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Abstract

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JEL Classification: E52, E58, D43, L11

Keywords: COVID-19, Pandemics, Inequality

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Will COVID-19 Have Long-Lasting Effects on Inequality? Evidence from Past Pandemics*

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Abstract

This paper provides evidence on the impact of major epidemics from the past two decades on income distribution. The pandemics in our sample, even though much smaller in scale than COVID-19, have led to increases in the Gini coefficient, raised the income share of higher-income deciles, and lowered the employment-to-population ratio for those with basic education compared to those with higher education. We provide some evidence that the distributional consequences from the current pandemic may be larger than those flowing from the historical pandemics in our sample, and larger than those following typical recessions and financial crises.

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I. Introduction

As of April 30, 2021, deaths from the COVID-19 pandemic have reached about three million worldwide according to official statistics. This tragic cost has been accompanied by the upending of millions of other lives as governments take necessary steps to limit the spread of the virus. For instance, at the beginning of 2021, The International Labor Organization (ILO) estimated an unprecedent worldwide loss of 255 million jobs as a result of the COVID-19 pandemic, with the unemployment rate rising by 1.1 percentage points to 6.5 percent, and 81 million workers pushed out of the labor market (ILO 2021). Far more than were lost over the entire Great Recession of 2008–09 (for a comparison in the case of the United States see for example, Coibion, Gorodnichenko and Weber 2020).

While most income groups are adversely affected by the pandemic, it is possible that lower-income deciles and those with lower skills end up being disproportionately hurt. Indeed, there is already evidence of such effects, raising the prospect at least of a persistent increase in inequality in the absence of forceful policy interventions. Using data from a large-scale survey of U.K. households, Crossley, Fisher and Low (2020) show that those in the lowest quintiles of income and those from minority ethnic groups have experienced the largest job losses. Similarly, using transaction data from a large Fintech company, Hacioglu, Känzig and Surico (2020) and Surico, Känzig and Hacioglu (2020) document a surge in market income inequality in the United Kingdom since the beginning of the COVID-19 crisis. Aspachs et al. (2020), using high-frequency data on bank records, wages and public transfers for Spain, provide evidence of increasing income inequality due to severe job losses for low-income households. Additional preliminary evidence (see Stantcheva 2021 and references cited therein) for selected countries (mostly in the EU) suggest a regressive effect caused by the COVID-19 pandemic outbreak. The increasing effect on market Gini ranges from about 0.7 percent (Italy) to 20 percent (Ireland) with the short-term policy support provided in response to the crisis, more than offsetting the negative distributional effects caused by the pandemic.[1]

The socio-economic impact of the pandemic, moreover, is not limited to income-related losses. Blundell (2020) documents adverse effects on health, education, labor market access and

[1] Stantcheva (2021) argues that the inequality is likely to raise in the medium term due to the broad adoption of remote work.

other socio-demographic indicators in United Kingdom. Similarly, using survey data, Aucejo et al. (2020) show that the pandemic is widening achievement gaps in higher education, with lower-income students being 55 percent more likely than their higher-income peers to delay graduation. There are also direct and immediate effects from lower-income groups being more prone to the disease: Schmitt-Grohe, Teoh and Uribe (2020) find that, in New York City, poor people are less likely to test negative for COVID-19: moving from the richest to the poorest zip codes is associated with a decline in the fraction of negative test results from 65 to 38 percent.

To shed light on possible medium-term distributional impacts of COVID-19, this paper uses data from major epidemics (referred to interchangeably below as pandemics) over the past two decades and their links to: income inequality; income shares of the top and bottom deciles; and employment prospects of people with low education levels (using educational attainment as a proxy for skills). Our results justify the concern that COVID-19 could end up exerting a significant medium-term impact on inequality. Past pandemics, even though much smaller in scale, have led to increases in the Gini coefficient, raised the income shares of higher-decile income groups, and lowered the employment-to-population ratio of those with basic education compared to those with higher education. Our evidence suggests that the distributional consequences from the current pandemic may be larger than those flowing from the historical pandemics in our sample, and larger than those following typical recessions and financial crises.

