordingly, we use a two-stage least squares (2SLS) procedure to address this source of endogeneity.

A central feature of the economic impact of the pandemic was the collapse in world trade. In consequence, even countries that were not hard-hit by the virus itself might have suffered its economic fallout through a decline in export demand. To measure this effect, we include merchandise exports as an explanatory variable in our model, and also control for its endogeneity with respect to domestic supply and demand effects using 2SLS.

The goal of our study is not just to measure the response of IP to its various determinants but to use those estimates to decompose the overall trajectory of IP over the course of the last year into the contributions made by those determinants. To our knowledge, this is the first study to apply such an exercise to a direct measure of global economic activity. In so doing, we apply this decomposition both to our complete country sample and, separately, to the countries in the richest, middle, and poorest third of our sample, based on GDP per capita.

Our basic findings are as follows:

- Changes in COVID-19 deaths, lockdown restrictions (OSI), and exports all affected IP growth to a statistically significant extent.
- Using the estimated model to decompose the trajectory of industrial production over the course of 2020 into the contributions of the explanatory variables, we find that the key factors depressing IP last March and April were increases in the stringency of lockdown restrictions and the collapse in global trade. By the same token, it was reversals in these factors that accounted for most of the rebound in IP in the May-July period. For the full country sample, COVID-19 deaths had a negligible influence on the trajectory of IP, even though their coefficient is statistically significant.
- The size and statistical significance of the coefficients in our model differ depending on whether economies were in the richest, middle, or poorest third of our sample, based on their GDP per capita. COVID-19 deaths are only statistically significant for the richest

economies; this is plausible, since the poor are less capable of stopping work to weather the pandemic (Dingel and Neiman 2020). OSI is significant in all three samples, but it exerted the strongest effects in poor countries. The response of IP to exports was also strongest in the poorest countries.

- Accordingly, the decomposition results differed importantly in the three country groups. For the richest countries, the collapse in IP last March and April mainly reflected the increased stringency of lockdown restrictions, but also the collapse in world trade and increase in deaths; the rebound in the May-July period largely reflected some reversal of those developments. For the middle and poorest countries, the effect of deaths was negligible, with movements in OSI and world trade dominating the initial decline and subsequent recovery of IP.

Perhaps the most distinctive finding of our study is the outsized role that global trade has played in the impact of the pandemic on economic activity, especially in the world's poorest countries. This meant that even in countries where COVID-19 numbers were subdued and lockdowns were less restrictive, the hit to industrial production last year was substantial. But looking ahead to the coming months, there may be a bit of silver lining in this otherwise very dark cloud: Although the poorest economies will almost certainly lag the advanced economies in vaccination, and will thus have to maintain some degree of lockdown restrictions for longer, they will at least benefit from a further recovery of aggregate demand and imports by the advanced economies.

The plan of the paper is as follows. Section 2 reviews past research on this topic, and Section 3 describes the data used in this project. Section 4 describes the results of estimating our basic panel regression model, and Section 5 uses these results to decompose the movements in IP over the course of last year. Section 6 concludes.

## **2. Literature review**

Only a year has passed since the coronavirus emerged on the global scene, yet there already exists a broad literature on the impact of the virus on the economy. While there is research on the impact of previous pandemics on the United States and global economies (Barro

2020; Barro, Ursua, and Weng 2020; Cooper 2006; James and Sargent 2006; Ma et al. 2020; McKibbin and Sidorenko 2006), it is unclear to what extent the findings of this research carry over to the current situation. Below, we review the attempts to measure the impact of the COVID-19 crisis on the economy.

One approach to measuring this impact is based on production or general equilibrium models. These models are shocked using estimates of the initial direct effects of COVID-19 shutdowns on spending and/or production, and then the simulated effects of these shutdowns are traced through to the broader economy. For example, Mandel and Veetil (2020) use a multi-sector open economy model based on input-output data for 44 countries, and incorporating supply-chain linkages among countries, to simulate a virus-related lockdown; they estimate the total impact of a fifty-day lockdown at 9 percent of global GDP.<sup>1</sup> Similar approaches are taken by Barrot et al. (2020) and Inoue and Todo (2020). Studies exploiting DSGE and CGE models, including Maliszewska et al. (2020), Malliet et al. (2020), McKibbin and Fernando (2020), and Walmsley et al. (2020), predict GDP losses between 0.2 percent and 9.8 percent.

Another strain of models integrates epidemiological insights to explicitly model the interrelation between the virus, lockdowns, and economic activity. For instance, Cakmakl et al. (2020) embed a Susceptible-Infected-Recovered model in a general equilibrium framework, calibrated to the case of Turkey. They find that stricter lockdowns lead to smaller reductions in GDP because they limit the spread of the virus.<sup>2</sup> Alvarez et al. (2020), Acemoglu et al. (2020),

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<sup>1</sup> Impact at the peak of the crisis is predicted to be as high as 33% of global output.

<sup>2</sup> Further insights from this paper include that small open economies and emerging markets have much bigger fiscal needs because reliance on external demand, trade, and capital flows amplifies the economic shock (also see Davis et al. (2020); Dingel and Neiman (2020)). The authors also found that once the number of infections reaches a certain threshold, demand stalls and remains sluggish until infection numbers exhibit a substantial decline. This is further evidence of the relative importance of voluntary distancing vis a vis lockdowns.



Alon et al. (2020), and Scherbina (2021) are additional examples of this approach, all emphasizing the medium-term benefits of strict lockdowns.

Model-based analyses of the effect of COVID-19 have the virtue of highlighting the channels of transmission of the disease through the economy, thus supporting analysis of alternative policy responses. However, their results depend heavily on the calibration of the models and the assumptions about how pandemic-responsive policies affect economic behavior. Accordingly, these analyses have been usefully complemented by more empirical approaches.

Some researchers have adopted an event study framework, examining the movement of proxies for economic activity following lockdown announcements. For example, Alexander and Karger (2020), utilizing US county-day level data, find that lockdown announcements were followed by declines in mobility<sup>3</sup> and small business revenue; however, these measures were falling even before the announcements, likely reflecting voluntary social distancing measures. Arnon et al. (2020) also use US county-level data for an event study of the effect of lockdowns on mobility and employment, and they then embed the results of this analysis into an epidemiological model to examine the joint behavior of restrictions, Covid-19 cases, and employment. As before, employment was found to be falling both ahead of and after the announcement of any government policies. Chen et al. (2020), examining the variation across US counties and European countries, also find that lockdown measures explained only part of the pandemic recession. However, Baker et al. (2020) find household spending dropped more in US states imposing lockdowns.

Useful as they are, it is difficult to pin down the precise impacts of the pandemic using event studies, as they do not quantify the magnitude of COVID-19 cases or the stringency of

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<sup>3</sup> This is most often measured using location data from cell-phone companies or the use of mapping programs like Google Maps.

lockdown measures, nor do they allow one to identify the separate, independent effects of these variables on economic outcomes. It is also difficult to control for the influence of related factors such as fiscal/monetary policies or international developments.

An alternative approach that better addresses these issues is the estimation of panel data regressions of economic outcomes on pandemic variables and relevant controls. Data on COVID-19 cases, deaths, and lockdown measures are available on a daily basis, but most data on economic activity, such as GDP or industrial production, are only available at lower frequencies. Accordingly, researchers using this approach have generally focused on higher-frequency proxies for economic activity. Deb et al. (2020) exploit a multi-country dataset of atmospheric NO<sub>2</sub> concentrations, which are significantly correlated with industrial production. They show that a full lockdown would have a 30-day cumulative impact on NO<sub>2</sub> emissions equivalent to a 15% drop in industrial production. Similarly, Roidt et al. (2020) and Fezzi and Fanghella (2020) find pandemic lockdowns depress water and energy consumption in Europe.

Other panel data analyses have used mobility data as an economic proxy—these data, derived from cellphone apps such as Google Maps, aggregate people’s movements and have been shown to be strongly correlated with GDP, consumption, and/or employment (Chen and Spence 2020; Baker et al. 2020). Using an analysis of multi-country Google data similar to Deb et al. (2020), the IMF (2020) finds that “mobility declines by 28 percent a week after the introduction of a lockdown; and a doubling of COVID-19 deaths leads to a reduction in mobility by 1.2 percent after 30 days.” Maloney and Taskin (2020) also conduct a multi-country panel analysis of Google data, finding that voluntary distancing (as reflected in the effect of cases) accounts for more of the decline in mobility than lockdowns, except for low-income countries. Consistent with that, Goolsbee and Syverson (2020), using Safegraph data on mobile phone

usage for US counties, find that legal shutdown orders account for only a modest share of the massive decline in mobility observed in the first few months of the pandemic. Conversely, Coibion et al. (2020), studying US county-level data, found lockdowns to be more important than COVID-19 cases in depressing employment and spending. Chetty et al. (2020) develop a zip-code level proxy for US economic activity and, while not distinguishing between the effects of voluntary social distancing and lockdowns, document a strong contractionary impact of the spread of COVID-19.

While studies of the effect of pandemic variables on the daily evolution of economic-activity proxies such as atmospheric emissions or mobility data are undoubtedly informative, their mapping to more traditional measures of economic activity remains uncertain.<sup>4</sup> Furceri et al. (2021) address this issue by examining the fall in GDP during the first two quarters of 2020 across a large sample of economies. They find that output losses were greater among countries that were poorer, experienced more deaths and lockdowns, and were more dependent on tourism, among other factors. However, owing to the paucity of more recent GDP data, the analysis is confined to cross-sectional analysis and cannot examine the evolution of economic activity over time.

Accordingly, our paper makes a novel contribution to the literature by analyzing the impact of pandemic variables on an actual measure of economic activity—industrial production—over the course of 2020 and across a wide range of economies. (See Stanger, 2020, Papapetrou, 2001, and Maio and Philip, 2018, for discussions of the use of IP as an economic indicator.) Using IP for systematic data analysis has only become possible recently, as sufficient

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<sup>4</sup> For instance, mobility measures remain depressed even as production has recovered to pre-pandemic levels in many areas around the world. The ability for some countries to maintain productivity while working from home might cause mobility-based studies to overstate the economic impact of lockdowns.

numbers of monthly observations have become available, and it still requires us to analyze a large multi-country dataset, as in Deb et al. (2020), IMF (2020), and Maloney and Taskin (2020). But doing so will enable us to answer a number of important questions regarding the direct and indirect impacts of COVID-19 on a direct measure of economic activity and how those impacts might differ across countries.

### **3. Data**

For this paper, we assemble a comprehensive panel dataset encompassing variables relating to COVID-19, government policies, country characteristics, and global activity. To match with industrial production, most variables are averaged monthly. Our unbalanced panel includes entries for 58 countries from January through December 2020.

#### *Coronavirus cases and deaths:*

Data relating to the virus are sourced from Johns Hopkins University, which provides daily figures for cases and deaths for 192 countries starting on January 22, 2020.<sup>5</sup> For each country, we calculate the average number of new cases and deaths per month and divide by the country's 2019 population in thousands.<sup>6</sup> As explained in further sections, we use the month-on-month arithmetic change in new cases/deaths per month as a primary explanatory variable.

