WP/21/119

IMF Working Paper

Will the Economic Impact of COVID-19 Persist? Prognosis from 21st Century Pandemics

by Johannes Emmerling, Davide Furceri, Francisco Líbano Monteiro, Prakash Loungani, Jonathan D. Ostry, Pietro Pizzuto and Massimo Tavoni

I N T E R N A T I O N A L   M O N E T A R Y   F U N D

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Asia and Pacific Department and Independent Evaluation Office

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April 2021

Abstract

COVID-19 has had a disruptive economic impact in 2020, but how long its impact will persist remains unclear. We offer a prognosis based on an analysis of the effects of five previous major epidemics in this century. We find that these pandemics led to significant and persistent reductions in disposable income, along with increases in unemployment, income inequality and public debt-to-GDP ratios. Energy use and CO_2 emissions dropped, but mostly because of the persistent decline in the level of economic activity rather than structural changes in the energy sector. Applying our empirical estimates to project the impact of COVID-19, we foresee significant scarring in economic performance and income distribution through 2025, which be associated with an increase in poverty of about 75 million people. Policy responses more effective than those in the past would be required to forestall these outcomes.

JEL Classification Numbers: E52, E58, D43, L11.

Keywords: COVID-19; pandemics; sustainability; poverty; climate; inequality.

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I. Introduction

The COVID-19 pandemic has had devastating impacts on economic activity in 2020. How long these impacts will persist remains unclear. Private sector forecasters and public agencies such as the IMF forecast a return to growth in 2021. The IMF's forecast is for global growth of 5.2 percent in 2021, erasing the effects of a projected 4.4 decline in 2020. For the United States, *Consensus Forecasts*—an average of several mostly private forecasts—predicts that after a 3.5% decline this year, GDP will grow 4 % in 2021 and 3% in 2022, thus raising incomes well above their pre-COVID level; forecasts for other major economies follow a similar pattern.

How credible are such forecasts that the adverse economic impacts of the pandemic will largely be contained to 2020, with little medium-term impact? And, looking beyond GDP, will the impact of the pandemic on other economic variables such as poverty and inequality—and on energy and environmental systems—be similarly short-lived? One approach to answering these questions has been to look to the medium- and long-term impacts of historical episodes such as the Black Death and the Spanish Flu of 1918. However, while these studies yield valuable insights into the effects of pandemics (Alfani 2020), their usefulness in predicting the medium-term impacts of COVID-19 may be limited. Despite its devastating death toll thus far, COVID-19 is expected to have mortality rates far below the magnitudes of the Black Death or the Spanish Flu; hence, as argued by Dosi, Fanti, Virgillito (2020), the nature and persistence of the economic impacts of COVID-19 is likely to be quite different from those historical episodes, particularly because of the much lower adverse impact on labor supply.

In this paper, we suggest that evidence on the impacts of more recent epidemics—SARS, H1N1, MERS, Ebola and Zika—might be a more useful guide for projections of the lingering impacts of COVID-19 on the economy. We go beyond existing work by examining the impact on a wide range of economic measures—including economic growth, unemployment and public debt; income inequality and poverty; and energy use and intensity and emissions—using a common econometric framework.[1] Our results show that previous pandemics have had significant and persistent negative repercussions for the macroeconomic outcomes we study: per capita income declines, unemployment goes up and income inequality increases. We also observe small declines

[1] Other recent studies have focused on one of these variables, such as income (Ma et al. (2020) and Jorda et al. (2020)), inequality (Furceri et al. (2020a)), and poverty (Valensisi (2020) and Sumner et al. (2020)).

in energy and emissions intensity, suggesting that without deliberate policy actions, initial environmental gains will not remain entrenched. Applying the historical estimates to project the impact of COVID-19 until 2025, we forecast a persistent decline in the level of economic activity and an increase in poverty. Our estimates are likely a lower bound since COVID-19 is more widespread than the average health crisis in our sample. Indeed, containment measures (travel restrictions, lockdowns, social distancing measures) are without precedents in terms of speed and severity, and the global nature of the COVID-19 shock is likely to affect global value chains more than in the past.

The paper is organized as follows. Section 2 describes the data, the construction of our measure of the incidence of pandemics, and the empirical strategy to investigate the impact of past pandemics. Section 3 provides the impulse response functions that trace out the impacts of pandemics on economic outcomes. Section 4 uses the empirical estimates to simulate the repercussions of COVID-19 for the next five years. Section 5 concludes with a discussion of policy options to mitigate the projected impacts.

II. Data and Empirical Strategy

Data

We use data on the incidence of five major pandemic events: SARS in 2003, H1N1 in 2009, MERS in 2012, Ebola in 2014, Zika in 2016. These historical pandemic events account for almost 7 million confirmed positive cases. The pandemic events considered in the sample occurred in 2% of the covered year and country observations. In terms of confirmed cases, including episodes without pandemics, 0.02 cases per 1000 inhabitants are reported with a maximum of 52 cases. The conditional mean during pandemics equals 0.783 cases per 1000 inhabitants—that is, about 25,000 cases in total.

We combine the infection data with a variety of economic and social variables such as GDP per capita, government debt, unemployment rate and the Gini index, as well as on environmental factors such as energy demand, and emissions of air pollutants and greenhouse gases. Data on economic variables come from the World Development Indicators (WDI) while data on energy aggregates comes from the IEA's World Energy Balances 2019. Emissions data for CO_2 are from the PRIMAP-hist dataset and for NOx from the Community Emissions Data

System (CEDS). Data on inequality are from the Standardized World Income Inequality Database (SWIID 8.3). Tables A1 and A2 in the Appendix report the summary statistics of the variables used in the empirical analysis.

For the forecast analysis of the medium-term impact of COVID-19, we combine these data with GDP and population projections from the IMF World Economic Outlook of October 2019 and October 2020 (IMF, 2019, 2020). We use inequality Gini projections from Rao et al. (2018) for SSP2 as our near-term baseline for the Gini index. For the energy and environmental variables, we use the International Energy Agency's World Economic Outlook 2019 and 2020 forecasts (IEA, 2019, 2020). While the IMF and Rao et al. (2018) forecasts are available at the country level, the IEA projections are available only for 14 large countries and macro-regions and in five-year time steps. Therefore, we disaggregate these values across countries using the primary energy shares of each country in 2015 and interpolate linearly for years that are not available.

We measure the effects of pandemics on several outcome variables using the number of cases in each pandemic episode. Specifically, we compute the logarithm of base 10 of the number of confirmed cases per 1000 inhabitants in each country—we add 1 to the cases-population ratio so that the new variable takes the value of zero in years without pandemics[2]:

$$log(cases_{i,t}) = log_{10}\left(1 + \frac{1000 \cdot confirmed\_cases_{i,t}}{population_{i,t}}\right) \quad (1)$$

Figure 1 shows the distribution of this variable for the various pandemics considered in this paper.

Empirical strategy

To estimate the medium-term impact of pandemics, we follow the method proposed by Jordà (2005) and estimate impulse response functions directly from local projections:

$$y_{i,t+k} = \beta_c^k log_{10}\left(1 + \frac{1000 \cdot confirmed\_cases_{i,t}}{population_{i,t}}\right) + \theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \epsilon_{i,t}^k \quad (2)$$

[2] That is, for zero cases, $log(cases_{i,t})$ takes on the value of zero, for 9 cases per 1000 inhabitants (around 1% of the population), it takes on the value of 1, and for 99 cases per 1000 inhabitants it takes on the value of 2.

where $y_{i,t+k}$ is our variable of interest for country *i* in year *t*, α_i^k are country fixed effects, included to control for unobservable country-specific factors. The terms γ_t^k are time fixed effects, included to take account of global shocks such as shifts in oil prices or the global business cycle. Finally, $X_{i,t}$ is a vector of controls that includes two lags of the dependent variable and the pandemic shock variable. Equation (2) is estimated for each horizon (year) *k*=0,..,5. Based on the estimated coefficient β_c^k, we compute impulse response functions and their confidence intervals based on the estimated standard errors clustered at the country level. Specifically, we evaluate the impact after k years of a pandemic event:

$$IRF_k^{log(cases)} = E(y_{t+k}|log(cases_{i,t}) = \zeta + 1; X_{i,t}) - E(y_{t+k}|log(cases_{i,t}) = \zeta; X_{i,t}) \quad (3)$$

In the figures we show the coefficients multiplied by the mean of cases in pandemic episodes transformed in $log(1 + E[\frac{1000 \cdot confirmed\_cases_{i,t}}{population_{i,t}}|confirmed\_cases_{i,t} > 0])$, based on the conditional mean of 0.8 cases per 1000 inhabitants. That is, the value we report should be interpreted as the change of the outcome variables for a pandemic episode of 0.8 cases per 1000 inhabitants. For higher incidence rates, the value then increases logarithmically. For instance, at 10.7 cases per 1000 (as the global average of COVID-19 at the end of 2020) to about four times its value, while at 52 cases per 1000, the impact equals seven times the reported values.

III. Effects of Past Pandemics

Figures 2 and 3 show the estimated dynamic response of the social, economic and environmental variables to a pandemic event.[3] Starting with GDP per capita, the analysis shows that pandemics significantly and negatively affect economic activity in both the short and medium term. In the year of an average size pandemic episode, economic activity declines by about 1.1 percent. As time goes by, the pandemic's impact on the growth rate fades away, becoming statistically insignificant after five years (as shown by the slope of the response function). This

[3] Table 1 and Table A3 in the Appendix present the associated regressions for k=5 and for all time horizons, respectively.

implies a persistent drop in the level of economic activity, culminating in a 3.6 percent reduction in GDP per capita five years after the pandemic. The results are qualitatively similar to the literature on the impact of recessions and financial crises (Cerra and Saxena 2008) as well as the evidence presented in Ma et al. (2020) on the GDP impact of previous pandemics.

Consistent with the decline in GDP per capita, unemployment rises following a pandemic event. Job losses cumulate over time, and the employment effects suggest a delayed and prolonged deterioration in the labor market. After five years, the increase of unemployment levels off at about 0.7 percentage point relative to the pre-pandemic level, a value similar to the estimates of Coibion et al. (2020) for the effect of COVID-19 in the United States.

We also evaluate the consequences for economic inequality. Figure 2 shows that an average pandemic episode leads to an increase of the Gini index of around 0.1 percentage points above pre-pandemic levels after five years. This implies that for the maximum incidence observed historically (52 cases per 1000 people), the Gini index would increase by 0.7 percentage point. These are sizable effects for an indicator that moves very slowly over time. In addition to aggregate inequality measures, we also looked, where data are available, at the income by percentile of the distribution (e.g., bottom 10th percentile, bottom 20th percentile). We find that at the lowest part of the income distribution, the negative impact of pandemics is much more substantial compared to the top of the distribution; the poor are more severely hit while the rich are resilient in terms of their income share. The regressive impact of the pandemic also persists over time, even after five years (see Figure A1 in the Appendix –Panels A and B). The evidence is similar to the one presented by Furceri et al. (2020a), who also find that pandemics lowered the employment-to-population ratio for those with basic education compared to those with higher education.

Another consequence of the pandemics is that they lead to an increase in the government debt-to-GDP ratio. This is accounted for both by lower economic activity (which lowers government revenues) and the expansionary fiscal response typically taken by governments to limit the negative economic effects of pandemics (Furceri et al. 2020b). Our analysis suggests that past pandemics have led to a rise in public debt of 2 to 5 per cent of GDP after one and five years, respectively (Figure 2).