This paper relates to two main strands of literature. The first is the literature on the economic effects of pandemics: Atkeson 2020; Barro et al. 2020; Eichenbaum et al. 2020; Jordà et al. 2020; Ma et al. 2020a. This literature provides evidence of large and persistent effects on economic activity from pandemics. Ma et al. (2020a) examined the same set of episodes used here and found that real GDP is 2.6 percent lower on average across 210 countries in the year the outbreak is officially declared and remains 3 percent below the pre-shock level five years later. The second strand of the literature relates to the effects of crises and recessions on inequality and employment including of the less skilled and youth: Camacho and Palmieri 2019; de Haan and Sturm 2017.

The remainder of the paper is structured as follows. Section II describes our data and econometric method and Section III presents our results. The last section concludes and outlines avenues for future work on this topic.

II. Data and Econometric Method

Income distribution

Our data on various measures of distribution come from three sources. Table 1 provides summary statistics on the variables used in the analysis.

- Gini coefficients are from the Standardized World Income Inequality Database (SWIID 8.3), which combines information from the United Nations World Income Database (UNWIDER) and the Luxembourg Income Study (LIS). SWIID provides comparable estimates of market and net income inequality for 177 countries from 1960 to the present (Solt 2009).[2]
- Income shares by decile are from the World Bank's World Development Indicators. This source provides internationally comparable statistics for a large number of economies; however, for many countries the time series is rather short, so in the end our results on income deciles are for a limited sample of 64 countries from 1981 to the present.
- Comparable data on employment by skill levels are difficult to obtain for a large group of countries. The ILO notes that "statistics on levels of educational attainment remain the best available indicators of labor force skill levels." Hence, we use ILO data on employment-to-population ratios for different education levels—advanced, tertiary and basic—for a limited sample of 76 countries from 1990 to the present.

Pandemic events

As in Ma et al. 2020a, we focus on five major events: SARS in 2003; H1N1 in 2009; MERS in 2012; Ebola in 2014; and Zika in 2016. The countries affected by each event are presented in Table 2 and Table A1 in the Appendix (we exclude countries for which income inequality data are unavailable). We construct a dummy variable, the pandemic event, which takes the value 1 when the WHO declares a pandemic for the country and 0 otherwise. Our baseline results estimate the evolution of inequality in the aftermath of the pandemic event. However, we also take account of how the severity of the pandemic affects distributional outcomes. The most

[2] We use data from SWIID as baseline because of the larger country and time coverage compared to other commonly used sources, such as WIDER and POVCAL. In the robustness checks, we show that our results hold when using data from these alternative sources.

widespread pandemic in our sample is H1N1 (Swine Flu Influenza), with more than six million confirmed cases across 148 countries (about one case per thousand people) and about 19,000 fatalities. While H1N1 spread across all regions, the other four events are mostly confined to specific regions: (i) SARS and MERS in Asia; (ii) Ebola in Africa; and (iii) Zika in the Americas (Figure 1). In terms of average mortality rates (deaths/confirmed cases), MERS and Ebola were the most severe (around 35 percent), followed by SARS and H1N1.

For the sake of comparison, as of April 2021, COVID-19 infections were confirmed in 223 countries, areas, or territories with more than 140 million confirmed cases (about 18 cases per thousand people) and a total mortality rate similar to H1N1 (about 0.40 percent). The median country in terms of cases to population ratio for COVID-19 is about 16 cases per thousand inhabitants—roughly corresponding to the severity of pandemic episode at the 99th percentile of the severity distribution in our sample. [3]

Empirical methodology

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

$$y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k} \tag{1}$$

where $y_{i,t}$ is a distribution variable (e.g. the Gini coefficient) for country *i* in year *t;* α_i are country fixed effects, included to take account of differences in countries' average income distribution; γ_t are time fixed effects, included to take account of global shocks such as shifts in oil prices or the global business cycle; $D_{i,t}$ is a dummy variable indicating a pandemic event in country *i* at year *t*. $X_{i,t}$ is a vector that includes two lags of the dependent variable and of the pandemic dummy. In the baseline, we do not include other controls on the grounds that the date of the pandemic event is likely to be exogenous to the economy. Indeed, as shown in Table 4, the dates of pandemic events are uncorrelated with past levels and changes of inequality. Nonetheless, we consider, subsequent to presenting our baseline findings, possible concerns

[3] For COVID-19 data see https://www.who.int/emergencies/diseases/novel-coronavirus-2019 (accessed on April 30, 2021)

arising from our empirical strategy (i.e. omitted variable bias and reverse causality): we present a wide range of robustness checks including an Augmented Inverse Probability Weighting (AIPW) estimation as in Jordà and Taylor (2016) and an Instrumental Variable approach.