#### *Excess deaths:*

Excess mortality is defined as the total number of deaths above the 'expected' (i.e., historical average) death toll in a given time frame. We gather our data from The Economist's excess mortality tracker.<sup>7</sup> The Economist uses weekly or monthly death totals from 2015 to 2019 to calibrate expected deaths for 71 countries and uses those estimates to calculate excess deaths

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<sup>5</sup> Accessed from [https://github.com/CSSEGISandData/COVID-19/tree/master/csse\\_covid\\_19\\_data](https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data).

<sup>6</sup> Population data is obtained from the United Nations' World Population Prospects 2019 report.

<sup>7</sup> Accessed from <https://github.com/TheEconomist/covid-19-excess-deaths-tracker>.

beginning on January 1, 2020. We divide these data by population to generate a monthly variable for excess deaths per 1,000 people.

*Government restrictions (Oxford Stringency Index):*

Information on the stringency of government restrictions is obtained from Oxford's COVID-19 Government Response Tracker4 (OxCGRT).<sup>8</sup> This source provides daily index values of government restrictions for 184 countries since January 6, 2020. OxCGRT averages policy stringency across eight dimensions: school closures; workplaces closures; public event cancellations; gathering restrictions; public transportation closures; stay-at-home orders; restrictions on internal movement; and international travel bans. This variable ranges from 0 (no restrictions) to 100 (the highest possible level of restrictions across all eight dimensions). Given the subjective element in assigning ratings, one should not place too much weight on the precision of this measure. Nevertheless, it is the best measure available to assess lockdown restrictions on an internationally consistent basis.

*Industrial Production:*

As noted in the introduction, industrial production (IP) represents the output of the mining, energy, utility, and manufacturing sectors. Our sample includes 58 countries, all but two of which provide monthly IP data through December 2020.

*International trade flows:*

Data on nominal merchandise exports for the individual economies in our sample are drawn from CEIC. Exports are calculated as the seasonally adjusted, nominal value of monthly exports in US dollars. These data are available for all 58 countries up to July and for 50 countries through December.

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<sup>8</sup> Accessed from [https://github.com/CSSEGISandData/COVID-19/tree/master/csse\\_covid\\_19\\_data](https://github.com/CSSEGISandData/COVID-19/tree/master/csse_covid_19_data).

Global imports are calculated as the nominal value of monthly imports, in US dollars, obtained from the OECD for the organization's members and other key economies. These comprise the lion's share of total global imports. A different global imports aggregate is constructed for each country by subtracting that country's imports from the total.

*Google mobility data:*

Google provides mobility data in their Community Mobility Reports, which estimate the daily deviations in mobility for 135 countries since February 15, 2020. Mobility is broken down according to specific areas: residential, workplaces, transit, retail and recreation, grocery and pharmacy, and parks. The deviations are calculated relative to the median mobility during the baseline period between January 3<sup>rd</sup> and February 6<sup>th</sup>, 2020. Statistical tests (not shown) indicate that workplace mobility is the most correlated with economic activity. Notably, China is one country that is not included in the mobility data.

*Fiscal and monetary policy:*

We use three variables to summarize the stance of fiscal and monetary policy. One estimate of fiscal policy is Oxford's Economic Support Index (ESI), which provides daily estimates of the extent of fiscal support in 185 countries. Like the OSI, the ESI ranks the average policy generosity of income support and debt relief between 0 and 100. However, it mainly focuses on narrow financial relief measures and does not capture the full extent of fiscal stimulus.

A second estimate of fiscal support is published by the International Monetary Fund Policy Tracker.<sup>9</sup> The Policy Tracker estimates additional spending and foregone revenue (as a share of GDP) through December 2020 for 195 countries from surveys of country authorities.

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<sup>9</sup> Accessed from <https://www.imf.org/en/Topics/imf-and-covid19/Fiscal-Policies-Database-in-Response-to-COVID-19>.

While this variable is time-invariant, it is a direct measure of how much each country spent last year to provide COVID-19 relief and support.

Monetary policy is represented by the central bank policy interest rate.

*Global and country characteristics:*

We source data on exports, manufacturing, and services as a share of 2019 GDP from the World Bank's World Development Indicators (WDI).<sup>10</sup> Data on tourism's total contribution to the economy as a share of 2019 GDP are sourced from the World Travel and Tourism Council.<sup>11</sup>

*Bilateral correlations:*

Figure 1 presents scatterplots of monthly percent changes in IP (y-axis) against monthly changes in its potential determinants (x-axis), using data from January through December of 2020.<sup>12</sup> The inserted data in each scatterplot indicate the equation for the slope of the bivariate regression line between the two variables, the  $R^2$ , and the probability that the coefficient on the x variable is equal to zero. Only a few variables appear to be significantly correlated with changes in IP: changes in pandemic deaths, OSI, and exports. (The slope coefficient on the Oxford Economic Support Index (ESI) is statistically significant but of the wrong—negative—sign, suggesting it is capturing the reverse causality running from economic weakness to greater support.)

Figure 2 compares the monthly evolution of IP growth to changes in cases, deaths, OSI, and nominal merchandise exports based on median averages across the countries in our sample.

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<sup>10</sup> Accessed from <https://data.worldbank.org/indicator/NV.SRV.TOTL.ZS>.

<sup>11</sup> Accessed from <https://knoema.com/WTTC2019/world-travel-and-tourism-council-data?variable=1000100>.

<sup>12</sup> In this figure, and in the regressions described below, the Oxford indexes of restriction stringency and economic support are specified as month-to-month arithmetic changes. We also use month-to-month changes in the number of new COVID-19 cases and deaths per month. The number of people falling ill or dying in a particular month should be related to the level of IP. Accordingly, we would expect the change in IP from month to month to be related to changes in the number of people falling ill or dying. We confirmed this relationship in our regression analysis.

The three domestic variables have been multiplied by (-1) to allow better appraisal of their correlation with IP. Clearly, OSI and exports are much better correlated with IP than cases or deaths.

## **4. A Regression Model for Industrial Production**

### *4.1 Basic regression model with domestic pandemic variables*

We estimate OLS panel regressions of monthly percent changes in IP on the potential determinants discussed above. Table 2 presents estimation results for the most limited set of explanatory variables. As with the data shown in Figure 1, the explanatory variables are specified as month-to-month arithmetic changes in monthly cases, deaths, and OSI. The data are drawn for 58 countries; all countries with at least 5 monthly observations were included. (See Appendix A for a listing of all countries in the database.)

Starting with column 1, the coefficient on the change in COVID-19 cases has the wrong sign, insofar as it suggests that increases in cases raise IP; as will be discussed in the next section, this may reflect endogeneity of cases with respect to shocks to either IP or social distancing. In any event, we drop this variable from subsequent equation estimations, as in column 2. The coefficients on changes in deaths and in OSI are negative, as expected, and statistically significant. Finally, the coefficient on the lagged dependent variable is negative but statistically indistinguishable from zero – this suggests that the impact of OSI and deaths on IP takes place wholly within the same month.

The coefficients are essentially unaffected by the addition of country fixed effects (column 3). They are reduced but remain statistically significant after the addition of fixed monthly time effects (column 4). Those time effects, represented by the coefficients on the



month dummy variables, suggest that deaths and OSI are unable to explain the full contraction in IP around the world in April and its rebound in subsequent months.

#### *4.2 Addressing potential endogeneity problems*

The equation shown in Table 2, column 2, is potentially subject to endogeneity problems. Consider, for example, a mine shutdown that leads both to reduced IP and, by reducing opportunities for workers to spread the disease to each other, reduced cases and deaths; this could in turn could motivate a loosening of COVID-19 restrictions, depressing OSI. Alternatively, a rise in voluntary social distancing that was not captured by the deaths variables could lead both to reduced cases, deaths, and OSI, on the one hand, and to reduced IP, on the other. In either case, the result would be coefficients on cases, deaths, and OSI that were biased upwards (that is, less negative). This could explain the positive coefficient on cases.

In practice, this endogeneity problem is not likely to substantially affect the coefficients on deaths or OSI. Changes in social distancing – whether owing to shocks to IP or to voluntary social distancing – will take some time to result in changes to cases; these, in turn, will take some three to four weeks to cause changes to deaths, and the effect on OSI might lag even further.<sup>13</sup> In consequence, the types of shocks likely to induce endogeneity bias are unlikely to affect deaths, OSI, and IP within the same month.

However, to address this concern more directly, we estimate two-stage least squares regressions. In the first stage, we separately regressed changes in both deaths and OSI on changes in cases in the same month. The residuals from these regressions would represent changes in deaths or OSI not caused by changes in contemporaneous cases, and thus would be

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<sup>13</sup> Grech and Scherb (2020) estimate that the delay from cases to deaths is roughly 21 days. Given initial CDC guidance setting “downward trajectory [of cases]...reported over a 14-day period” as a requirement for relaxing restrictions and the unlikelihood of governments easing if deaths were rising (CDC 2020), it is likely it would take more than a month for social distancing to impact policy decisions.

exogenous to the effects of changes in IP or social distancing referenced above. In the second stage, we substitute those residuals for the actual values of deaths and OSI, and re-estimate the regression for IP growth that is shown in Table 2, column 2.<sup>14</sup>

As indicated in Table 2, column 5, estimation of the equation using our two-stage least square approach leads to a more negative coefficient on deaths compared with column 2, but no change in the coefficient on OSI.<sup>15</sup> As in the case of the OLS equation in column 4, addition of time fixed effects in column 6 reduces the absolute size of the coefficients on deaths and OSI, but they remain significantly different from zero.

#### *4.3 Addressing mismeasurement problems*

It is well-known that in many countries, cases and deaths are significantly undercounted. Table 3, column 2 presents equation estimates in which deaths have been replaced as an explanatory variable by the excess deaths data described in Section 3.<sup>16</sup> These data are only available for 46 countries, so the sample size is a little smaller. Even so, comparing column 1 (which uses actual deaths) with column 2 (using excess deaths), even if the higher *level* of excess deaths is more accurate than the level of official deaths, the results provide no reason to believe that monthly *changes* in excess deaths provide a better read on COVID-19 deaths than the official count. The coefficient on this variable is small and not significantly different from zero.

#### *4.4 Estimation results for richer vs. poorer countries*

It is likely that the impact of pandemic variables on economic activity would differ between richer and poorer countries. It is also possible that the mismeasurement problem is

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<sup>14</sup> See Barro (2020) for a description of a 2LS correction for the endogeneity of lockdown restrictions during the 1918-19 influenza pandemic.

<sup>15</sup> This reflects the fact that in the first-stage regressions, not shown, contemporaneous cases explain almost none of the variation in OSI but about a quarter of the variation in deaths.

<sup>16</sup> We use OLS rather than the two-stage least squares procedure described above, since the number of cases is also likely to be subject to official undercount.

more acute for lower-income countries. Table 3 presents separate estimates for rich (top 20 economies by per capita income), middle-income (middle 18), and poor (lowest 20) economies. (The list of countries in each set is detailed in the appendix.) Three findings are worth highlighting.