As economic activity plummets in response to pandemic events, energy consumption declines too. Figure 3 shows a considerable contraction of final energy demand. An increase of cases to average pandemic levels is associated with a medium-term reduction in energy demand of about 5 percent. A smaller energy system translates into lower emissions of greenhouse gases and air pollutants. CO_2 emissions drop by as much as 11% and we find a similar drop in NOx, an air pollutant closely related to transportation (Figure A1 in the Appendix – Panel F). We also see a significant reduction in oil consumption (Figure A1 – Panel C), while the decrease in electricity consumption is smaller (Figure A1 – Panel D). Among generation technologies, Solar Photovoltaics significantly increases (Figure A1 – Panel E).

The reduction of greenhouse gases can be interpreted as a sign of environmental progress. However, it is essential to differentiate the consequences of reduced economic activity from structural transformation towards a low carbon energy system. To disentangle structural and cyclical effects, we compute energy and emission intensities—respectively defined as the ratio of primary energy to GDP and emissions to primary energy. The results show that energy intensity declines only marginally in the medium term (Figure 3). Emission intensity decreases by up to 4 percent after five years. A shift to electricity demand and more substantial reduction in oil consumption, and an increase in solar photovoltaic generation explain this (small) emission intensity gain. However, compared to the 11 percent drop in total CO_2 emissions from fossil fuel combustion and industry, this indicates that around one-third of the reduction is due to carbon intensity improvements while the remaining two-thirds is due to the contraction of energy demand. From the observed changes in electricity consumption and in particular Solar PV generation, a slight shift towards (residential) electricity consumption leads to shifts from higher carbon-content sources of energy. The reduction in oil demand is the most significant. Moreover, in terms of power generation mix, there is evidence for an increase in Solar PV generation leading to a reduction in carbon intensity of electricity. These factors are however dominated by the reduction in energy demand, which ultimately explains two thirds of the overall CO2 emissions reduction. Overall, these efficiency gains are too small to make a significant contribution to efforts to combat climate change, unless policy actions are taken to lock in these declines when demand recovers.

Robustness checks

We performed several robustness checks of all regressions to validate our results. First, we repeat our analysis using an alternative identification strategy previously adopted by Furceri et al. (2020a) and Ma et al. (2020). We construct a dummy variable, $pand\_epis_{i,t}$, which takes the value of one in the year when WHO declares a pandemic for the country and 0 otherwise. This approach addresses the concern of possible measurement errors in cases detection due to different testing strategies and/or different efficiency of the health sectors of the countries considered. Moreover, the date of the pandemic event is likely to be more exogenous to the economy than the number of cases. The drawback of this approach, however, is that it considers all episodes as equal. In particular, we estimate the following model:

$$y_{i,t+k} = \beta_p^k pand\_epis_{i,t} + \theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \epsilon_{i,t}^k \quad (4)$$

with impulse response functions computed as follows:

$$IRF_k^{dummy} = E\left(y_{t+k} \middle| pand_{epis_{i,t}} = 1; X_{i,t}\right) - E\left(y_{t+k} \middle| pand_{epis_{i,t}} = 0; X_{i,t}\right) \quad (5)$$

Figure A2 in the Appendix shows that the results of this exercise are very similar to, and not statistically different from, those presented in the text. The main difference with respect to the baseline results concerns the demand of final energy and CO_2 emissions for which the estimations based on pandemic dummy do not point to significant effects. These results may be related to the fact that the effect on emissions crucially depends on the severity of the pandemics, which is not taken into account in this dummy variable approach.

Second, to address the issue of potential omitted variable bias, we add several control variables in the baseline regression, such as proxies for the level of economic development, demographics, and measures of trade and financial globalization. The results for these exercises, reported in Figure A3, are also very similar to, and not statistically different from, those presented in the text.

Third, we run a placebo test through the estimation of impulse response functions obtained by attributing randomly the values of our measure of shock across the whole sample. Figure A4 shows that the results of this exercise do not point to significant results, thus, confirming the validity of the *parallel trend assumption* in the evolution of our outcome variables before the pandemic.

Finally, to address possible concerns of estimating equation (2) by OLS, we employ an instrumental variable (IV) approach. At the outset, we should note that our econometric methods already tackle to a great extent many concerns that arise with the use of OLS. The first concern is omitted variable bias. This is attenuated in our case since we include in our baseline estimations both country and time fixed effects of accounting for unobserved cross-country and yearly heterogeneity and provide results for robustness checks using several control variables. The second concern is endogeneity since our empirical strategy may suffer from reverse causality. For example, pandemics may increase income inequality and, conversely, higher existing income inequalities may increase the probability to experience a pandemic due to the higher vulnerability of marginalized people that usually have lower economic resources, lack of access to health care and live in less healthy places. Finally, measurement errors related to the total cases detected could be an issue due to different testing strategies or different health sectors' efficiency of the countries considered. However, we have already shown some robustness checks on this point based on an alternative identification strategy based on a dummy variable approach. Nevertheless, IV estimation can provide a check on whether our results are robust to any remaining weaknesses of the OLS estimation.

Following Nunn and Quian (2014), our IV approach consists of interacting a time-varying global term and a constant country-specific term. The global term we consider is a dummy variable that takes the value of 1 for all countries in the years of pandemic outbreaks. The country term we consider captures the exposure of countries to pandemic events. For this purpose, we consider the average temperature and degree of urbanization. As shown in Deb et al. (2020), both factors are important drivers of the evolution of pandemics, such as COVID-19. Depending on the outcome variable, these measures seem to be suitable since it can reasonably be assumed that these indicators are randomly distributed across countries and do not affect our outcome variables. Our IV estimation is as follows:

$$y_{i,t+k} = \beta_c^k log(\widehat{cases}_{\iota,t}) = +\theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \epsilon_{i,t}^k \qquad (6)$$

with $$log(\widehat{cases}_{\iota,t}) = \vartheta^k S_{i,t} + \varphi^k X_{i,t} + \alpha_i^k + \gamma_t^k + v_{i,t}^k, \qquad (7)$$

where S is the instrument. The analysis also controls for country and time fixed effects and can therefore be seen as a *differences-in-differences* approach. As baseline instrument, we use the interaction between the dummy indicating the year of the pandemics and the average country temperature, supplementing it with the interaction between the dummy and the average degree of urbanization when the latter exhibits a stronger F-test in the first stage regression.

Table 2 and Table A4 in the Appendix shows the results of this exercise for k=5 and for all time horizons, respectively. Overall, our IV results qualitatively support the findings obtained with OLS estimates. The first-stage estimates suggest that the instrument is strong and statistically significant. The Kleibergen–Paap rk Wald F-statistic—which is equivalent to the F-effective statistic for non-homoscedastic error in case of one endogenous variable and one instrument (Andrews et al., 2019)—is higher than the associated Stock-Yogo critical value. Moreover, the magnitude of the coefficient is approximately five to six times as large as the OLS estimate, which provides useful corroboration that our OLS estimates are conservative estimates of the likely impacts.

IV. Projecting the repercussions of COVID-19

The empirical evidence we found using past pandemic episodes allows us to perform a simulation exercise to estimate the impact of COVID-19 into the future. Specifically, we construct our out-of-sample forecast of the short- to medium-term effect of the COVID-19 pandemic based on the estimated impacts of past pandemics.

As a first step, we build a counterfactual scenario to project what would have occurred in the absence of the current pandemic. We use the latest (October 2019) projections from the International Monetary Fund (IMF) and the International Energy Agency (IEA) before the onset of the pandemic. We combine historical and reference projection for each country to obtain a time series 2005-2024 for all variables of interest, $y_{i,t+k}^{ref}$, where now we consider $t = 2005, \ldots, 2020$ and $k = 0, \ldots, 4$ so we consider the projection for a total of 5 years (since projections dated October 2019 were available only for five years).

In the second step, we compute the COVID-19 incidence as follows:

$$log_{10}\left(1 + \frac{1000 \cdot confirmed\_cases_{i,2020}}{population_{i,2020}}\right)$$

based on the World Health Organization (WHO) data as of December 31st, 2020[4], thus covering the whole year. At the world level we detected about 81.5 million confirmed cases –on average 10.7 cases per 1000– with the variable taking the average value of 1.07. We compute the forecast of the variable of interest $\hat{y}_{i,t+k}$ ceteris paribus as:

$$\hat{y}_{i,2020+k} = y_{i,2020+k}^{ref} + \beta_c^k log_{10}\left(1 + \frac{1000 \cdot confirmed\_cases_{i,2020}}{population_{i,2020}}\right) \qquad (8)$$

To obtain the global values, we aggregate the country-level forecasts:

$$\hat{y}_{2020+k}^{World} = \sum_{i=1}^{n} w_{i,2019}\hat{y}_{i,2020+k}$$

where we use the appropriate weights based on the latest available historical data point (2019 for economic and 2017 for environmental variables) where applicable—quantities including energy, emissions, and GDP are just aggregated ($w_{i,2019} = 1$), for the debt ratio and energy intensity we use GDP weights, for unemployment rate population weights, and for emission intensity we use primary energy as weights.

We perform this simulation at the country level, and aggregate results up to the global values, that are shown in Figure 4. In Table 3, we summarize the estimated global impacts in relative terms to the reference scenario. In the analysis we also report the updated projections by the IMF and IEA as of October 2020 for the years 2020-2024 and compare these official projections to our empirically-based forecasts from effects of past pandemics.

We foresee sizable medium-term output losses of COVID-19, larger than those currently projected by the IMF and in the order of magnitude of past severe financial crises (Romer and Romer 2017). The increase in the Gini index (average across countries) is also to expected to be significant—of about 0.4 point. Energy demand is expected to drop significantly but the decline in energy intensity of GDP is likely to be small. In terms of CO_2 emissions, we project a reduction of about 7% in 2020—within the range of estimates (5-9%) of Le Quéré et al. (2020) and of about

[4] https://covid19.who.int

23% in 2024—while the emission intensity of energy decreases by 1.7% in the short term and 8.0% in the medium term.[5]

Finally, we use the GDP per capita across countries and our estimates on the impact on the Gini index to estimate the impact of COVID-19 on absolute poverty. Previous estimates of the impacts on poverty range widely, from 37 million (Gates Foundation/IHME), 68 million (Valensisi 2020), up to 85–420 million (Sumner, Hoy, and Ortiz-Juarez 2020). We improve upon these studies by using a robust econometric model including linear, quadratic, and interactions of GDP and inequality, which explain about 98 percent of the variance in poverty rates.[6] We estimate the following fixed effects regression, including country and year fixed effects:

$$log(1 + poverty\_rate_{i,t}) = \beta_0 + \beta_1 Gini_{i,t} + \beta_2 log(GDPpc_{i,t}) + \beta_3 Gini_{i,t}^2 + \beta_4 log(GDPpc_{i,t})^2 + \beta_5 Gini_{i,t} * log(GDPpc_{i,t}) + \alpha_i + \gamma_t + \epsilon_{i,t} \tag{9}$$

The regression yields an overall adjusted R^2 of 0.963, implying an in-sample correlation of 0.981 with the observed poverty variable. Table 4 shows the estimated coefficients of interest. Evaluating all the transformed variables at the mean, we can compute the marginal effect of a one-point increase in the Gini index. We find that it increases the poverty rate by about 0.8 percentage point. Based on this model and the projections on GDP and inequality, we predict the poverty rate across countries from 2020 onward (Figure 5). Our results suggest an increase of global poverty numbers—defined as those people with income below 1.9$ per day—from 662 to 738 million people in 2020 or an increase of 75 million people. This effect is projected to be persistent, declining only slightly in 2021 to 61 million above the pre-COVID scenario.[7] Looking at the regional level, we find that the increase in global poverty is concentrated in Southern Asia (India, Afghanistan) and Sub-Saharan Africa (Democratic Republic of Congo, Niger, Chad, Nigeria, Zimbabwe, and Madagascar).