Equation (1) is estimated for an unbalanced panel of 177 countries over the period 1960–2019, for each horizon (year) k=0,..,5. Impulse response functions are computed using the estimated coefficients β^k, and the confidence bands associated with the estimated impulse-response functions are obtained using the estimated standard errors of the coefficients β^k, based on robust standard errors clustered at the country level.

III. Distributional Impacts of Pandemics

Impacts on Gini coefficients

Figure 2 shows the estimated dynamic response of net Gini to a pandemic event over the five-year period following the event, together with the 90 percent confidence interval around the point estimate. Table 3 reports the associated regressions. Pandemics lead to a persistent increase in inequality with a peak effect of about 0.4 five years after the pandemic—that is an average increase of 1.1 percent. Given that the Gini is a slow-moving variable, these are quantitatively important effects: peak effects correspond to about a 1½ standard deviation of the average change of the Gini in the sample.[4]

Robustness checks

We have carried out several robustness checks of these findings. First, we check the sensitivity of our results to alternative measures of inequality, such as the market Gini from SWIID and the Ginis from the World Bank POVCAL database—which covers the period 1978–2017 and includes 171 countries (1711 observations)—and the World Institute for Development Research WIDER (WIID) dataset—which covers the period 1948–2014 and includes 166 countries (1386 observations).[5] The results in Figures 3-4 confirm our main findings: results based on the

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[4] The Gini coefficient on net income has increased cumulatively by about 10 percent in the US during the period 1980-2010 (from about 0.45 in 1980 to about 0.5 in 2010—see, among others, Coibion et al. 2017).

[5] Data are taken from the All the Ginis (ALG) Database (https://stonecenter.gc.cuny.edu/research/all-the-ginis-alg-dataset-version-february-2019/). See Jenkins (2015) and Chapter 2 in Ostry, Loungani and Berg (2019) for a discussion of the pros and cons of SWIID data set relative to others.

POVCAL/WIDER datasets point to even higher medium-term effects: about 1.5-2.0—statistically significant at 1 and 5 percent level, respectively.

Second, as an alternative empirical strategy, we present results from the autoregressive distributed lag (ADL) approach of Romer and Romer (2010) and Furceri, Loungani and Ostry (2019). Third, since the episodes in our sample occurred in the latest two decades, we replicate the analysis using a restricted sample that begins in 1990. Fourth, in order to mitigate omitted variable bias, we include several control variables that could be related to inequality—such as proxies for the level of economic development, demographics, measures of trade and financial globalization and country-specific time trends. The results presented in Figures 5-8 are similar to, and not statistically different from, the baseline.

We also checked the validity of the *parallel trend assumption*—that is, the assumption that the inequality in the treatment and counterfactual were following a parallel trend before the pandemic—in the evolution of inequality before the pandemic between countries by running a placebo test. Reassuringly, the impulse response functions obtained by attributing randomly pandemic dates across the whole sample do not point to significant results (Figure 9).

Addressing endogeneity

In order to further address endogeneity, we adapt the approach proposed by Jordà and Taylor (2016) to estimate the causal effect of austerity, and we use the Augmented Inverse Probability weighting (AIPW). The rationale of this approach is to address potential endogeneity in the measure of treatment (the pandemic event in our case). Indeed, pandemics may not be fully exogenous events and be related to pre-existing country characteristics. We therefore construct a predictive model for the likelihood of pandemics using various specifications including the level of GDP level its growth rate, average country temperature, total health expenditures, government final expenditures, mortality rate, and other controls. "*The predictive model serves to reallocate probability mass from the regions of the distributions in the treatment/control subpopulations that are oversampled to those regions that are under-sampled, thus enabling identification in the framework of the Rubin Causal Model*" (Jordà and Taylor, 2016). Table 4 reports the Probit regression results. As shown in the table, the dates of pandemic events are uncorrelated with past levels and changes of inequality but depend on some country characteristics such as temperature and GDP per capita.