First, the coefficient on excess deaths remains either smaller than that on official deaths (the rich countries) or positive (the middle and poor countries); so, again, it appears unlikely that monthly changes in excess deaths represent more reliable data than the official count. Second, whereas official deaths have statistically significant effects on economic activity in rich countries, the coefficient on official deaths is not statistically significant in the economies of poorer countries. Third, and conversely, the stringency of lockdowns (OSI) appears to have smaller effects on IP in rich countries than in middle and (to a lesser extent) poor countries. These last two findings make sense – poor households are less likely to reduce their work unless lockdowns are imposed by the government – and are consistent with findings by Maloney and Taskin (2020).

#### *4.5 Addition of an external demand variable*

Even an economy with no COVID-19 cases or deaths and no lockdown restrictions could be affected by the pandemic through its effect on global trade, as other countries affected by the pandemic reduce their imports. To gauge the strength of this effect, Table 4, column 2, which reverts to focusing on all countries in our sample, adds the monthly percent change in nominal dollar-value merchandise exports as an explanatory variable. (Column 1 merely repeats the estimate shown in Table 2, column 2, for purposes of comparison.<sup>17</sup>) Not surprisingly, exports exert a statistically significant positive effect on IP, and this remains even after the inclusion of

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<sup>17</sup> The sample size is slightly smaller, owing to the unavailability of export data for several countries.

time fixed effects in column 3. Of course, that would be true, even in the absence of the pandemic. To gauge the effect of the pandemic on economies working indirectly through international trade channels, we will need to assess the broad pandemic-induced swing in global trade and how it impacts individual economies, an exercise described in Section 5 below.

The presence of the export growth variable poses another endogeneity problem. In principle, we would like to gauge the effect on IP of COVID-induced fluctuations in external demand. However, exports in any given economy could be influenced not only by external demand, but also by supply shocks emanating from that economy's variations in cases, deaths, lockdowns, and preferences for social distancing. Exports could also be affected by domestic demand shocks that reduce the supply of goods available for exports. To control for these domestic supply and demand shocks, we estimate a two-stage least square procedure where, in the first stage regression, we regress the countries' merchandise export growth on the growth of the imports of the world's major economies; the fitted value of this regression is then used in the second-stage regression, ensuring that only export fluctuations induced by global demand are used as an explanatory variable.<sup>18</sup> As in Table 2, column 5, the second-stage regression also controls for the endogeneity of deaths and OSI, using the residuals from their first-stage regression on contemporaneous cases.<sup>19</sup>

Table 4, column 4, presents the results of the two-stage least squares estimation, including exports. Controlling for endogeneity appears to increase the effects on IP of all three

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<sup>18</sup> To ensure that the global imports variable is strictly exogenous with respect to the economy in question, we delete the contribution to total global import growth of that economy's imports.

<sup>19</sup> Note that we use different approaches to instrument for deaths and OSI, on the one hand, and exports, on the other. For death and OSI, the objective is to eliminate fluctuations in these variables caused by shocks to social distancing that would simultaneously impact IP, on the one hand, and cases, deaths, and OSI, on the other; thus, we seek to use variations in deaths and OSI that are orthogonal to cases. For exports, we seek to use fluctuations not associated with any contemporaneous domestic variable, and thus rely exclusively on their relation to global imports.

variables: deaths, OSI, and exports. (We do not include an estimation with time fixed effects, since there is little variation across countries in the instrumented export variable, which is a linear function of global imports, and thus it is highly collinear with time fixed effects.)

Tables 5-7 repeat the analysis of Table 4 for the rich, middle, and poor country groups described above. Focusing on the two-stage least squares estimates, the basic messages from our previous analysis are re-affirmed: OSI exerts strongest effects on IP in the poorest countries, whereas deaths exert the strongest effects in the rich countries. Additionally, and less intuitively, exports appear to affect IP much more strongly in poor countries than in rich ones.

Two other points bear mentioning. First, we would ideally use real rather than nominal exports to explain changes in IP. However, data on export volumes are not available on a timely monthly basis for many of the economies in the sample. Moreover, when we estimated monthly export volumes by deflating nominal exports by regional trade price deflators, the results were broadly similar to those shown in column 2 of these tables.<sup>20</sup> Second, in principle, export growth should have a different effect on IP growth, depending on the share of exports in industrial production. However, we found that when export growth was interacted with measures of the ratio of exports either to estimates of the value of industrial production or to overall GDP, these interaction variables did not add to the explanatory power of the equation, relative to export growth by itself. It is likely that because industrial products are tradeable goods which can be sold either domestically or externally, growth of industrial production is influenced by external demand, regardless of its share.

#### *4.5 The role of structural characteristics*

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<sup>20</sup> Data on merchandise export deflators for selected countries and regional aggregates are available from the Netherlands Bureau for Economic Policy Analysis, <https://www.cpb.nl/en/world-trade-monitor-december-2020>.

To what extent has the performance of economies during the pandemic been influenced by their structural characteristics, including their prior trend growth in IP and the shares of their economies devoted to manufacturing, services, exports, and tourism. Table 8 adds these measures to the basic regression that is shown in column 4 of Table 4. Column 1 merely repeats that equation, estimated for the slightly smaller set of observations available for these additional explanatory variables. In the remaining columns, each of the additional structural variables are added both separately – with coefficient results in the row labeled “Characteristic” – and interacted with OSI and with deaths.

The results indicate that only a couple of coefficients on these explanatory variables are statistically significant, and even in these cases, the rise in  $R^2$  is very slight. The fact that these basic characteristics do not affect the responses to the pandemic is surprising. It could reflect the focus on industrial production – a broader measure of GDP might show greater sensitivity to the share of production linked to close personal contact, like services. Furceri et al. (2021), for example, find a significant negative impact on GDP from higher dependence on tourism.

#### *4.6 The role of fiscal and monetary policy*

A notable feature of the pandemic was the extent of fiscal and monetary policy stimulus, especially in the advanced economies, but even in most emerging market and developing economies. In principle, it should be possible to identify the support to the economy provided by this stimulus by controlling for the adverse effects of the pandemic. In practice, however, this is challenging: Timely monthly measures of fiscal stimulus are not available on a consistent cross-country basis; it is similarly difficult to measure the all-in effects of monetary stimulus besides reductions in policy interest rates; both fiscal and monetary stimulus are likely endogenous with respect to the state of the economy, biasing their measured impact; and many stimulus measures

are designed to offer financial relief rather than boost economic activity. On top of all that, because IP mainly involves production of tradeable goods facing external demand, it may be less responsive to domestic demand policies than broader measures of GDP.

With those provisos in mind, Table 9 examines the contribution of several policy proxies to the basic regression shown in column 4 of Table 4. One fiscal proxy is the IMF measure of fiscal stimulus spending, measured as a fraction of GDP; only a single value of this is available for each country. The other fiscal proxy is the month-to-month arithmetic change in the Oxford economic support index (ESI), which is available on a high-frequency basis, but is not considered a comprehensive measure of fiscal stimulus. Finally, monetary policy is measured as month-to-month percentage point changes in the nominal policy interest rate. As these data are available for different sets of countries, in each case we pair the regression with the basic specification shown in Table 4, so as to be able to judge their separate contributions to explaining the change in IP.

As indicated in Table 9, the coefficients on the two fiscal stimulus variables are the wrong sign, and the coefficient on policy interest rates is not significantly different from zero. All told, reflecting some combination of the issues summarized above, none of these policy measures appears to have significantly affected IP growth.

## **5. Decomposition of 2020's Industrial Production Movements**

In this section, we use our regression models to estimate the contribution of the different pandemic factors to the evolution of IP over the course of 2020. Figure 3 displays this decomposition for the entire country sample. The solid black line depicts the median growth of IP across the countries in the sample for every month. The colored bars represent the contribution of the different explanatory variables, calculated as the estimated coefficient

multiplied by the median value of the variable in that month. Our methodology identifies only minute contributions of COVID-19 deaths to the evolution of IP growth last year. Instead, the key factors pushing IP down in March and April and up in June and July appear to have been OSI and global imports. After July, the trajectory of global IP growth flattens out, as does the contribution of the explanatory variables (except for the relatively large miss in October).

Note that this decomposition is constructed from the standpoint of the individual economies – that is, for a given economy, the effect of the pandemic is estimated as partly reflecting its domestic variables (deaths and OSI) and partly the transmission of the pandemic to that economy through the contraction in global trade. Of course, the contraction in global trade was itself the outcome of pandemic effects on the economy’s trade partners, and thus represents the indirect effect, rather than the direct domestic effect, of the pandemic on the economy in question.

Figures 4 through 6 repeat the analysis shown in Figure 3, but applied to the separate country groupings described earlier. The results are broadly consistent with the pattern of estimated coefficients across the three groupings. For the rich countries, the surge and subsequent decline in pandemic deaths accounts for a material part of the collapse and rebound in IP, along with OSI and global trade. Conversely, for the middle and poor countries, deaths play almost no part, with variations in OSI and exports accounting for nearly all the variation.

## **6. Conclusion**

In this paper, we estimate panel data regressions of the monthly growth in industrial production (IP) on its determinants for 58 countries, as well as subsets of richer and poorer countries, over the period March through December of 2020. We then use our estimated model



to decompose the trajectory of IP growth over the course of 2020 into the contributions of its various determinants.

We find that readings on the number of COVID-19 deaths had a statistically significant but small effect on IP in our aggregate sample, though it was more important in wealthier countries. Changes in the stringency of the lockdown measures taken by governments to restrict the spread of the virus, often referred to as lockdown restrictions, are a more important determinant of the growth of IP than deaths, especially in poorer countries. In addition to these domestic pandemic effects, global trade—as measured by merchandise exports—represented an important channel through which the economic effects of the pandemic spilled across national borders, again especially in poorer countries.

Our work represents some of the first research to gauge the effect of the pandemic on a direct measure of economic activity – industrial production – around the world. It is also among the first efforts to distinguish between the role of domestic variables and global trade in transmitting the economic effects of COVID-19. Going forward, we hope to extend our analysis to examine the impact of the eradication of the virus on global economic activity as vaccination proceed.