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[5] Figure A5 in the Appendix presents the projections for some additional variables previously discussed (i.e. Total Oil consumption, Electricity Consumption, Solar Photovoltaics electricity generation).

[6] The strong link of poverty and inequality has already been made in Lakner et al. (2020).

[7] For the projections up to 2024 see Figure A6 in the Appendix.

V. Conclusions

We empirically estimate how past pandemics affected economic activity, unemployment, poverty, income inequality, public debt and energy use and emissions. We find significant and persistent reductions of GDP, along with increases in unemployment and income inequality and public debt-to-GDP ratios. Moreover, energy demand and CO_2 emissions drop significantly during a pandemic event. However, in terms of systemic change, we find only a small effect: energy intensity declines only about 2 percent five years after the pandemic and only about one-third of the emission reduction is due to improvements in the carbon emission intensity of energy.

Using these historical estimates to trace the likely impact of the COVID-19 pandemic, our results indicate a persistent decline in the level of per capita GDP, with long-lasting effects on income inequality and an increase in the number of people living in absolute poverty of some 75 million people. It is worth noting that our resultslikely provide lower-bound estimates of the effects of COVID-19 since it is more widespread than the average health crisis in our sample and containment measures undertaken to limit the contagion are without precedents.

While energy demand and emissions decrease substantially, we find that this effect is mostly driven by the cyclical changes in economic activity rather than by gains in energy and carbon efficiency. For CO_2 emissions, about one-third of the overall reduction can be attributed to the decarbonization of energy, notably due to a reduction in oil demand and shifting to electricity. However, these gains are not sufficient to contribute significantly to a greener economy.

These projections point to the need for a strong policy response to counter the lingering adverse effects of COVID-19. The projected increase in public debt-to-GDP ratios may prompt concerns about debt sustainability in many countries. However, a hasty turn toward austerity is likely to further add to declines in per capita GDP, thereby frustrating the attempt to lower the debt-to-GDP ratio (Furceri et al., 2020b). Instead, fiscal and other macro policies should be calibrated to achieve equitable and sustainable growth. Moreover, there is a need for a "green" design of stimulus packages, to not only address economic and social impacts, but also to ensure medium- and long-term improvement in energy and emission intensity, including alleviating the costs of future climate mitigation action (Hanna et al., 2020).

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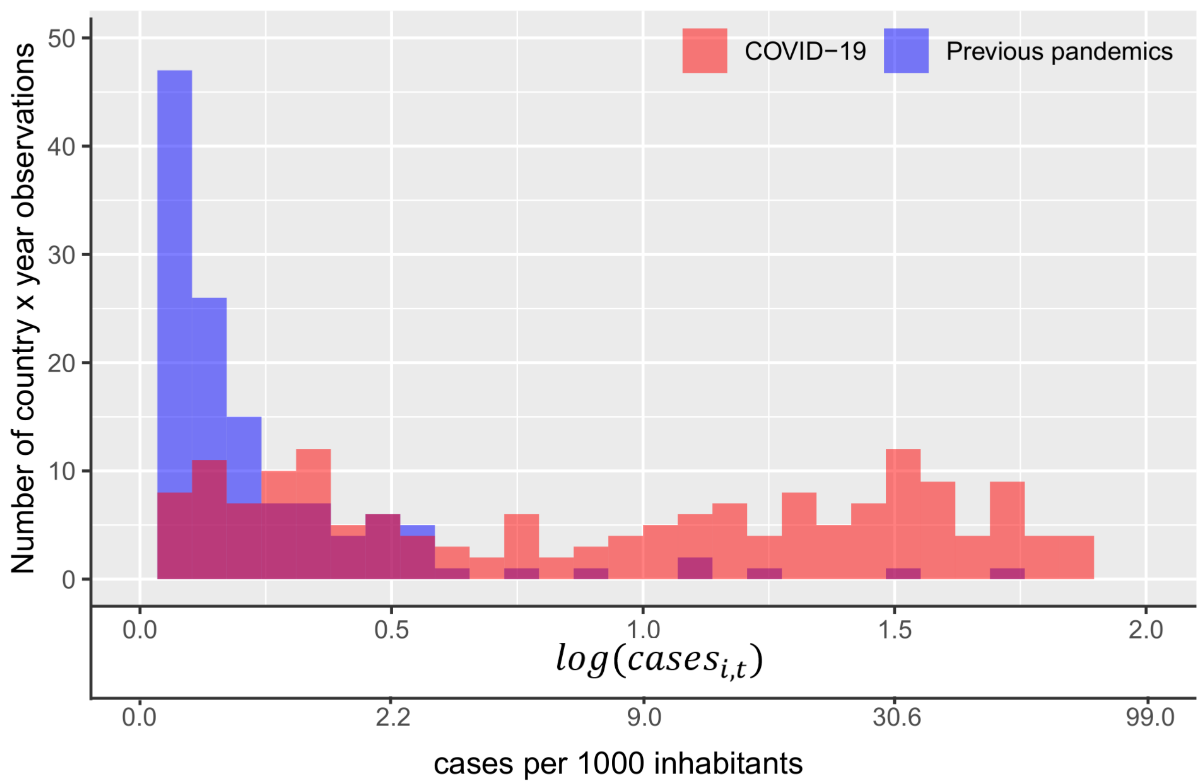
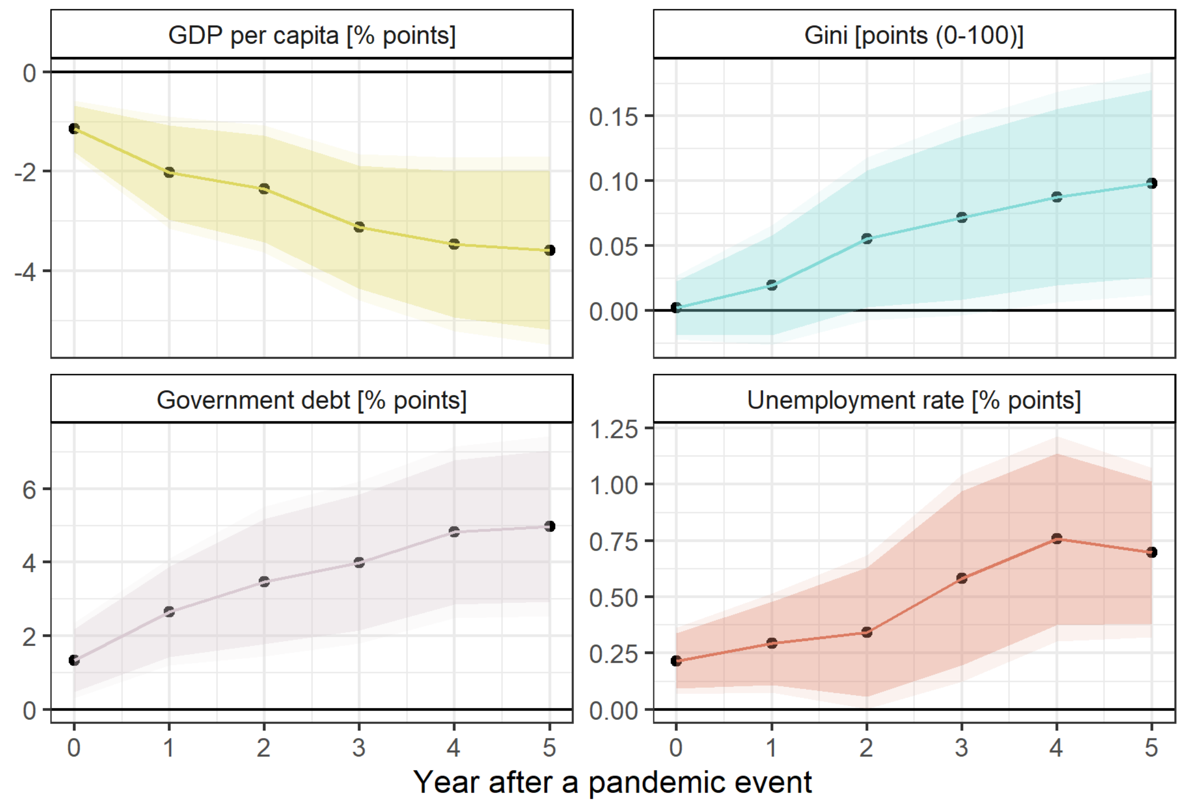
FIGURE 1. HISTOGRAM OF CASES FOR PAST PANDEMICS AND COVID-19 AS OF END 2020



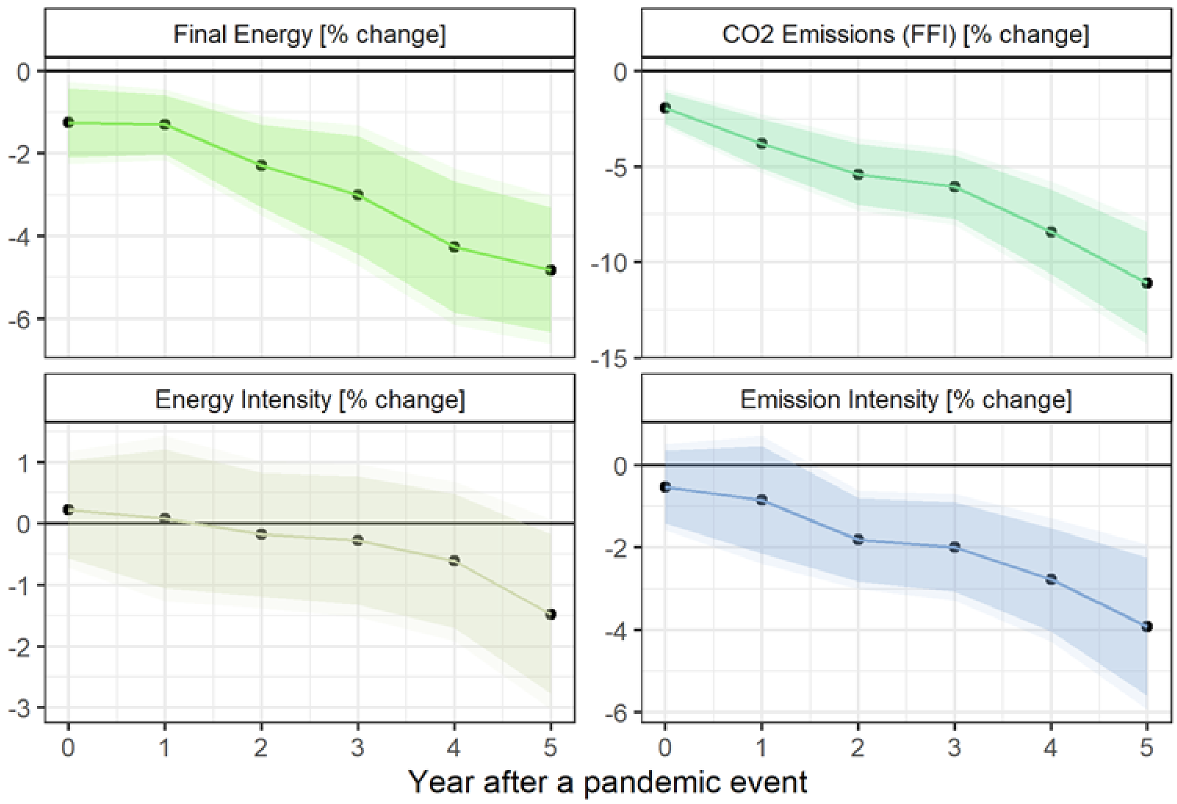
Notes: The histogram refers to the distribution of the number of cases (in log) – upper horizontal axis – and the number of cases per 1000 inhabitants (in log) – lower horizontal axis. Red bars refer to COVID-19; blue bars refer to past pandemics. Purple bars are displayed when the distributions are overlapping. Only observations with positive number of cases are considered.