Since we are interested in estimating the Average Treatment Effect (ATE) we use an augmented regression-adjusted estimation instead, denoted AIPW, which combines IPW with regression control and adjusts the estimator to achieve semi-parametric efficiency. Specifically, we estimate the following model

$$y_{i,t+k} = \alpha_i^k + \gamma_t^k + \Lambda^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k} \quad (2)$$

with:

$$\widehat{\Lambda}_{AIPW}^k = \frac{1}{n}\sum_t \left\{ \left[\frac{D_t(y_{t+k})}{\hat{p}_t} - \frac{(1-D_t)(y_{t+k})}{(1-\hat{p}_t)}\right] - \frac{(D_t-\hat{p}_t)}{\hat{p}_t(1-\hat{p}_t)}\left[(1-\hat{p}_t)m_1^h\left(X_t,\hat{\theta}_1^h\right) + \hat{p}_t m_0^h\left(X_t,\hat{\theta}_0^h\right)\right]\right\}$$

where**:** $\hat{p}_t$ is the propensity score obtained from estimating the Probit models as in Table 4; $m_j^h\left(X_t,\hat{\theta}_j^h\right)$ for *j*= 1,0 is the conditional mean from the first-step regression of $(y_{i,t+k})$ on X_t; $\hat{\theta}_j^h$ is the parameter accounting for the differential effect of the treatment conditioned to the value of the X_t; $y_{i,t}$ is our distribution variable (e.g. the Gini coefficient) for country *i* in year *t;* α_i are country fixed effects, included to take account of differences in countries' average income distribution; γ_t are time fixed effects, included to take account of global shocks such as shifts in oil prices or the global business cycle; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country *i* in year *t*. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. The results are reported in Table 5. Regardless of the specification chosen, they point to statistically significant impact of pandemics on income inequality with effects being quantitatively close to those shown in Figure 1.

Impact on other indicators of distribution

To shed light on the channels through which pandemics affect inequality, we explore the impact of pandemic events on income shares and employment outcomes by educational groups. These results are for a smaller set of countries given data availability.

The results for the impact of pandemics on the income shares held by the top (bottom) 20 percent are shown in Figure 10. It is evident that the impact is to raise the shares of the upper-income quintile and reduce those of the lower-income quintile. The impacts are statistically significant and quantitatively sizable. For instance, the share of income going to the top two deciles is 46 percent on average; five years after the pandemic, this share increases to nearly 48 percent. The share of income going to the bottom two deciles is 6 percent; five years after the pandemic, this share falls to 5.5 percent. We find similar effects when looking at the top (bottom) 10 and 40 percent (Figure 11).

Figure 12 shows the disparate impact on the employment of people with different levels of educational attainment. Those with non-basic levels of education are scarcely affected, whereas the employment to population ratio of those with basic levels of education falls significantly, by more than 5 percent in the medium term—the effect is statistically significant at 5 percent.

Pandemics vs. financial crises and other recessions

Are pandemics different from other recessions and crises? To answer this question, we augment our framework to include financial crises (taken from Laeven and Valencia 2019) and recession episodes—defined as years of negative real GDP growth (rather than in terms of output gaps, which are poorly measured in the case of developing countries). This exercise also allows us to address the concern that some pandemic events in our sample may have occurred also during a period of crisis or recession. We estimate the following equation:

$$y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \vartheta^k C_{i,t} + \theta^k M_{i,t} + \varepsilon_{i,t+k} \tag{3}$$

where C denotes the year of occurrence of a financial crisis or a year in which growth was negative, and M includes our earlier set of control variable X augmented by two lags of the financial crisis or recession dummy.[6]

The results in Figure 13 suggest that the distributional effects of pandemics are larger than those associated with financial crises or recessions: financial crises do not have a significant effect on inequality, and the Gini increases by about 0.05 following a typical recession—

[6] Qualitatively similar results are obtained including financial crises and recessions at the same time.

compared to more than 0.4 for pandemics.[7] We find similar results when looking at income shares. While recessions seem to result in higher top income shares, top shares tend to decline in the medium term following a financial crisis (see Figure 15)—consistent with the fact the financial income tends to be highly concentrated in the upper part of the income distribution.[8] Finally, the medium-term effects on the employment to population ratio of those with basic education falls significantly in all types of crises, suggesting that the difference in distributional effects between pandemics and other recessions is not due to this channel (see Figure 16).