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Table 1: OLS Panel Data Regressions for Quarterly GDP Growth

	(1)	(2)	(3)
(Intercept)	-0.0089 *** (0.0029)	0.0171 *** (0.0049)	0.0005 (0.0029)
%Δ Industrial Production	0.5707 *** (0.0281)		0.4446 *** (0.0294)
%Δ Google Workplace Mobility		0.3760 *** (0.0313)	0.1404 *** (0.0257)
R <sup>2</sup>	0.8071	0.5938	0.8505
Adj. R <sup>2</sup>	0.8057	0.5909	0.8483
Num. obs.	142	142	142
RMSE	0.0346	0.0502	0.0306

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 2: Equations for Monthly Percent Change in IP – Domestic Determinants

	OLS	OLS	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.0206 *** (0.0042)	0.0222 *** (0.0041)	0.0358 (0.0262)	-0.0071 (0.0236)	0.0048 (.0038)	-0.0108 (0.0242)
$\Delta$ Cases	0.0040 *** (0.0009)					
$\Delta$ Deaths	-0.2792 *** (0.0700)	-0.1813 *** (0.0577)	-0.1908 *** (0.0655)	-0.1324 ** (0.0618)	-0.2793 *** (0.0690)	-0.1627 ** (0.0700)
$\Delta$ OSI	-0.0027 *** (0.0003)	-0.0027 *** (0.0003)	-0.0027 *** (0.0003)	-0.0011 ** (0.0005)	-0.0027 *** (0.0003)	-0.0011 ** (0.0005)
Lagged % $\Delta$ IP	-0.0926 (0.0674)	-0.0852 (0.0675)	-0.0937 (0.0715)	-0.1129 (0.0753)	-0.0935 (0.0668)	
Date = 2020-04-01				-0.0989 *** (0.0212)		-0.0998 *** (0.0210)
Date = 2020-05-01				0.0589 * (0.0324)		0.0553* (0.0329)
Date = 2020-06-01				0.0858 *** (0.0307)		0.0816 *** (0.0315)
Date = 2020-07-01				0.0498 * (0.0287)		0.0470 (0.0290)
Date = 2020-08-01				0.0111 (0.0242)		0.0085 (0.0245)
Date = 2020-09-01				0.0171 (0.0251)		0.0139 (0.0256)
Date = 2020-10-01				0.0221 (0.0234)		0.0158 (0.0242)
Date = 2020-11-01				0.0309 (0.0257)		0.0182 (0.0265)
Date = 2020-12-01				0.0220 (0.0243)		0.0185 (0.0242)
R <sup>2</sup>	0.2615	0.2538	0.2629	0.3599	0.2592	0.3597
Adj. R <sup>2</sup>	0.2563	0.2499	0.1770	0.3463	0.2552	0.3461
Num. obs.	576	576	576	576	576	576
Fixed Effects	None	None	<b>Country</b>	<b>Time</b>	None	<b>Time</b>
RMSE	0.0904	0.0908	0.0951	0.0847	0.0904	0.0848

Standard errors in parentheses

\*\*\* p &lt; 0.01; \*\* p &lt; 0.05; \* p &lt; 0.1

Table 3: OLS Equations for Monthly Percent Change in IP – Using Excess Deaths

	All	All	Rich	Rich	Middle	Middle	Poor	Poor
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
(Intercept)	0.0201 *** (0.0041)	0.0194 *** (0.0042)	0.0170 *** (0.0054)	0.0166 *** (0.0049)	0.0200 *** (0.0067)	0.0171 *** (0.0064)	0.0196 * (0.0114)	0.0163 (0.0119)
$\Delta$ Deaths	-0.1966 *** (0.0631)		-0.3772 *** (0.1131)		0.0205 (0.0503)		-0.2115 (0.1884)	
$\Delta$ Excess Deaths		-0.0541 (0.0332)		-0.2901 *** (0.0592)		0.0753 ** (0.0379)		0.0135 (0.0430)
$\Delta$ OSI	-0.0025 *** (0.0002)	-0.0026 *** (0.0003)	-0.0020 *** (0.0004)	-0.0014 *** (0.0004)	-0.0030 *** (0.0004)	-0.0032 *** (0.0004)	-0.0023 *** (0.0005)	-0.0023 *** (0.0005)
Lagged % $\Delta$ IP	-0.0404 (0.0677)	-0.0290 (0.0682)	-0.0618 (0.1004)	0.0027 (0.0858)	0.0042 (0.1263)	-0.0058 (0.1254)	-0.1146 (0.1303)	-0.1120 (0.1309)
R <sup>2</sup>	0.3146	0.3027	0.4140	0.4665	0.4054	0.4141	0.1853	0.1789
Adj. R <sup>2</sup>	0.3099	0.2979	0.4044	0.4577	0.3939	0.4029	0.1576	0.1509
Num. obs.	439	439	187	187	160	160	92	92
RMSE	0.0760	0.0767	0.0619	0.0591	0.0694	0.0689	0.1056	0.1060

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 4: Monthly Percent Change in IP – Global Determinants – All Countries

	OLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(4)
(Intercept)	0.0224 *** (0.0042)	0.0073 * (0.0039)	-0.0002 (0.0158)	-0.0013 (0.0039)
Δ Deaths	-0.1808 *** (0.0578)	-0.1230 *** (0.0448)	-0.0994 * (0.0538)	-0.1872*** (0.0643)
Δ OSI	-0.0027 *** (0.0003)	-0.0011 *** (0.0003)	-0.0004 (0.0004)	-0.0021*** (0.0003)
Lagged %Δ IP	-0.0847 (0.0676)	-0.0764 (0.0501)	-0.0756 (0.0629)	-0.1567** (0.0824)
%Δ Exports		0.4234 *** (0.0454)	0.3712 *** (0.0455)	0.5202*** (0.0831)
R <sup>2</sup>	0.2556	0.4681	0.5070	0.3189
Adj. R <sup>2</sup>	0.2516	0.4643	0.4954	0.3163
Num. obs.	566	566	566	566
Fixed Effects	None	None	<b>Time</b>	None
RMSE	0.0911	0.0771	0.0748	0.0873

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1



Table 5: Monthly Percent Change in IP – Global Determinants – Rich Countries

	OLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(4)
(Intercept)	0.0183 *** (0.0057)	0.0033 (0.0051)	0.0210 (0.0330)	-0.0004 (0.0055)
Δ Deaths	-0.4279 *** (0.1101)	-0.2448 *** (0.0927)	-0.2775 ** (0.1139)	-0.3971 *** (0.1213)
Δ OSI	-0.0017 *** (0.0004)	-0.0003 (0.0005)	-0.0006 (0.0008)	-0.0014*** (0.0005)
Lagged %Δ IP	-0.1302 (0.1053)	-0.1613 ** (0.0771)	-0.2040 ** (0.0849)	-0.1794 (0.0919)
%Δ Exports		0.4714 *** (0.0990)	0.4395 *** (0.1207)	0.3369*** (0.1131)
R <sup>2</sup>	0.3047	0.4912	0.5150	0.3516
Adj. R <sup>2</sup>	0.2941	0.4808	0.4811	0.3442
Num. obs.	200	200	200	200
Fixed Effects	None	None	<b>Time</b>	None
RMSE	0.0777	0.0667	0.0666	0.0753

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 6: Monthly Percent Change in IP – Global Determinants – Middle Countries

	OLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(4)
(Intercept)	0.0193 *** (0.0067)	0.0048 (0.0065)	-0.0456 (0.0291)	-0.0036 (0.0064)
Δ Deaths	0.0134 (0.0506)	-0.0356 (0.0448)	-0.1163 ** (0.0555)	-0.0937** (0.0463)
Δ OSI	-0.0028 *** (0.0004)	-0.0012 *** (0.0005)	0.0001 (0.0006)	-0.0022*** (0.0003)
Lagged %Δ IP	0.0075 (0.1147)	-0.0263 (0.0952)	-0.0166 (0.1419)	-0.0985 (0.1140)
%Δ Exports		0.3656 *** (0.0895)	0.2832 *** (0.0826)	0.4116*** (0.0064)
R <sup>2</sup>	0.3393	0.5146	0.5748	0.4071
Adj. R <sup>2</sup>	0.3279	0.5034	0.5411	0.3982
Num. obs.	178	178	178	178
Fixed Effects	None	None	<b>Time</b>	None
RMSE	0.0760	0.0653	0.0628	0.0722

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 7: Monthly Percent Change in IP – Global Determinants – Poor Countries

	OLS	OLS	OLS	2SLS
	(1)	(2)	(3)	(4)
(Intercept)	0.0257 *** (0.0090)	0.0124 (0.0080)	0.0060 (0.0245)	0.0013 (0.0084)
$\Delta$ Deaths	-0.0760 (0.0958)	-0.0735 (0.0738)	-0.1045 (0.0817)	-0.0437 (0.0919)
$\Delta$ OSI	-0.0032 *** (0.0005)	-0.0015 *** (0.0004)	-0.0004 (0.0005)	-0.0024 *** (0.0005)
Lagged % $\Delta$ IP	-0.1389 (0.1111)	-0.0770 (0.0819)	-0.0545 (0.0987)	-0.1971* (0.1052)
% $\Delta$ Exports		0.4251 *** (0.0624)	0.3998 *** (0.0549)	0.7961 *** (0.2146)
R <sup>2</sup>	0.2299	0.4537	0.5330	0.2838
Adj. R <sup>2</sup>	0.2174	0.4418	0.4981	0.2770
Num. obs.	188	188	188	188
Fixed Effects	None	None	<b>Time</b>	None
RMSE	0.1129	0.0954	0.0904	0.1092

Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 8: Role of Structural Characteristics – 2SLS Estimates for IP Growth

	Baseline	Prior Trend IP Growth	Prior Trend IP Growth	Manufacturing (% of GDP)	Manufacturing (% of GDP)	Services (% of GDP)	Services (% of GDP)	Exports (% of GDP)	Exports (% of GDP)	Tourism (% of GDP)	Tourism (% of GDP)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(Intercept)	-0.0012 (0.0041)	-0.0026 (0.0058)	-0.0025 (0.0058)	-0.0118 (0.0129)	-0.011 (0.0131)	0.0081 (0.0289)	0.0074 (0.0286)	-0.0002 (0.0075)	-0.0006 (0.0075)	0.0009 (0.0088)	0.0007 (0.0090)
$\Delta$ Deaths	-0.1960*** (0.0701)	-0.1950*** (0.0706)	-0.1320 (0.0946)	-0.1970*** (0.0702)	-0.0856 (0.2050)	-0.1950*** (0.0702)	-0.3630 (0.484)	-0.1950*** (0.0702)	-0.3990*** (0.1280)	-0.1950*** (0.0705)	-0.0063 (0.1620)
$\Delta$ OSI	-0.0021*** (0.0003)	-0.0021*** (0.0003)	-0.0024*** (0.0004)	-0.0021*** (0.0003)	-0.0015* (0.0008)	-0.0021*** (0.0003)	0.0006 (0.0016)	-0.0021*** (0.0003)	-0.0022*** (0.0005)	-0.0021*** (0.0003)	-0.0012** (0.0005)
Lagged % $\Delta$ IP	-0.1590** (0.0645)	-0.160** (0.0647)	-0.1590** (0.0646)	-0.1620** (0.0648)	-0.1600** (0.0652)	-0.1600** (0.0646)	-0.1610** (0.0648)	-0.1590** (0.0644)	-0.1620** (0.0647)	-0.1600** (0.0645)	-0.1670*** (0.0645)
% $\Delta$ Exports	0.5200*** (0.0849)	0.5210*** (0.0852)	0.5270*** (0.0861)	0.5220*** (0.0855)	0.5240*** (0.0850)	0.5210*** (0.0850)	0.5320*** (0.0843)	0.5200*** (0.0849)	0.5180*** (0.0850)	0.5200*** (0.0850)	0.5280*** (0.0847)
Char.		0.307 (1.204)	0.244 (1.203)	0.0745 (0.0934)	0.0713 (0.0957)	-0.0157 (0.0454)	-0.015 (0.0450)	-0.0019 (0.0114)	-0.0013 (0.0115)	-0.0212 (0.0756)	-0.0183 (0.0784)
Char.* $\Delta$ Deaths			-17.60 (18.58)		-0.8460 (1.418)		0.3080 (0.787)		0.3360* (0.172)		-1.897 (1.481)
Char.* $\Delta$ OSI			0.0555 (0.0555)		-0.0042 (0.0058)		-0.0046* (0.0026)		0.0001 (0.00076)		-0.0087* (0.0046)
R <sup>2</sup>	0.3190	0.3200	0.3230	0.3210	0.3230	0.3190	0.3240	0.3190	0.3230	0.3190	0.3280
Adj. R <sup>2</sup>	0.3143	0.3133	0.3138	0.3145	0.3141	0.3132	0.3149	0.3131	0.3140	0.3131	0.3188
Num. obs.	546	546	546	546	546	546	546	546	546	546	546
RMSE	0.0887	0.0887	0.0887	0.0887	0.0887	0.0887	0.0886	0.0888	0.8868	0.0887	0.0884