FIGURE 2. IMPULSE RESPONSE FUNCTIONS OF PAST PANDEMICS ON FOUR MACRO-ECONOMIC VARIABLES



Notes: Estimates based on equation (2). The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Dotted lines indicate the dynamic effect of an increase in the number of infections equivalent to the size of an average pandemic (0.80 cases per 1000). Shaded areas indicate 90% (95% lighter) confidence intervals. See Table A2 in the Appendix for the full list of pandemic events

FIGURE 3. IMPULSE RESPONSE FUNCTIONS OF PAST PANDEMICS ON FOUR ENERGY AND CLIMATE MACRO VARIABLES



Notes: Estimates based on equation (2). The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Dotted lines indicate the dynamic effect of an increase in the number of infections equivalent to the size of an average pandemic (0.80 cases per 1000). Shaded areas indicate 90% (95% lighter) confidence intervals. See Table A2 in the Appendix for the full list of pandemic events.

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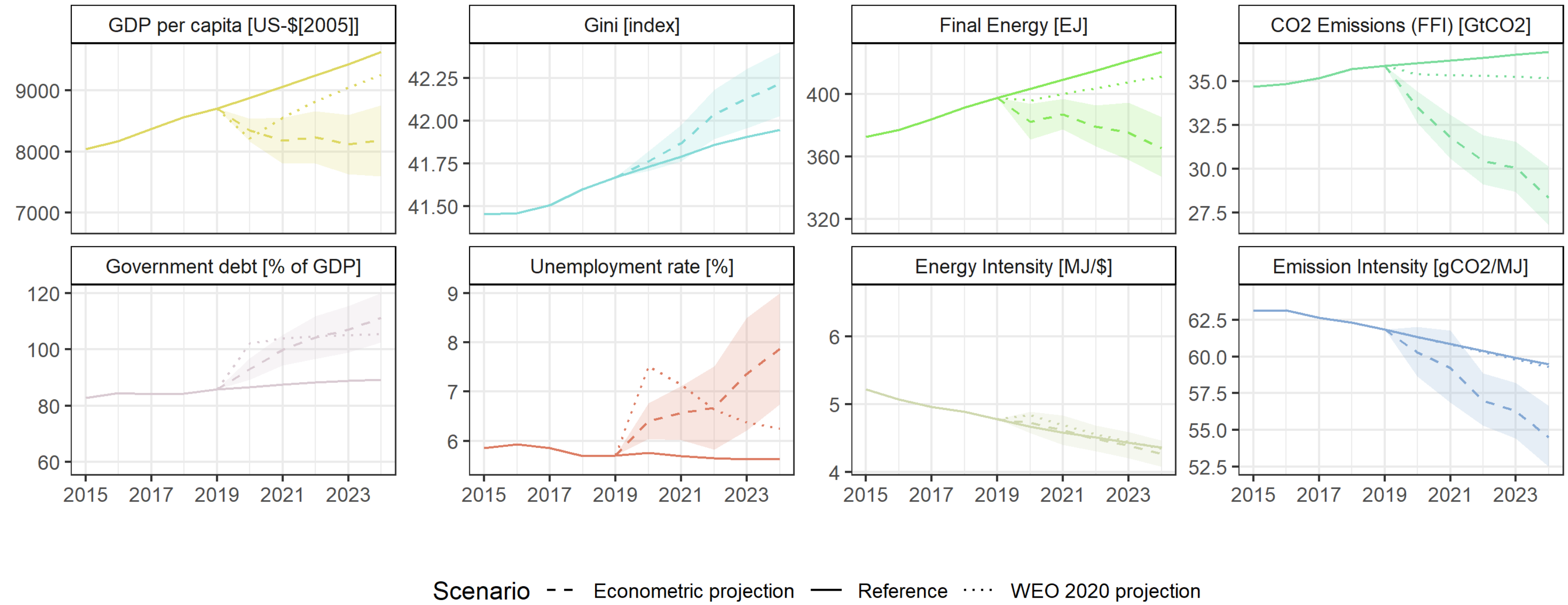
FIGURE 4. GLOBAL PROJECTION OF INDICATORS WITH AND WITHOUT COVID-19



Notes: Estimates based on equation (8). The x-axis shows years. Solid lines show the projections from IMF and IEA before the pandemic (2019); dotted lines show the projection as of October 2020; dashed lines portray our empirical forecasts of the COVID-19 impact (90% confidence intervals shaded).

FIGURE 5. REGIONAL DISTRIBUTION OF THE ADDITIONAL ABSOLUTE POOR DUE TO COVID-19

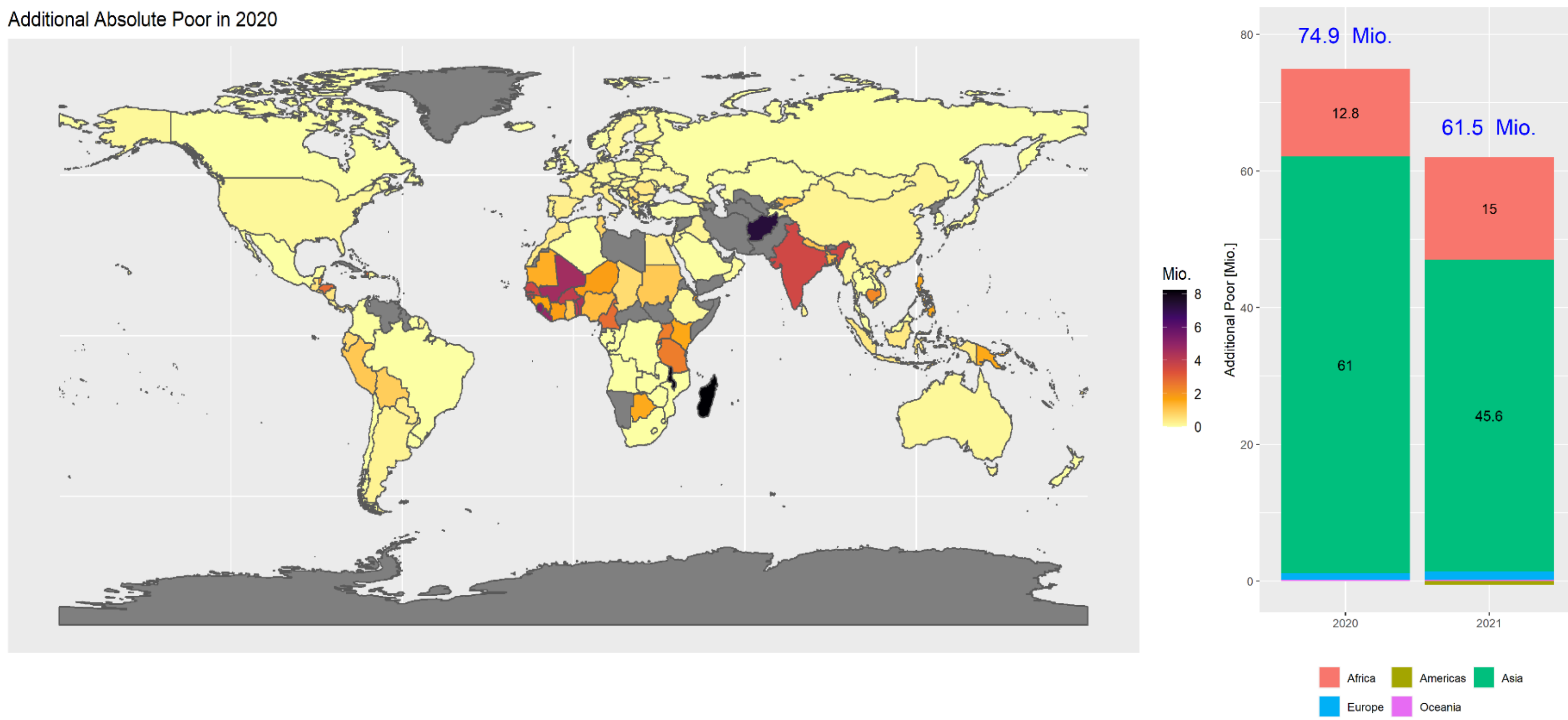


TABLE 1. THE SOCIAL, ECONOMIC AND ENVIRONMENTAL EFFECTS OF PANDEMICS – BASELINE REGRESSION RESULTS (K=5)

	Gini index	GDP per capita	Government Debt	Unemployment rate	Final Energy	CO2 Emissions	Energy Intensity	Emission Intensity
$log(cases_{i,t})$	0.384**	-14.073***	19.546***	2.735***	-0.189***	-0.435***	-0.059*	-0.154***
	(2.233)	(-3.710)	(4.011)	(3.632)	(-5.190)	(-6.746)	(-1.909)	(-3.889)
$log(cases_{i,t-1})$	0.473***	-5.666*	9.996**	1.812**	-0.146***	-0.411***	-0.080**	-0.146***
	(3.095)	(-1.701)	(2.258)	(2.346)	(-4.001)	(-6.086)	(-2.375)	(-3.649)
$log(cases_{i,t-2})$	0.390**	-3.457	4.613	1.357**	-0.160***	-0.387***	-0.096***	-0.150***
	(2.148)	(-1.093)	(0.976)	(2.267)	(-4.386)	(-5.954)	(-2.954)	(-3.409)
$y_{i,t-1}$	2.275***	0.307*	0.455***	-0.058	0.710***	0.712***	0.740***	0.327***
	(11.423)	(1.661)	(6.646)	(-0.907)	(8.225)	(15.791)	(10.243)	(4.726)
$y_{i,t-2}$	-1.578***	0.135	-0.184***	-0.591***	-0.078	0.018	0.007	0.128***
	(-8.283)	(1.089)	(-3.644)	(-8.242)	(-0.995)	(0.524)	(0.123)	(3.794)
Observations	3,467	4,172	3,299	3,818	3,725	11,253	3,643	3,725
R-squared	0.991	0.998	0.746	0.995	0.992	0.983	0.994	0.924

Notes: Estimates based on equation (1) for k=5. Robust t-statistics based on standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects as well as control variables included but not reported.