Heterogeneity across episodes depend on the severity of pandemics

The average response of inequality to pandemic events may mask significant heterogeneity across episodes, based on the severity of the pandemic event, both in terms of confirmed cases and its economic effects. To probe further, we use two approaches. In the first, we replace pandemic dummy with a continuous variable using the information of the number of cases (Emmerling et al., forthcoming). Specifically, we estimate the following equation:

$$y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta_c^k cases + \theta^k X_{i,t} + \epsilon_{i,t}^k \qquad (4)$$

where, the variable proxying the severity of the pandemic is alternatively, $cases = log_{10}(1 + x)$ or $cases = ln\left(x + (x^2 + 1)^{1/2}\right)$ with $x = \left(\frac{1000 \cdot confirmed\_cases_{i,t}}{population_{i,t}}\right)$. The latter (i.e., the inverse hyperbolic sine transformation – IHS) is particularly useful to transform skewed variables that include zero or negative values.

While the use of this continuous variable has the advantage of differentiating episodes based on their severity, it has two important drawbacks. First, it may be more prone to reverse causality as higher initial levels of inequality may increase the number of infections due to the higher economic and health vulnerability of marginalized people. Second, measurement errors

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[7] This result is consistent with Camacho and Palmieri (2019) who did not find significant positive impacts of economic downturns and financial crises on income distribution. Consistent with the insignificant effect of financial crises on inequality, we also find that the effect of the H1N1 pandemic during the Global Financial Crisis is lower than that in other pandemic episodes (see Figure 14).

[8] Income comprises labor, business financial income and transfers.

related to total cases detected is likely to be non-negligible. To address these concerns, we resort to an instrumental variable approach. Following Nunn and Quian (2014), our Instrumental Variable (IV) approach consists of interacting a time-varying global term and a constant country-specific term. The global term 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 factors affecting the severity of the pandemic. For this purpose, we consider the average temperature. As shown in several recent studies (i.e. Ma et al, 2020b; Ujiie et al. 2020), temperature is an important driver of the evolution of pandemics and it can reasonably be assumed to be exogenous. Our IV estimation reads as follows:

$$y_{i,t+k} = \beta_c^k(\widehat{cases_{\iota,t}}) = +\theta^k X_{i,t} + \alpha_i^k + \gamma_t^k + \epsilon_{i,t}^k \qquad (5)$$

with $$(\widehat{cases_{\iota,t}}) = \vartheta^k S_{i,t} + \varphi^k X_{i,t} + \alpha_i^k + \gamma_t^k + \nu_{i,t}^k,$$

where S is the instrument and $cases$ is, alternatively, one of the transformations discussed above. The analysis also controls for country and time fixed effects and can therefore be seen as a *differences-in-differences* approach (Nunn and Quian 2014).[9]

In the second approach, we estimate the following equation:

$$y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + F(z_{it})\left[\beta_L^k D_{i,t} + \theta_L^k X_{i,t}\right] + \left(1 - F(z_{it})\right)\left[\beta_H^k D_{i,t} + \theta_H^k X_{i,t}\right] + \varepsilon_{i,t+k}$$

with $$F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(1+exp^{-\gamma z_{it}})}, \quad \gamma = 3.5 \qquad (6)$$

where z is an indicator of the severity of the pandemic (which is either the ratio of confirmed cases to population, or GDP growth), normalized to have zero mean and a unit variance. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that

[9] 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 (Table 7).