Standard errors in parentheses; \*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Table 9: Role of Fiscal and Monetary Stimulus – 2SLS Estimates for IP Growth

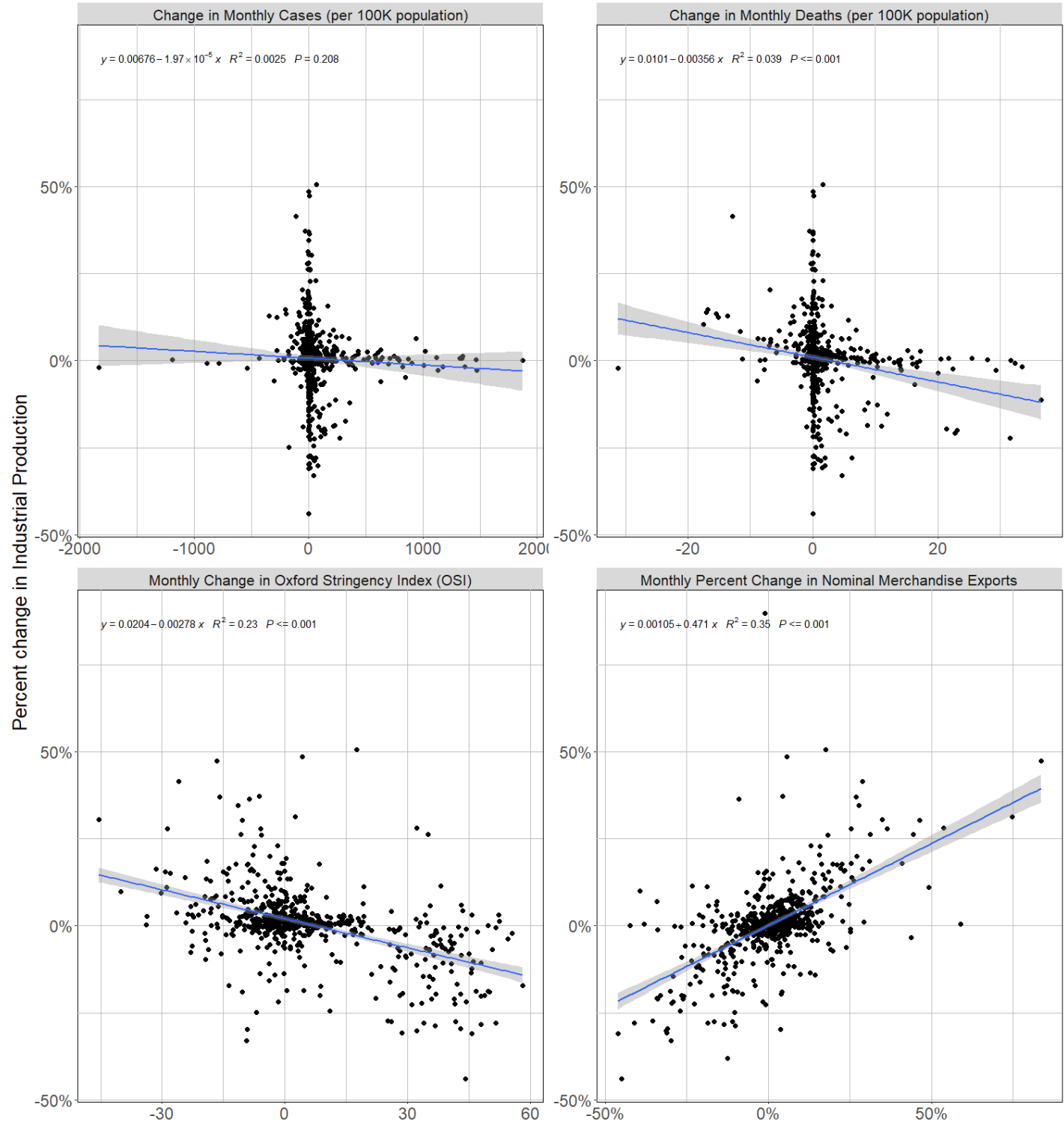
	Fiscal Policy (IMF) [% of GDP]		Fiscal Policy (ESI)		Policy Rate (percentage points)	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	-0.0016 (0.0041)	-0.0009 (0.0066)	-0.0013 (0.0039)	0.0021 (0.0040)	-0.0011 (0.0041)	-0.0015 (0.0040)
$\Delta$ Deaths	-0.1860*** (0.0662)	-0.1850*** (0.0662)	-0.1870*** (0.0658)	-0.1860*** (0.0644)	-0.1840*** (0.0680)	-0.1830*** (0.0679)
$\Delta$ OSI	-0.0021*** (0.0003)	-0.0021*** (0.0003)	-0.0021*** (0.0003)	-0.0020*** (0.0003)	-0.0022*** (0.0003)	-0.0023*** (0.0003)
Lagged % $\Delta$ IP	-0.1600** (0.0647)	-0.1600** (0.0647)	-0.1570** (0.0643)	-0.1580** (0.0650)	-0.1630** (0.0657)	-0.1620** (0.0656)
% $\Delta$ Exports	0.5350*** (0.0869)	0.5350*** (0.0870)	0.5200*** (0.0831)	0.4690*** (0.0820)	0.5370*** (0.0856)	0.5370*** (0.0857)
Stimulus Variable		-0.0119 (0.0764)		-0.0004* (0.0002)		-0.0050 (0.0044)
R <sup>2</sup>	0.3201	0.3201	0.3189	0.3237	0.3318	0.3324
Adj. R <sup>2</sup>	0.3150	0.3138	0.3141	0.3176	0.3268	0.3262
Num. obs.	546	546	566	566	537	537
RMSE	0.0886	0.0887	0.0873	0.0870	0.0881	0.0881

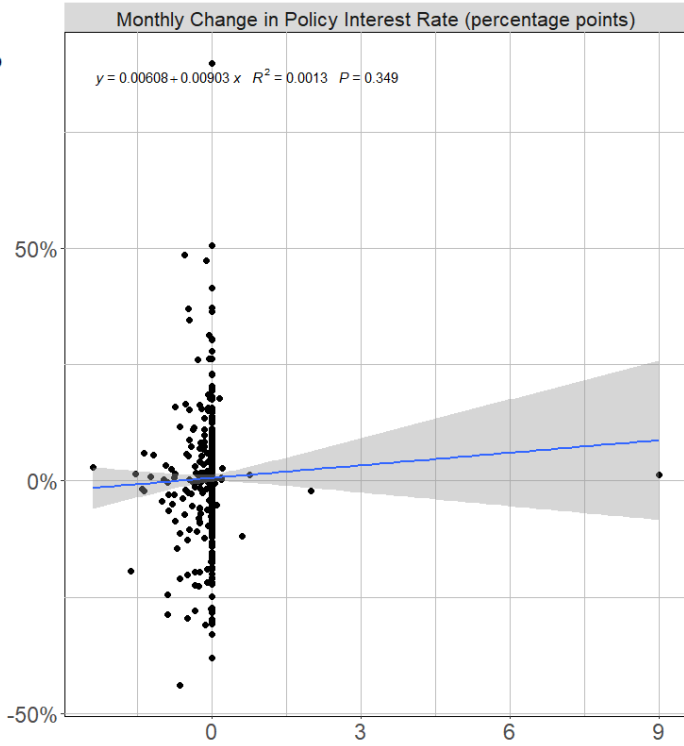
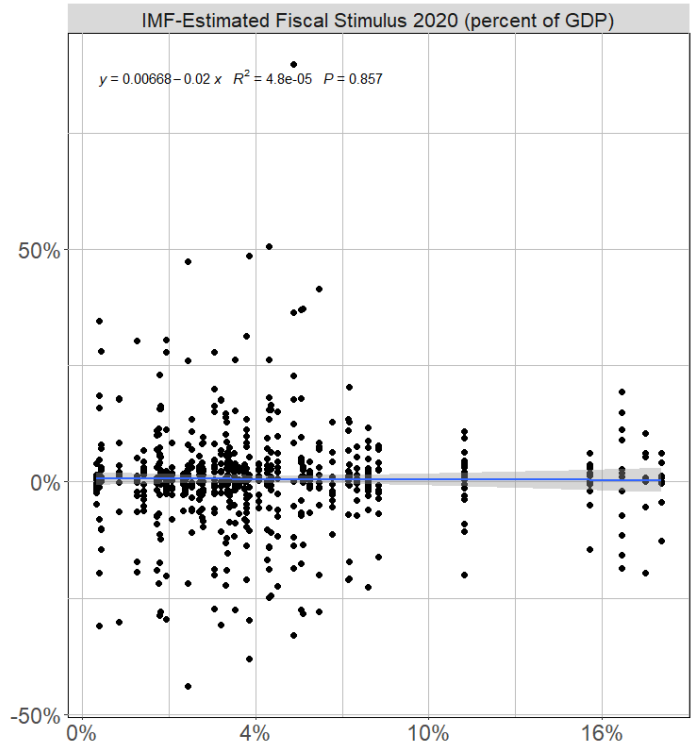
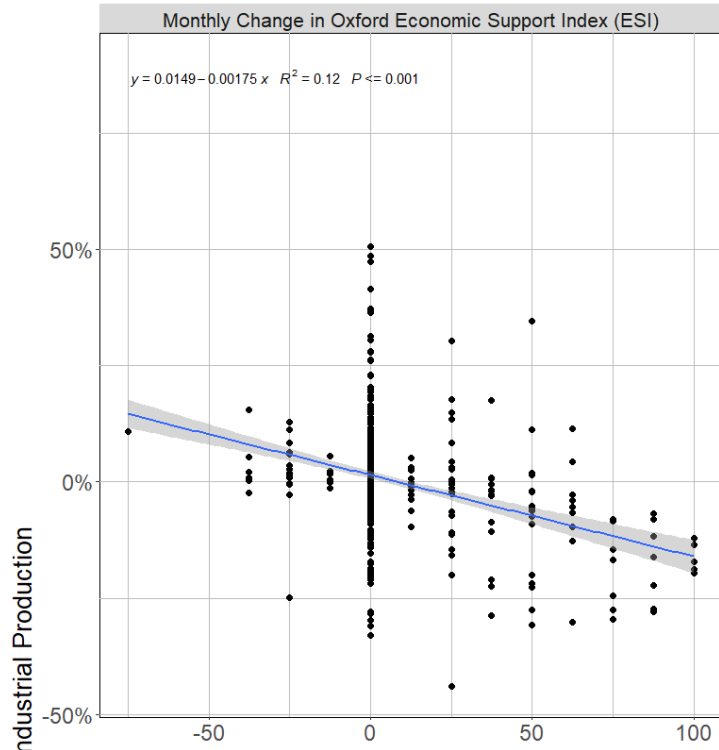
Standard errors in parentheses