TABLE 2. THE SOCIAL, ECONOMIC AND ENVIRONMENTAL EFFECTS OF PANDEMICS – INSTRUMENTAL VARIABLE (IV) REGRESSION RESULTS (K=5)

	Gini index	GDP per capita	Government Debt	Unemployment rate	Final Energy	CO2 Emissions	Energy Intensity	Emission Intensity
$log(cases_{i,t})$	2.980**	-110.794***	54.180*	-4.998	-1.754***	-5.539***	-1.123**	-1.753***
	(2.056)	(-3.652)	(1.777)	(-1.219)	(-2.937)	(-3.829)	(-2.271)	(-2.768)
$log(cases_{i,t-1})$	0.588***	-9.598***	11.903***	1.398*	-0.211***	-0.497***	-0.114***	-0.202***
	(3.266)	(-3.211)	(2.884)	(1.885)	(-4.981)	(-7.480)	(-3.299)	(-4.778)
$log(cases_{i,t-2})$	0.504***	-7.467***	6.470	0.951	-0.223***	-0.486***	-0.126***	-0.203***
	(2.628)	(-2.599)	(1.475)	(1.596)	(-5.447)	(-7.460)	(-3.893)	(-4.608)
$y_{i,t-1}$	2.251***	0.293***	0.453***	-0.056	0.724***	0.722***	0.742***	0.319***
	(15.767)	(3.012)	(7.942)	(-0.831)	(11.442)	(15.126)	(10.937)	(3.848)
$y_{i,t-2}$	-1.555***	0.132	-0.181***	-0.600***	-0.095	0.023	0.002	0.121*
	(-10.846)	(1.453)	(-3.696)	(-8.649)	(-1.615)	(0.515)	(0.033)	(1.843)
Observations	3,344	5,295	3,282	3,593	3,663	10,173	3,601	3,663
R-squared	0.629	-0.021	0.213	0.091	0.678	0.795	0.574	0.049
Kleibergen-Paap rk Wald F-statistic	18.26	27.22	27.35	26.85	11.54	14.96	11.20	10.46

Notes: Estimates based on equation (1) for k=5. Robust t-statistics based on standard errors clustered at the country level in parentheses. Instrument for columns 1 and 5-8: Interaction of year of pandemic with average country temperature. Instrument for columns 2-4: Interaction of year of pandemic with average country urbanizations. *** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects as well as control variables included but not reported.

TABLE 3. COVID-19 GLOBAL AVERAGE IMPACT FOR 2020 AND 2024 IN % OF ITS REFERENCE SCENARIO VALUE

Variable	2020	2024
GDP per capita	-6.1% (-8.2%;-3.9%)	-16.7% (-23.3%;-10.0%)
Gini	+0.1% (-0.1%;+0.2%)	+0.6% (+0.2%;+1.1%)
Government debt	+7.4% (+3.0%;+11.9%)	+25.6% (+15.5%;+35.8%)
Unemployment rate	+11.3% (+4.9%;+17.7%)	+39.4% (+19.6%;+59.1%)
CO2 Emissions (FFI)	-7.0% (-9.4%;-4.5%)	-23.2% (-27.6%;-18.2%)
Emission Intensity	-1.7% (-4.4%;+1.1%)	-8.0% (-11.3%;-4.6%)
Energy Intensity	+1.2% (-2.0%;+4.6%)	-2.1% (-6.0%;+2.1%)
Final Energy	-5.3% (-8.1%;-2.4%)	-15.5% (-20.1%;-10.4%)
Absolute Poverty	+3.2% (na)	+10.3% (na)

Notes: COVID-19 global average impact for 2020 and 2024 in % of its reference scenario value (90% confidence interval in parenthesis). Note that to be comparable, all values are in % relative to the projected reference scenario. For poverty, as it is based on IMF GDP projections for 2020 and an additional poverty regression model, we don’t report confidence intervals.

TABLE 4. POVERTY REGRESSION

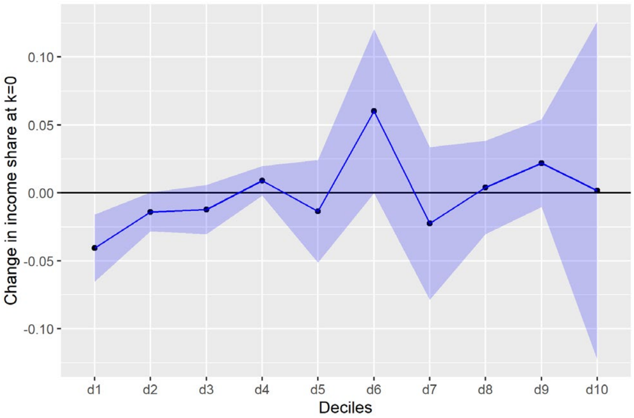
	Dependent variable Log(1 + Poverty Rate)
Gini	0.331***
	(0.043)
Log(GDPpc[PPP])	-2.154***
	(0.332)
Gini Squared	-0.002***
	(0.0003)
log(GDPpc[PPP])Squared	0.067***
	(0.015)
Gini x log(GDPpc[PPP])	-0.007***
	(0.004)
Observations	3,009
R^2 (within)	0.348
Adjusted R^2	0.304
R^2 (total)	0.965
Adjusted R^2 (total)	0.963
F-Statistic	300.885*** (df = 5; 2828)

Notes: *** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects included but not reported.

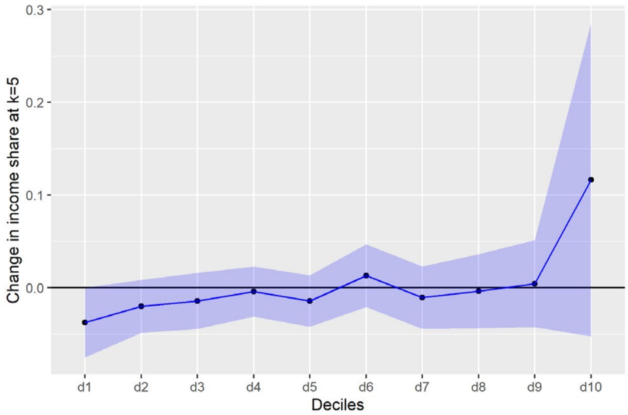
ANNEX

Figure A1. The social, economic and environmental effects of pandemics – Additional variables

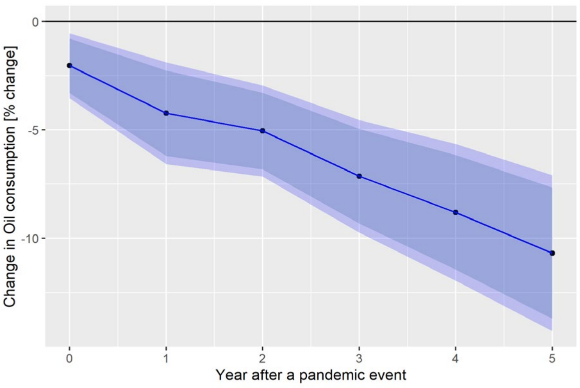
Panel A: Deciles in the income distribution (k=0)



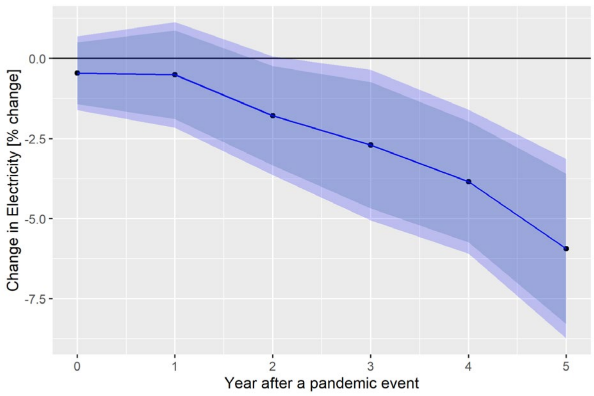
Panel B: Deciles in the income distribution (k=5)