\*\*\* p < 0.01; \*\* p < 0.05; \* p < 0.1

Figure 1: Bilateral correlations between explanatory variables and industrial production (IP)

(The y-axis in all scatterplots depicts month-to-month percent changes in IP during March-December 2020)





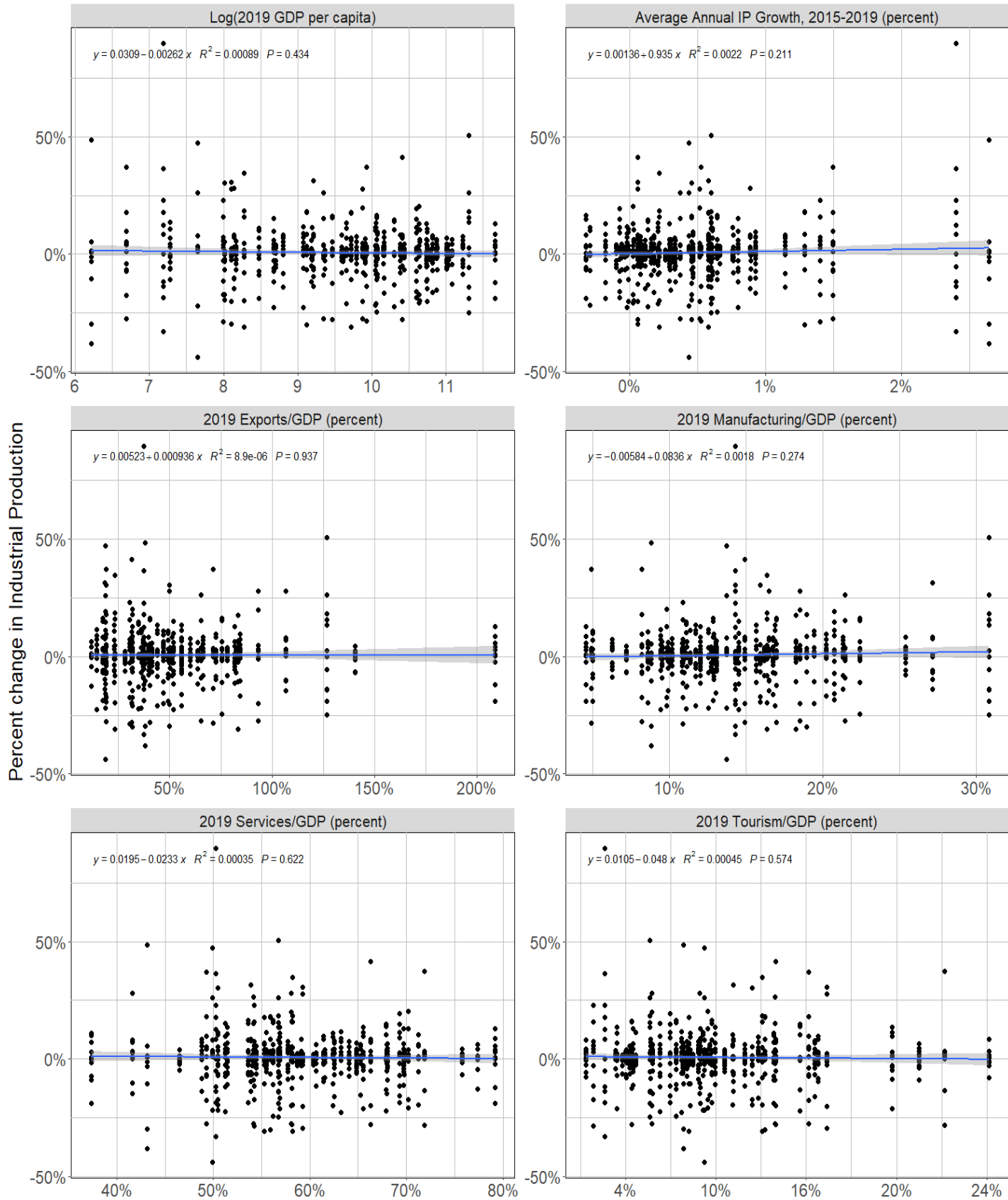
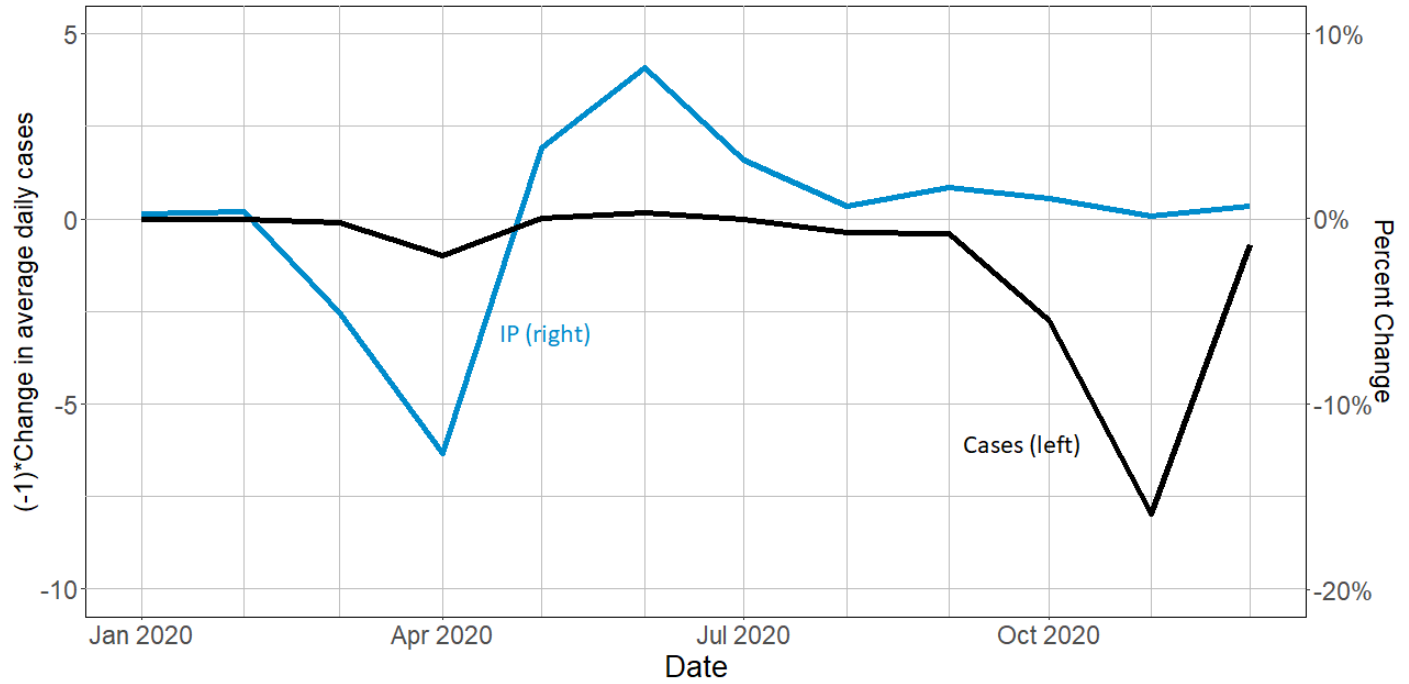


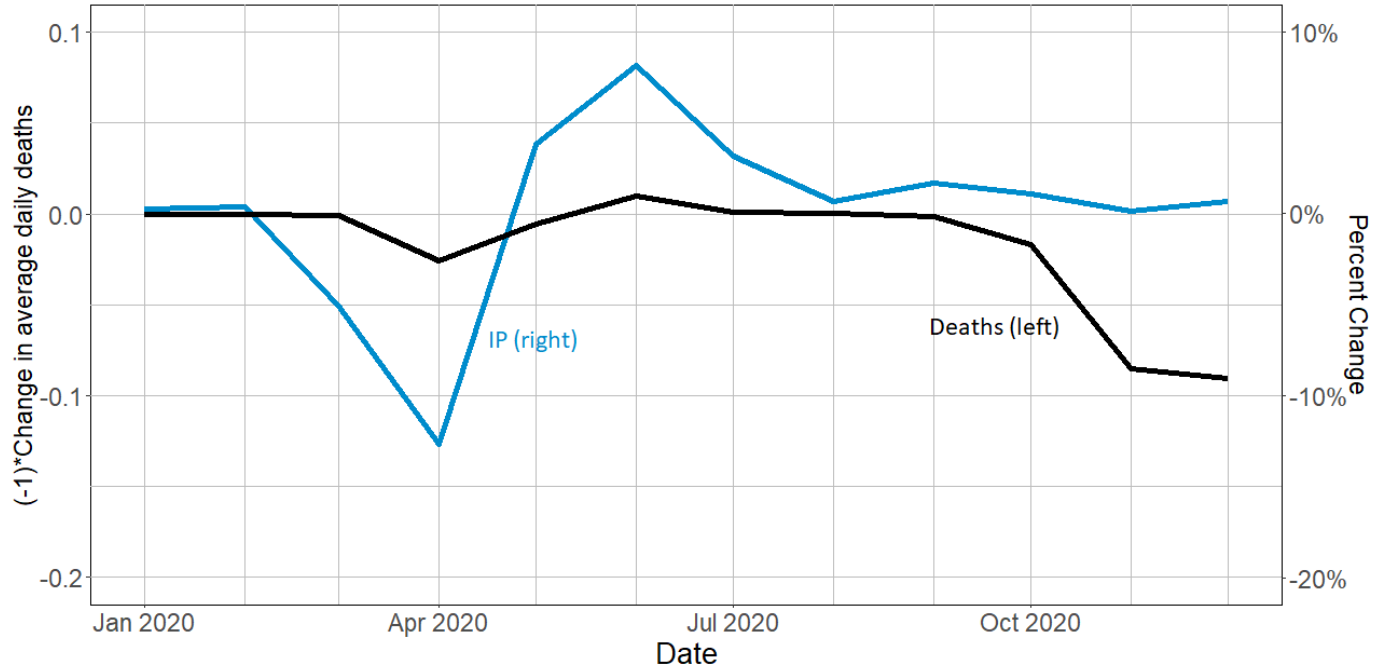


Figure 2a: Industrial Production (IP) and Daily COVID-19 Cases (per 100K)  
 Median monthly changes