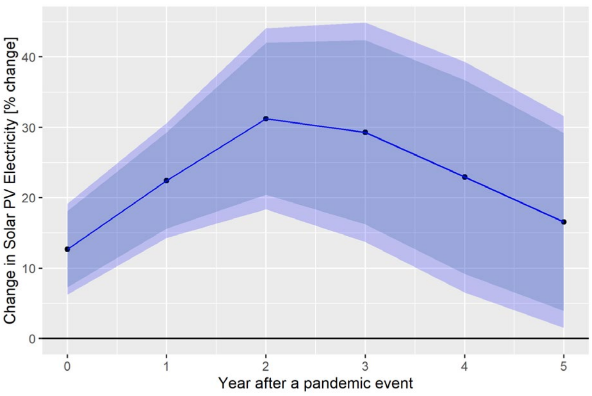
Panel C: Total Oil Consumption



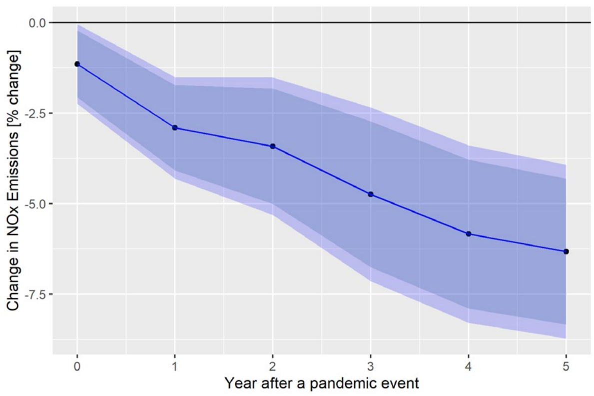
Panel D: Electricity consumption



Panel E: Solar PV generation



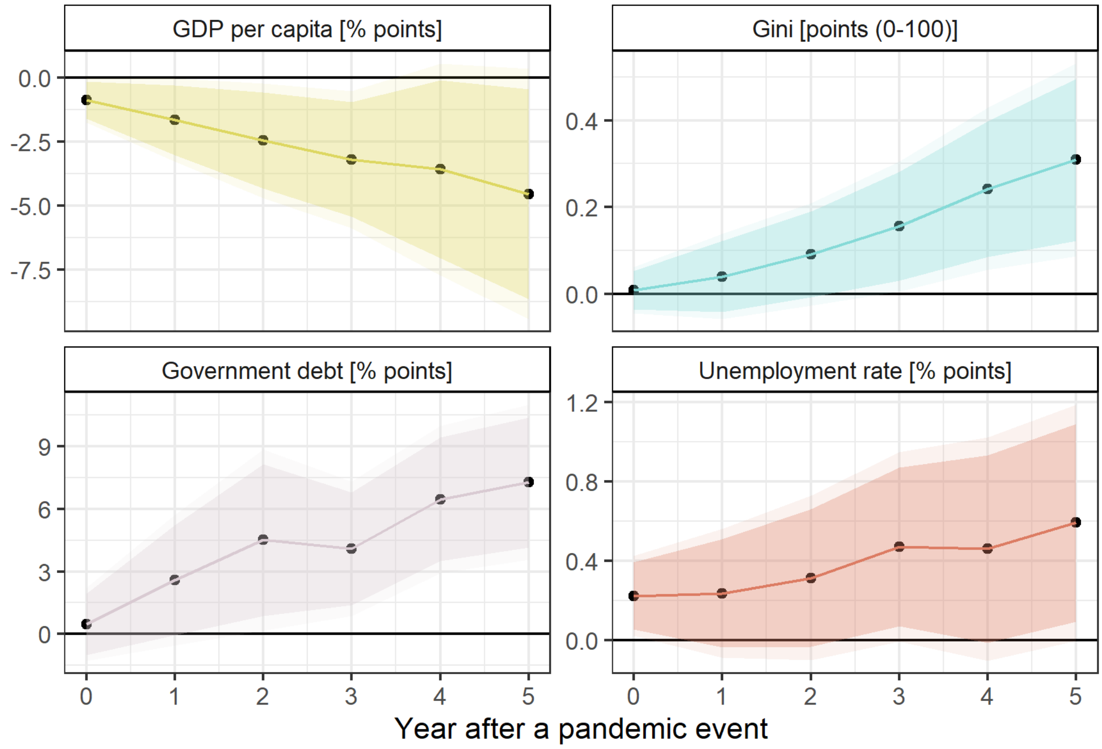
Panel F: NOx emissions



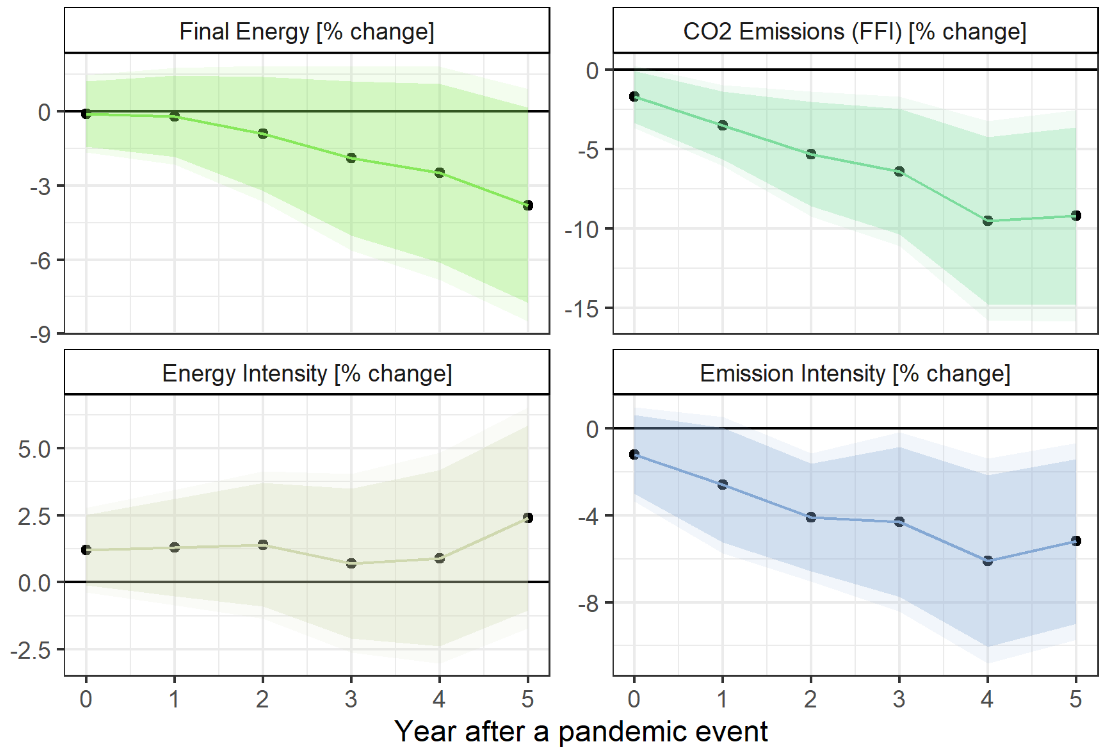
Notes: The solid lines indicate the response of the outcome variables to pandemics. The darker (lighter) shadow areas represent 90% (95%) confidence intervals. The x-axis denotes time: k = 0 is the year of the pandemic. The estimates are based on Equation (2).

Figure A2. Robustness Checks – dummy variable approach

Economic and social variables:



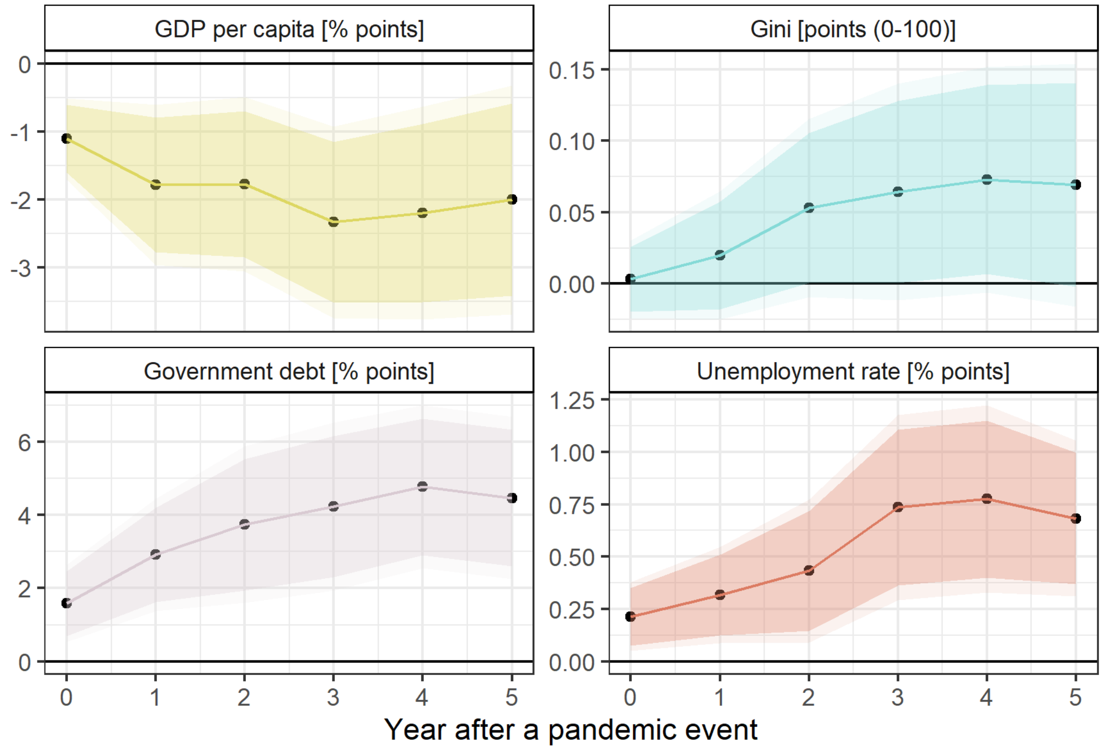
Environmental variables:



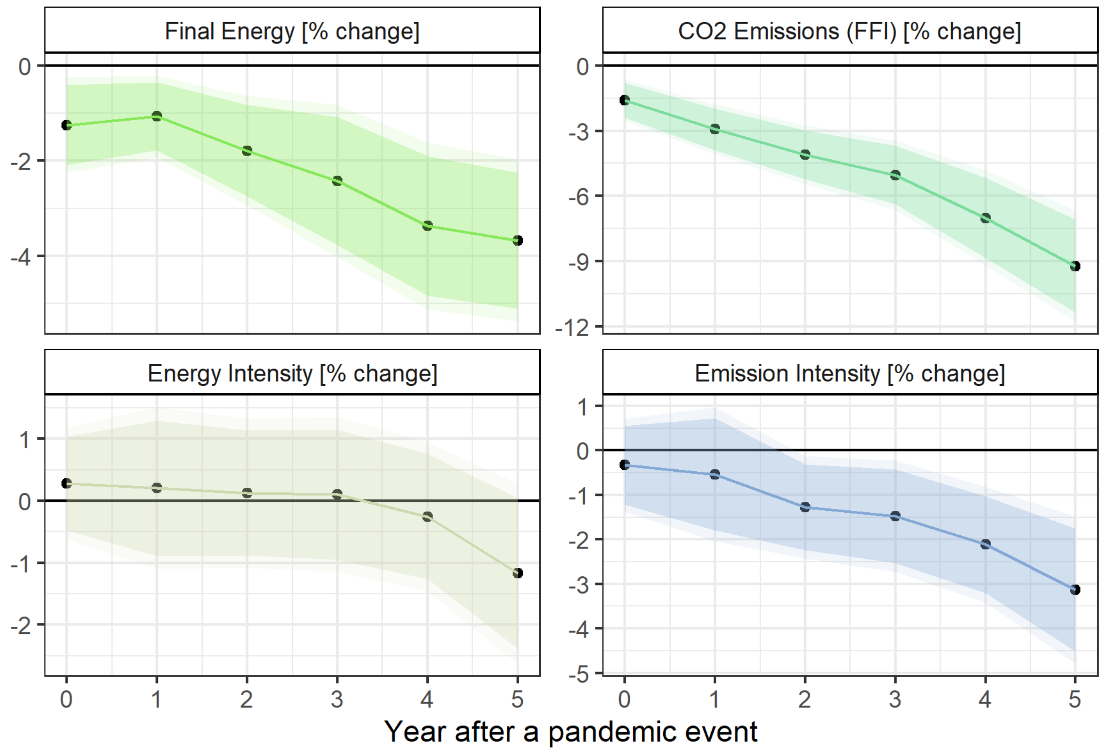
Notes: The solid lines indicate the response of the outcome variables to pandemics. The darker (lighter) shadow areas represent 90% (95%) confidence intervals. The x-axis denotes time: k = 0 is the year of the pandemic. The estimates are based on Equation (4).

Figure A3. Robustness Checks – additional controls

Economic and social variables:



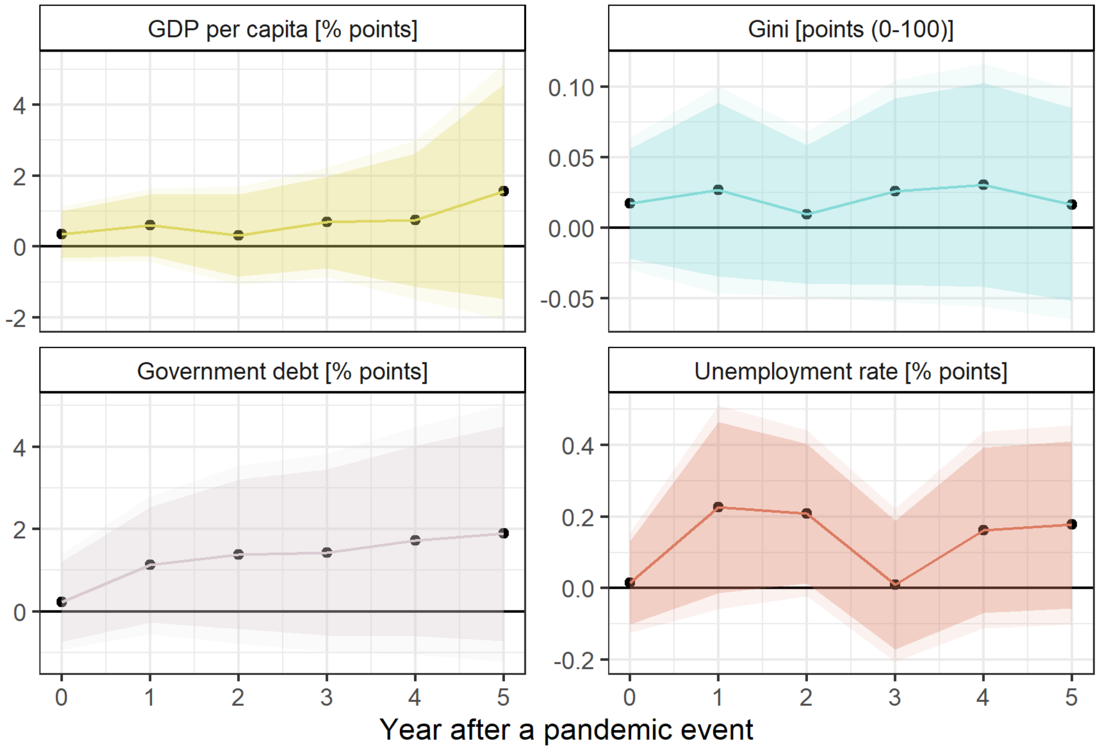
Environmental variables:



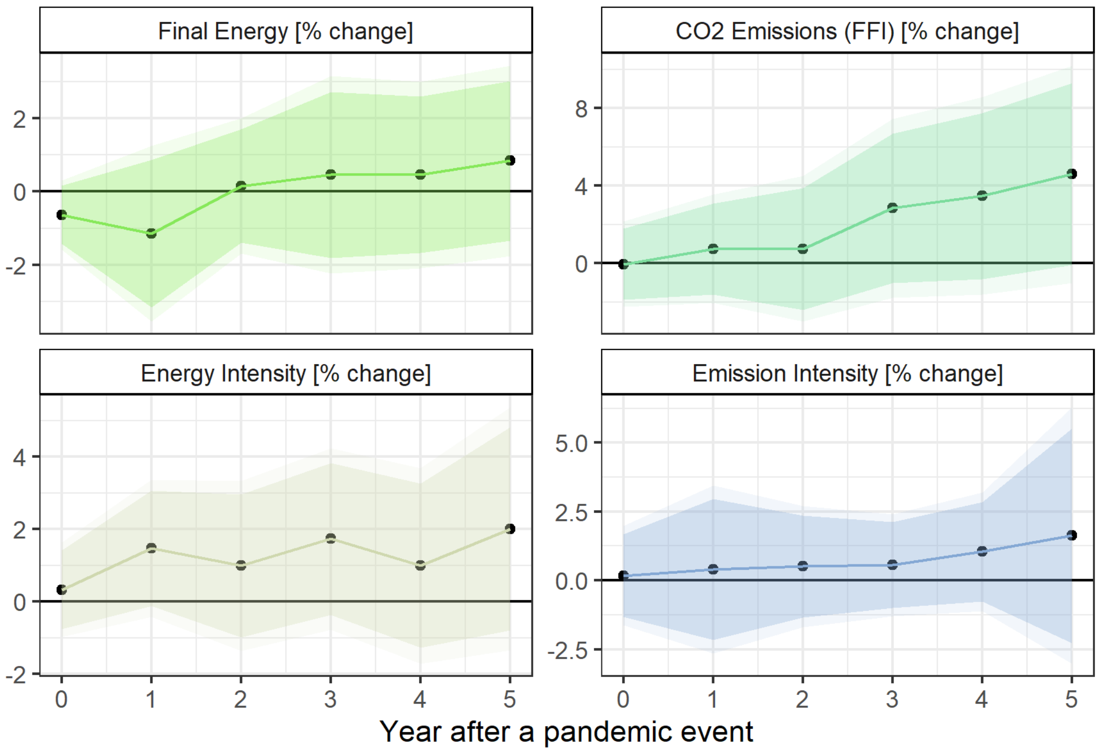
Notes: The solid lines indicate the response of the outcome variables to pandemics. The darker (lighter) shadow areas represent 90% (95%) confidence intervals. The x-axis denotes time: k = 0 is the year of the pandemic. The estimates are based on Equation (2).

Figure A4. Robustness Checks – Placebo estimations

Economic and social variables:



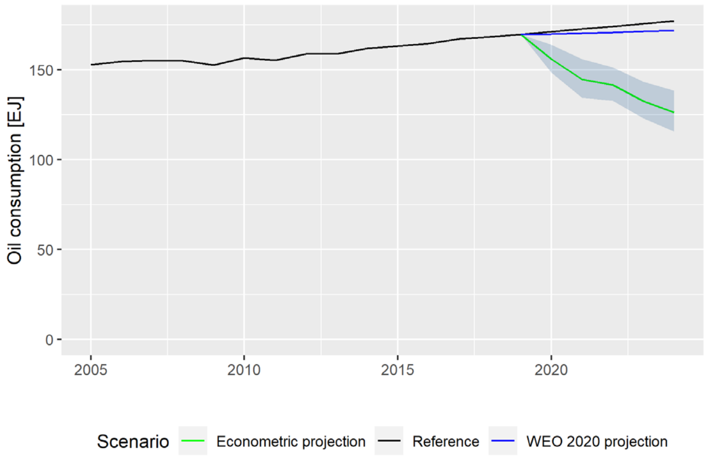
Environmental variables:



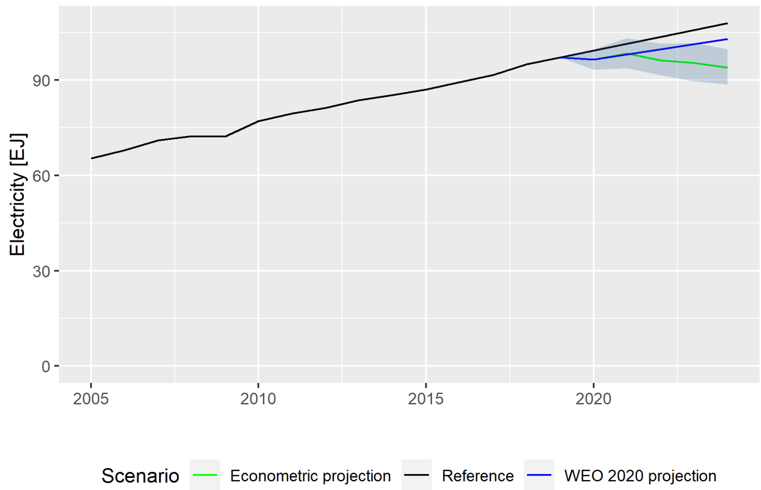
Notes: The solid lines indicate the response of the outcome variables to pandemics. The darker (lighter) shadow areas represent 90% (95%) confidence intervals. The x-axis denotes time: k = 0 is the year of the pandemic. The estimates are based on Equation (2) with values of our measure of shock randomly attributed.

Figure A5. Projections 2020-2024 – Additional variables

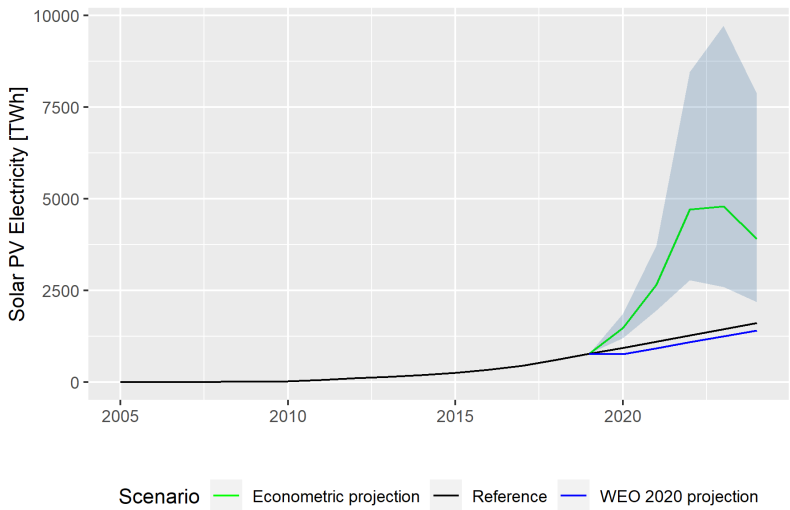
Panel A: Total Oil Consumption



Panel B: Electricity Consumption

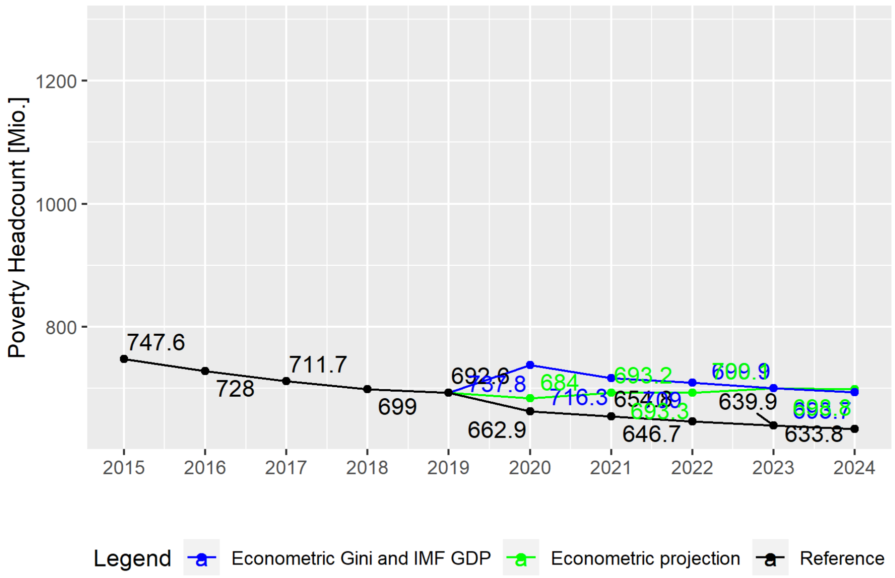


Panel C: Solar PV electricity generation



Notes: We report the globally aggregated values, showing in black the historical values and reference projection, as explained in the Methods section. In green, we show our projection based on the empirical models, including 90% confidence intervals, and in blue the updated WEO projection as of October 2020

Figure A6. Projections 2020-2024 – Poverty



Notes: For the case of poverty, we show the global headcount based on the full econometric model based on Gini and GDP per capita projection and the poverty regression, (in green), and the same forecast, but using the GDP projection of the IMF for 2020 as of October 2020 instead (in blue).

Table A1. Descriptive Statistics

Statistic	Source	N. Obs.	Mean	Std.Dev.	Min	Max	Period	Countries
Confirmed Cases of Pandemics	various	13,176	517.37	31,980.40	0	3,064,933	1980-2019	191
Gini Net	SWIIID 8.3[8]	4,711	38.75	8.63	19.50	66.50	1980-2019	173
GDP (per-capita)	IMF - WEO	6,847	9,514.11	14,042.44	113.37	89,502.20	1980-2019	189
Government Debt (in % to GDP)	IMF - WEO	4,607	56.86	44.24	0.05	514.92	1980-2019	186
Unemployment rate	IMF - WEO	5,018	7.94	6.16	0.09	37.98	1991-2019	177
Final Energy	IEA - WEO	4,676	616.93	1,993.86	1.52	23,098.23	1980-2017	135
Total Oil Consumption	IEA - WEO	4,676	299.77	956.97	0.42	10,806.37	1980-2017	135
CO2 Emissions	PRIMAP[9]	12,597	108.62	518.83	0.002	10,330.00	1980-2017	190
NOx Emissions	CEDS[10]	4,709	0.66	2.45	0.0002	35.24	1980-2015	187
Solar PV Electricity generation	IEA - WEO	1,220	1.37	6.75	0.00	130.69	1983-2017	110
Electricity generation	IEA - WEO	4,676	122.43	442.14	0.01	6,602.15	1980-2017	135
Emission Intensity	computed	4,676	0.20	0.24	0.01	15.62	1980-2017	135
Energy Intensity	computed	4,581	0.35	1.71	0.00	31.08	1980-2017	134

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[8] Solt et al. (2016).
[9] Gütschow et al. (2019).
[10] Hoesly et al. (2018).