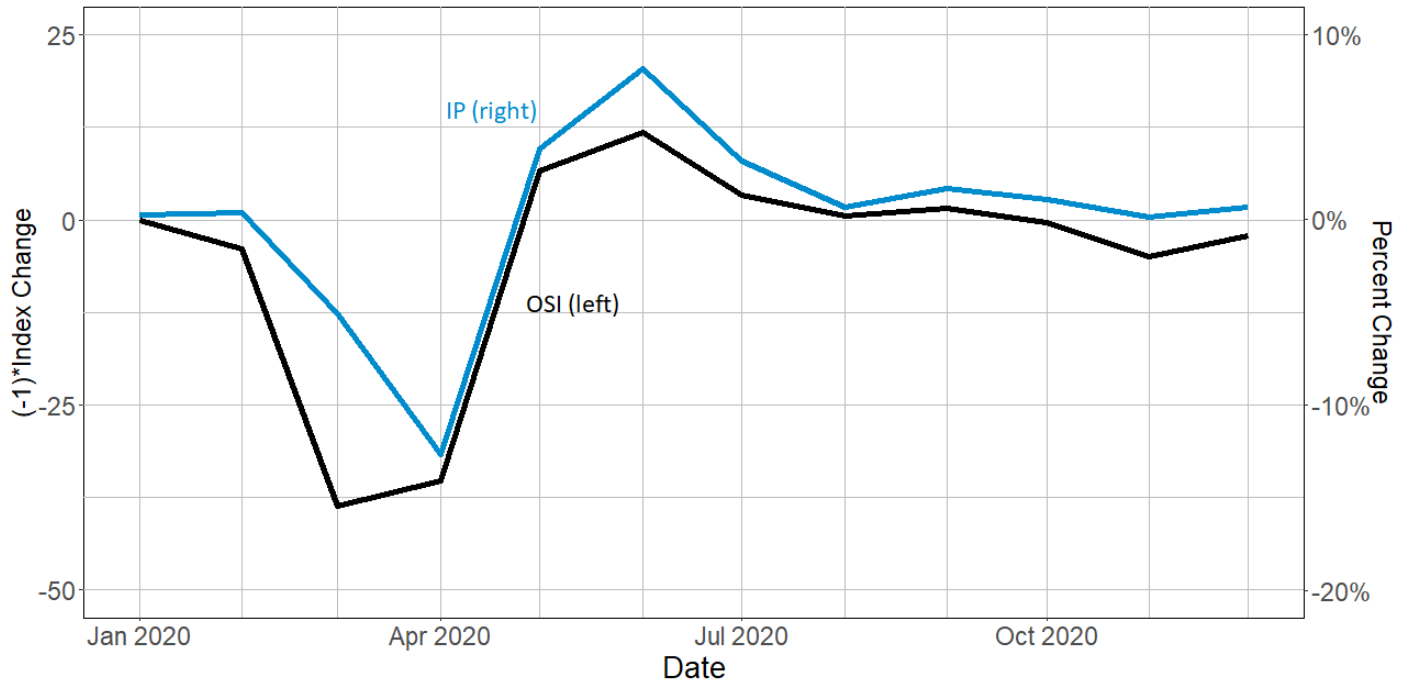
Sources: CEIC; Johns Hopkins University; Oxford University

Figure 2b: Industrial Production (IP) and Daily COVID-19 Deaths (per 100K)  
 Median monthly changes



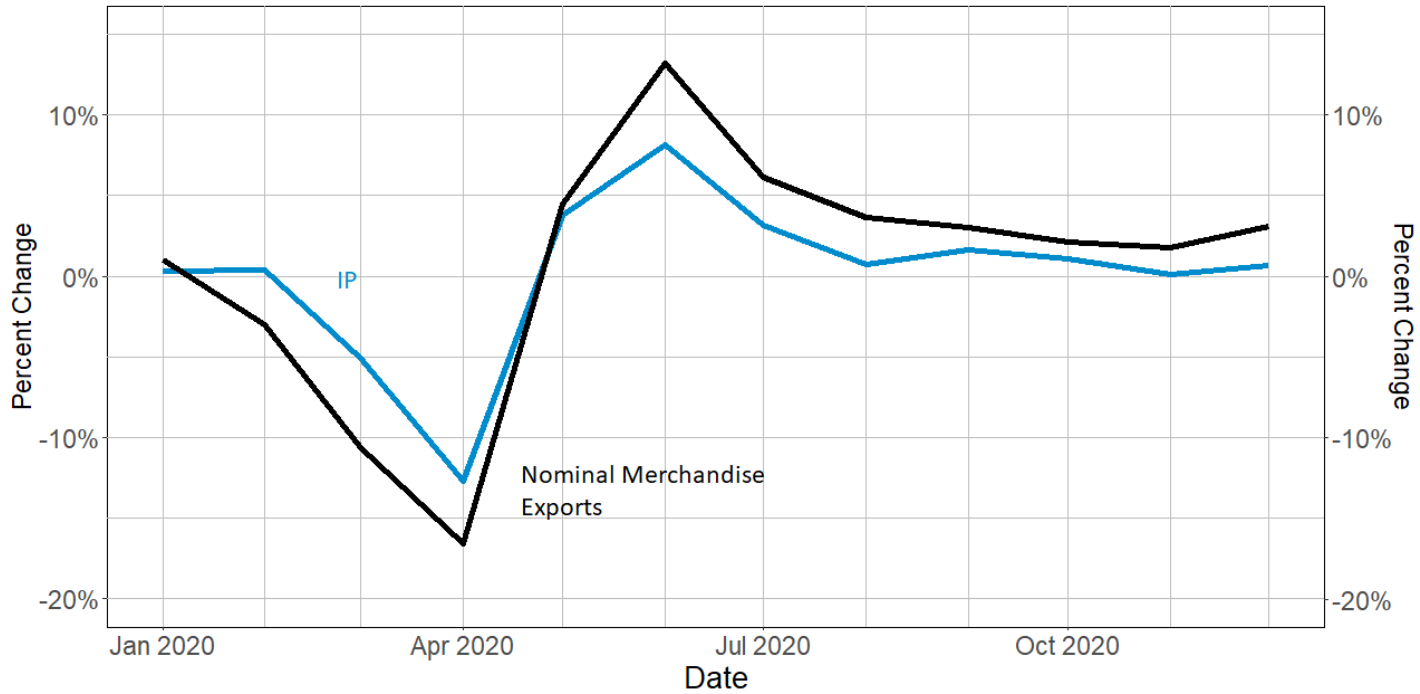
Sources: CEIC; Johns Hopkins University; Oxford University

Figure 2c: Industrial Production (IP) and Oxford Stringency Index (OSI)  
Median monthly changes



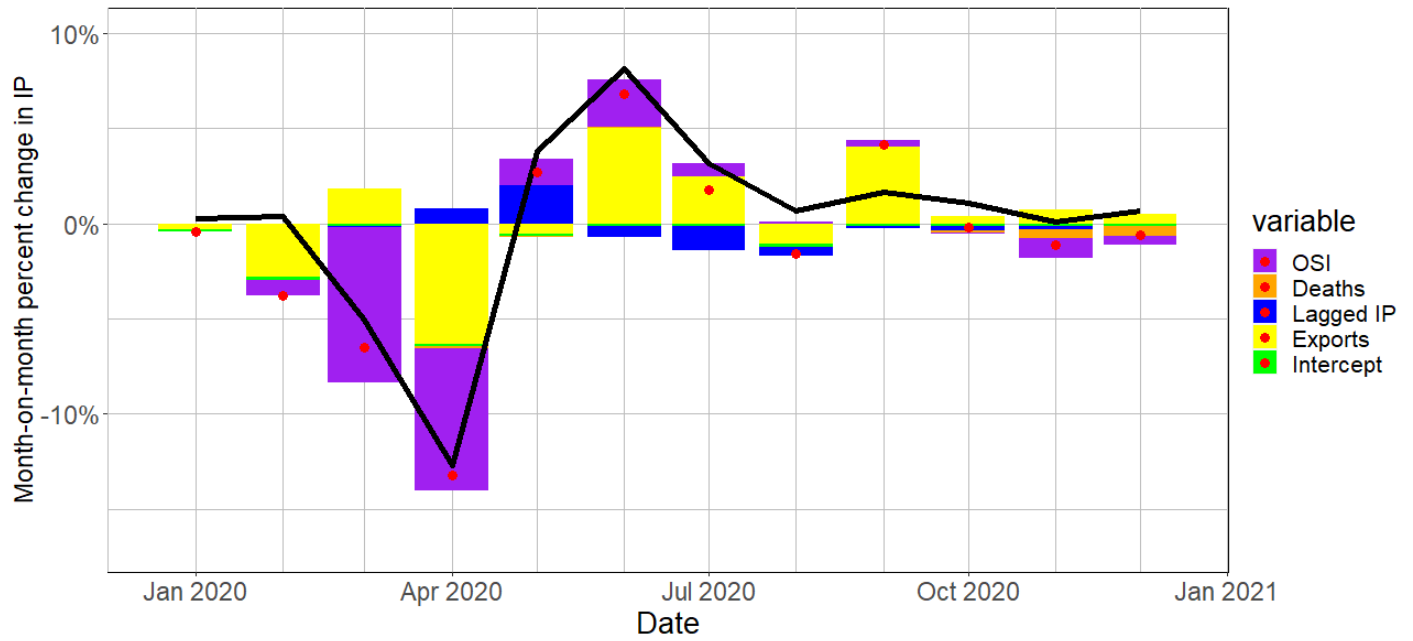
Sources: CEIC; Johns Hopkins University; Oxford University

Figure 2d: Industrial Production (IP) and Nominal Merchandise Exports  
Median monthly changes