Table A2. List of Pandemic and Epidemic Episodes

Starting year	Announced month	Event Name	Affected Countries	Number of countries	Total Deaths	Total Cases	Total Mortality rate (%)	Average Cases/Pop (*1,000)	Average Mortality rate (%)
2003	2	SARS	AUS CAN CHE CHN DEU ESP FRA GBR HKG IDN IND IRL ITA KOR KWT MNG MYS NZL PHL RUS SGP SWE THA TWN USA VNM ZAF	27	774	8,094	9.56	0.013	9.77
2009	4	H1N1	AFG AGO ALB ARE ARG ARM ATG AUS AUT AZE BDI BEL BGD BGR BHR BHS BIH BLR BLZ BOL BRA BRB BRN BTN BWA CAN CHE CHL CHN CIV CMR COG COL CPV CRI CYP CZE DEU DJI DMA DNK DOM DZA ECU EGY ESP EST ETH FIN FJI FRA FSM GAB GBR GEO GHA GRC GRD GTM GUY HND HRV HTI HUN IDN IND IRL IRN IRQ ISL ISR ITA JAM JOR JPN KAZ KEN KHM KIR KNA KOR KWT LAO LBN LBY LCA LKA LSO LTU LUX LVA MAR MDA MDG MDV MEX MHL MKD MLI MLT MMR MNE MNG MOZ MUS MWI MYS NAM NGA NIC NLD NOR NPL NZL OMN PAK PAN PER PHL PLW PNG POL PRI PRT PRY QAT RUS RWA SAU SDN SGP SLB SLV SOM STP SUR SVK SVN SWE SWZ SYC SYR TCD THA TJK TON TTO TUN TUR TUV TZA UGA UKR URY USA VCT VEN VNM VUT WSM YEM ZAF ZMB ZWE	164	19,207	6,514,828	0.30	1.089	3.91
2012	3	MERS	ARE AUT CHN DEU DZA EGY FRA GBR GRC IRN ITA JOR KOR KWT LBN MYS NLD OMN PHL QAT SAU THA TUN TUR USA YEM	26	588	1,545	38.06	0.003	36.07
2014	8	Ebola	ESP GBR GIN ITA LBR MLI NGA SEN SLE USA	10	11,325	28,652	39.53	0.480	27.98
2016	2	Zika	ARG ATG BHS BLZ BOL BRA BRB CAN CHL COL CRI DMA DOM ECU GRD GTM GUY HND HTI JAM KNA LCA NIC PAN PER PRI PRY SLV SUR TTO URY USA VCT VEN	34	20	205,691	0.01	0.636	0.02
			Total Pandemic and Epidemic Events	**261**					

Sources: WHO, Ma and others (2020) Furceri and others (2020); ECDC, CDC; PAHO; Wikipedia. Information in the table refers to countries for which data on Net Gini are available (i.e. for Ebola not all countries affected by the epidemic event are included in our analysis due to data constraints). The sources of the number of cases/deaths are as follows (accessed on June 24, 2020). Data on Population are from the World Bank's World Development Indicator Database.
SARS: https://www.who.int/csr/sars/country/table2004_04_21/en/;
H1N1: https://en.wikipedia.org/wiki/2009_swine_flu_pandemic_by_country and https://www.ecdc.europa.eu/en/seasonal-influenza/2009-influenza-h1n1;
MERS: https://www.ecdc.europa.eu/en/news-events/epidemiological-update-middle-east-respiratory-syndrome-coronavirus-mers-cov-1-0;
EBOLA: https://www.cdc.gov/vhf/ebola/history/2014-2016-outbreak/index.html;
ZIKA: https://www.paho.org/hq/index.php?option=com_content&view=article&id=12390:zika-cumulative-cases&Itemid=42090&lang=en.

Table A3. The social, economic and environmental effects of pandemics – Baseline estimates

Economic and social variables:

Gini index

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	0.009	0.077	0.217*	0.280*	0.343**	0.384**
	(0.193)	(0.834)	(1.745)	(1.870)	(2.118)	(2.233)
Observations	4,349	4,172	3,995	3,818	3,642	3,467
R-squared	1.000	0.998	0.997	0.995	0.993	0.991

GDP per capita

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-4.471***	-7.914***	-9.207***	-12.246***	-13.580***	-14.073***
	(-4.001)	(-3.502)	(-3.597)	(-4.164)	(-3.886)	(-3.710)
Observations	6,277	6,087	5,897	5,707	5,517	5,327
R-squared	0.181	0.243	0.297	0.333	0.374	0.408

Government Debt

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	5.217**	10.405***	13.640***	15.669***	18.901***	19.546***
	(2.541)	(3.573)	(3.362)	(3.559)	(4.045)	(4.011)
Observations	4,233	4,046	3,859	3,672	3,485	3,299
R-squared	0.937	0.872	0.819	0.784	0.760	0.746

Unemployment rate

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	0.848***	1.155***	1.348**	2.288**	2.970***	2.735***
	(2.887)	(2.623)	(1.976)	(2.485)	(3.264)	(3.632)
Observations	4,484	4,306	4,128	3,950	3,772	3,594
R-squared	0.209	0.181	0.177	0.192	0.219	0.247

Environmental variables:

Final Energy

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-0.049**	-0.051***	-0.090***	-0.118***	-0.167***	-0.189***
	(-2.414)	(-2.957)	(-3.819)	(-3.450)	(-4.378)	(-5.190)
Observations	4,404	4,268	4,132	3,996	3,860	3,725
R-squared	0.998	0.996	0.995	0.994	0.993	0.992

CO2 Emissions

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-0.076***	-0.149***	-0.212***	-0.238***	-0.330***	-0.435***
	(-3.810)	(-4.863)	(-5.622)	(-6.003)	(-6.179)	(-6.746)
Observations	12,213	12,021	11,829	11,637	11,445	11,253
R-squared	0.996	0.993	0.990	0.988	0.985	0.983

Energy Intensity

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	0.009	0.004	-0.005	-0.008	-0.022	-0.059*
	(0.516)	(0.146)	(-0.190)	(-0.332)	(-0.859)	(-1.909)
Observations	4,313	4,179	4,045	3,911	3,777	3,643
R-squared	0.999	0.997	0.996	0.995	0.994	0.994

Emission Intensity

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-0.021	-0.033	-0.071***	-0.078***	-0.109***	-0.154***
	(-0.974)	(-1.081)	(-3.015)	(-3.049)	(-3.701)	(-3.889)
Observations	4,404	4,268	4,132	3,996	3,860	3,725
R-squared	0.964	0.949	0.941	0.934	0.929	0.924

Notes: k=0 is the year of the pandemic. k=1,2,3,4,5 are the years after the pandemic event.. Estimates based on equation (1). Robust t-statistics based on standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects as well as control variables included but not reported.

Table A4. Instrumental Variable results

Economic and social variables:

Gini index: IV – Instrument: Interaction of year of pandemic with average country temperature

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-0.059	0.643	1.195	1.728	2.751*	2.980**
	(-0.092)	(0.670)	(0.995)	(1.271)	(1.708)	(2.056)
Observations	4,167	4,002	3,836	3,671	3,506	3,344
R-squared	0.985	0.945	0.885	0.804	0.714	0.629
Kleibergen-Paap_rk_LM_statistic	7.586***	12.28***	12.03***	14.11***	14.18***	17.61***
Kleibergen-Paap_rk_Wald_F_statistic	7.421	12.06	11.84	14.03	14.18	18.26

GDP per capita: IV – Instrument: Interaction of year of pandemic with average country urbanization

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-34.033***	-32.781**	-61.923***	-71.259***	-75.684***	-110.794***
	(-3.012)	(-2.211)	(-2.959)	(-3.125)	(-3.144)	(-3.652)
Observations	6,240	6,051	5,862	5,673	5,484	5,295
R-squared	0.012	0.060	0.025	0.021	0.029	-0.021
Kleibergen-Paap_rk_LM_statistic	23.63***	23.64***	23.60***	23.58***	25.82***	25.88***
Kleibergen-Paap_rk_Wald_F_statistic	24.47	24.48	24.44	24.42	27.14	27.22

Government Debt: IV – Instrument: Interaction of year of pandemic with average country urbanization

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	10.896	17.227	37.082	50.590*	54.852*	54.180*
	(0.625)	(0.770)	(1.248)	(1.662)	(1.759)	(1.777)
Observations	4,212	4,026	3,840	3,653	3,468	3,282
R-squared	0.857	0.699	0.540	0.406	0.300	0.213
Kleibergen-Paap_rk_LM_statistic	24.80***	24.89***	24.85***	24.78***	26.10***	26.16***
Kleibergen-Paap_rk_Wald_F_statistic	25.48	25.55	25.49	25.43	27.24	27.35

Unemployment rate: IV – Instrument: Interaction of year of pandemic with average country urbanization

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	7.104***	5.368**	2.107	-1.413	-2.858	-4.998
	(3.687)	(2.190)	(0.742)	(-0.422)	(-0.754)	(-1.219)
Observations	4,484	4,306	4,128	3,950	3,772	3,593
R-squared	0.067	0.118	0.114	0.101	0.100	0.091
Kleibergen-Paap_rk_LM_statistic	24.59***	24.61***	24.53***	24.44***	25.60***	25.69***
Kleibergen-Paap_rk_Wald_F_statistic	25.41	25.41	25.31	25.21	26.78	26.85

Environmental variables:

Final Energy: IV – Instrument: Interaction of year of pandemic with average country temperature

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-1.126**	-1.268**	-1.447***	-1.764***	-1.429***	-1.754***
	(-2.510)	(-2.282)	(-2.815)	(-2.850)	(-2.778)	(-2.937)
Observations	4,328	4,195	4,062	3,929	3,796	3,663
R-squared	0.931	0.872	0.820	0.759	0.748	0.678
Kleibergen-Paap_rk_LM_statistic	8.279***	8.442***	11.27***	11.43***	11.18***	11.34***
Kleibergen-Paap_rk_Wald_F_statistic	8.311	8.479	11.39	11.56	11.37	11.54

CO2 Emissions: IV – Instrument: Interaction of year of pandemic with average country temperature

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-3.095***	-5.281***	-5.034***	-6.065***	-4.608***	-5.539***
	(-2.646)	(-2.726)	(-3.287)	(-3.315)	(-3.755)	(-3.829)
Observations	11,023	10,853	10,683	10,513	10,343	10,173
R-squared	0.961	0.914	0.889	0.848	0.838	0.795
Kleibergen-Paap_rk_LM_statistic	7.893***	7.891***	11.35***	11.36***	14.57***	14.60***
Kleibergen-Paap_rk_Wald_F_statistic	7.923	7.920	11.48	11.50	14.94	14.96

Energy Intensity: IV – Instrument: Interaction of year of pandemic with average country temperature

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-0.519	-0.577	-0.819**	-0.983**	-0.886**	-1.123**
	(-1.623)	(-1.357)	(-2.021)	(-2.133)	(-2.098)	(-2.271)
Observations	4,261	4,129	3,997	3,865	3,733	3,601
R-squared	0.926	0.859	0.789	0.714	0.658	0.574
Kleibergen-Paap_rk_LM_statistic	7.799***	7.914***	10.83***	10.97***	10.84***	10.98***
Kleibergen-Paap_rk_Wald_F_statistic	7.824	7.943	10.95	11.10	11.04	11.20

Emission Intensity: IV – Instrument: Interaction of year of pandemic with average country temperature

	k=0	k=1	k=2	k=3	k=4	k=5
$log(cases_{i,t})$	-1.230*	-2.135**	-1.695***	-1.837***	-1.170**	-1.753***
	(-1.853)	(-2.262)	(-2.652)	(-2.649)	(-2.309)	(-2.768)
Observations	4,328	4,195	4,062	3,929	3,796	3,663
R-squared	0.595	0.281	0.282	0.169	0.210	0.049
Kleibergen-Paap_rk_LM_statistic	7.294***	7.277***	10.29***	10.27***	10.36***	10.35***
Kleibergen-Paap_rk_Wald_F_statistic	7.292	7.274	10.35	10.32	10.47	10.46

Notes: k=0 is the year of the pandemic. k=1,2,3,4,5 are the years after the pandemic event. Estimates based on equation (3). Robust t-statistics based on standard errors clustered at the country level in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects, as well as control variables, included but not reported. The Kleibergen–Paap rk LM-statistic tests the null hypothesis that the excluded instruments are not correlated with the endogenous regressor; the Kleibergen–Paap rk Wald F-statistic tests for weak identification.