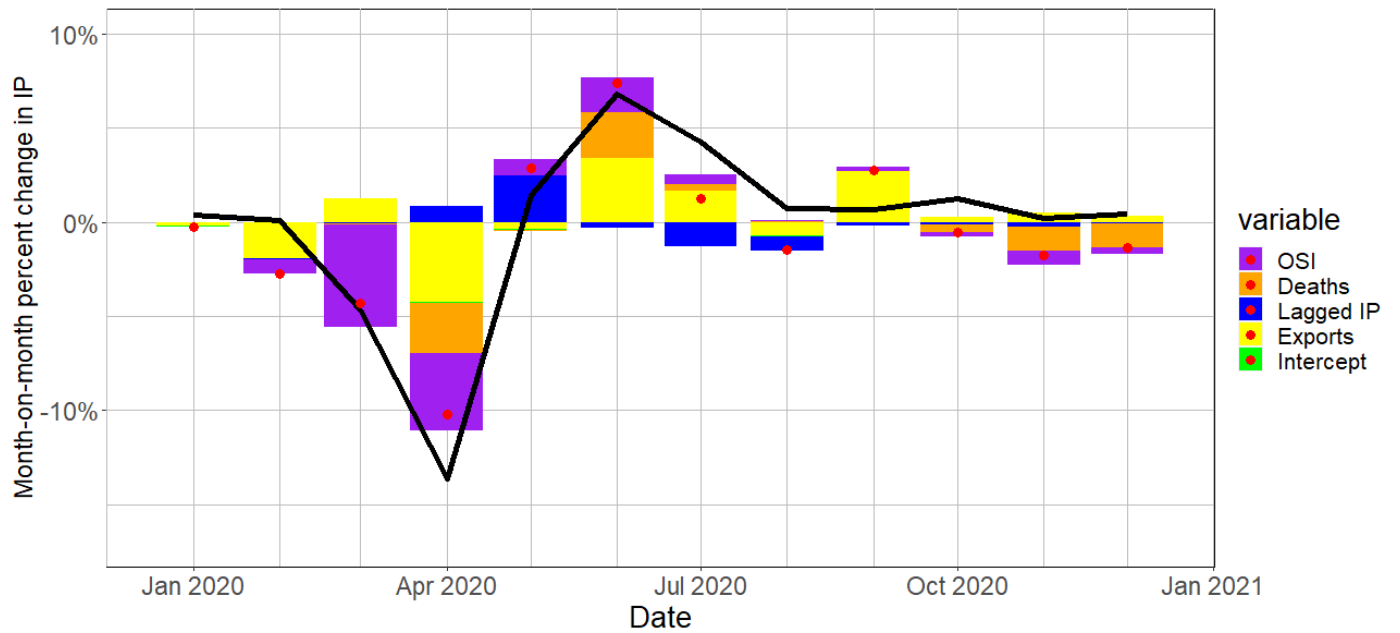
Sources: CEIC; Johns Hopkins University; Oxford University

Figure 3: IP decomposition for full sample (median)



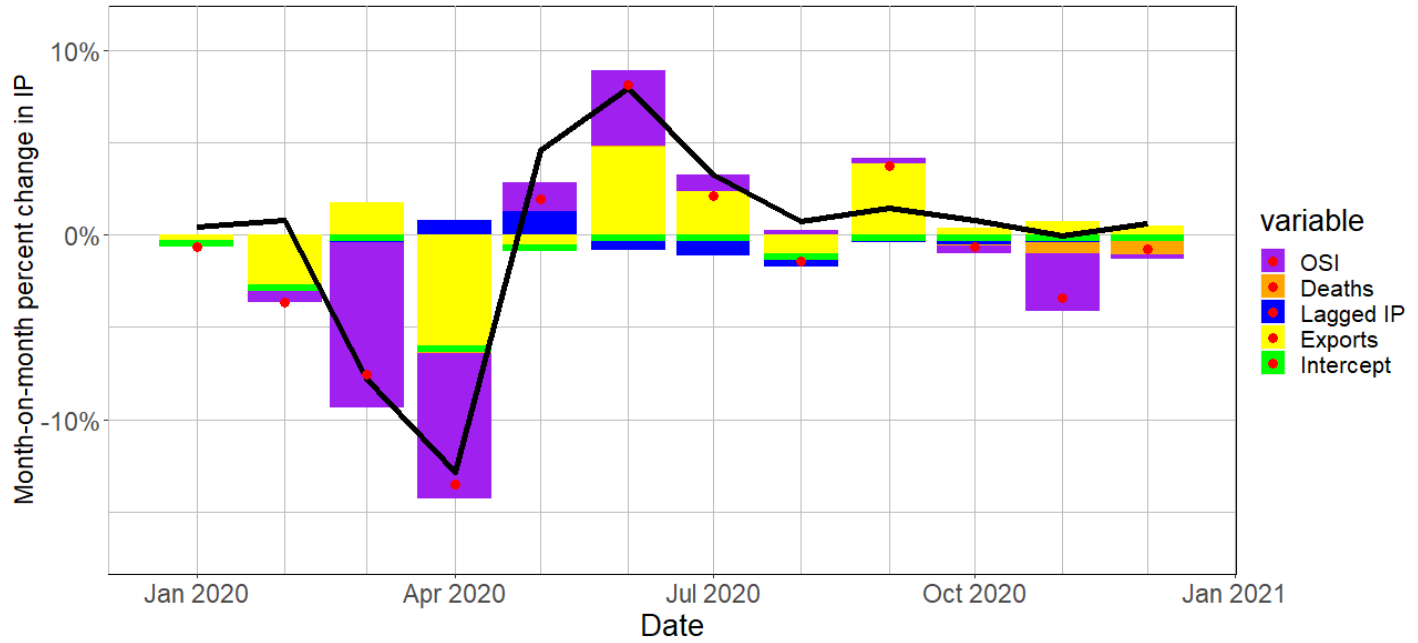
Sources: CEIC; Johns Hopkins University; OECD  
 The red dot represents the fitted value of the regression.  
 The black line is the actual path of IP

Figure 4: IP decomposition for 20 richest countries (median)



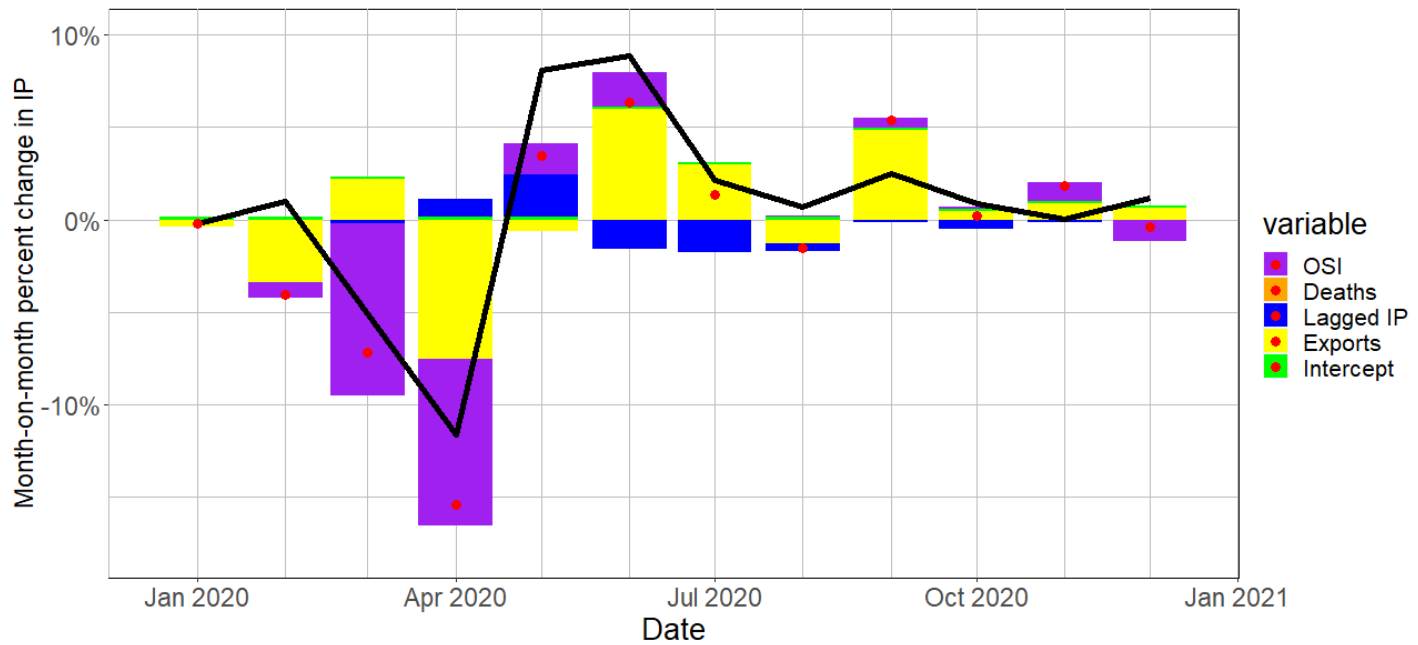
Sources: CEIC; Johns Hopkins University; OECD  
 The red dot represents the fitted value of the regression.  
 The black line is the actual path of IP

Figure 5: IP decomposition for 18 middle-income countries (median)



Sources: CEIC; Johns Hopkins University; OECD  
 The red dot represents the fitted value of the regression.  
 The black line is the actual path of IP

Figure 6: IP decomposition for 20 poorest countries (median)



Sources: CEIC; Johns Hopkins University; OECD  
 The red dot represents the fitted value of the regression.  
 The black line is the actual path of IP

Appendix A: Sampled Countries

'Rich'	'Middle Income'	'Poor'
Luxembourg	Slovenia	Bulgaria
Ireland	Taiwan	China
Norway	Estonia	Argentina
United States	Czech Republic	Kazakhstan
Qatar	Portugal	Turkey
Denmark	Saudi Arabia	Brazil
Netherlands	Cyprus	Belarus
Sweden	Greece	Bosnia and Herzegovina
Austria	Lithuania	Serbia
Finland	Slovak Republic	Azerbaijan
Canada	Latvia	Sri Lanka
Germany	Hungary	Ukraine
Belgium	Poland	Vietnam
United Kingdom	Chile	Tunisia
France	Croatia	Egypt
Japan	Romania	Moldova
Malta	Russia	India
Italy	Malaysia	Senegal
South Korea		Kyrgyz Republic
Spain		Mozambique

Note: Columns are ranked by GDP per capita (2019) descending.

Appendix B: Summary statistics for relevant variables

Category	Description	Source	Obs.	Sample Median (SE)
<b>Economic performance</b>	Monthly IP % growth (Mar.-Dec. 2020)	CEIC	704	0.68% (0.50)
	Average monthly IP % growth (2015-2019)	CEIC	59	0.37% (0.09)
	YOY IP % growth (Mar.-Dec. 2020)	CEIC	704	-3.03% (0.50)
	Decline in workplace mobility (relative to Jan. 2020 baseline) (%)	Google	604	-24.00% (2.61)
	Monthly \$Nominal Export % Growth (Mar.-Dec. 2020)	CEIC	689	1.74% (0.64)
<b>Domestic factors</b>	Monthly cases (per 100K)	Johns Hopkins University	708	28.07 (18.38)
	Monthly deaths (per 100K)	Johns Hopkins University	708	0.50 (0.36)
	Oxford Stringency Index	OxCGRT	708	54.38 (1.21)
<b>Structural characteristics</b>	Manufacturing (% of GDP)	World Bank	58	13.05% (0.90)
	Services (% of GDP)	World Bank	59	58.13% (1.43)
	Exports (% of GDP)	World Bank	59	40.76% (5.63)
	Exports (% of IP)	World Bank	57	100.21% (13.76)
	IP (% of GDP)	World Bank	58	38.50% (1.42)
	Tourism (% of GDP)	WTTC	59	9.12% (0.77)
	GDP per Capita	IMF	59	\$19,320.83 (3878.49)
<b>Fiscal and monetary policy</b>	Economic Support Index	OxCGRT	708	50.00 (1.60)
	Fiscal Spending (% of GDP)	IMF	57	4.40% (0.62)
	Monthly change in policy rate (percentage points)	CEIC	672	-0.09 (0.03)