$F(z_{it})$ can be interpreted as the probability of being in a given state of the pandemic. The coefficients $\beta_L^k$and β_H^k capture the distributional impact of a pandemic event at each horizon *k* in cases of mild pandemics in terms of cases-to-population ratio (or alternatively, higher output growth) ($F(z_{it}) \approx 1$ when *z* goes to minus infinity) and extremely severe pandemic events in terms of cases-to-population ratio (or alternatively, lower output growth) ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively—$F(z_{it})$=0.5 is the cutoff between severe and weak pandemic event. We choose $\gamma = 3.5$, following Tenreyro and Thwaites (2016).

The results in Figure 17 show that the distributional effect of pandemic events varies with their severity. Using the continuous variable instead of a (0-1) dummy, the results point to larger effects of pandemics on inequality as case-to-population ratios increase: a one percent increase in the measure of severity implies a rise in net Gini of about 0.4 (0.15 when using the inverse hyperbolic sine transformation) (Figure 17 - Panels A and B). In other words, the effect of an *average pandemic*—based on the average infection rate in our dataset (0.80 cases per thousand inhabitants)—is associated with a medium-term increase in the net Gini of about 0.1. This implies that for a severe pandemic in our sample (i.e. at the 99th percentile, with 15 cases per thousand people), the Gini index would increase, on average, by 0.6 percentage point. Taking this effect at face value and translating it to the current pandemic, it implies that COVID-19 would lead to a medium-term increase in the Gini of at least 0.5/0.7 percentage point (indeed, as of April 30th, 2021, the pandemic counted on average 18.22 cases per thousand inhabitants, with a maximum rate of about 152 infections per thousand and this number is expected to further increase). The IV results confirm the adverse distributional effects of pandemics, with the magnitude of the coefficient significantly larger than the corresponding OLS.

The results obtained from estimating equation (6) show that for episodes associated with a larger number of cases relative to population (such as Croatia, H1N1, 2009), the effect is statistically significant and larger than the average effect shown in Figure 1 (the medium-term effect on Gini increases from 0.4 to about 0.8), while it is not statistically different from zero for episodes associated with small outbreaks (such as Philippines, SARS, 2003) (Figure 17 – Panel B). Similarly, the results in Panel C show that the medium-term effect is larger (about 0.7) in episodes associated with low growth (such as Korea, MERS, 2012), while it is not statistically different from zero for episodes associated with high growth (such as China, H1N1, 2009).[10]

IV. Conclusion

The COVID-19 crisis is already showing how the more vulnerable socio-economic groups suffer from a greater risk of financial exposure, greater health risks, and worse housing conditions during the lockdown period. These factors may exacerbate inequalities.

Our paper explores this possibility by providing evidence on the impact of pandemics and major epidemics from the past two decades on income distribution. Our results justify the concern that, in the absence of long-lasting supportive policies to protect the vulnerable, the pandemic could end up exerting a significant impact on inequality: past events of this kind, even though much smaller in scale, have led to increases in the Gini coefficient, raised the income shares accruing to the higher deciles of the income distribution, and lowered the employment-to-population ratio for those with basic education compared to those with higher educations. Evidence from previous pandemics shows that the response of income inequality to pandemics also depends on fiscal policy. Austerity breeds K-shaped recoveries: the rise in inequality is higher when fiscal policy is tighter, while when the fiscal response is supportive, inequality barely increases. (Furceri, Loungani, Ostry and Pizzuto 2021).

In addition, the result that the impact of past pandemics on inequality has been more greater in the more severe ones (both either in terms of number of cases or the output effects of the pandemic) suggests that the distributional consequences of COVID-19 may be larger than those following earlier pandemics in our sample. Our estimates are likely a lower bound since COVID-19 is more widespread than the average health crisis in our sample, with the median country affected by COVID-19 roughly corresponding to the pandemic episode at 99th percentile of the distribution in our sample. That said, the he short-term fiscal support provided to face the current crisis has been also unprecedented and if not withdrawn soon will help mitigating the regressive effects of the pandemic.

[10] The F-test of the difference between the estimations in the case of low and high regime of the interaction variable with the pandemic dummy are shown in Table 6.

Our results leave several questions for future research. First, the distributional effects of pandemic events are likely to vary considerably across countries, depending on country-specific characteristics, initial income distribution, the stringency of containment measures as well as the policy response. Second, there is growing evidence that the economic effects of COVID-19 may also vary between different segments of the population including by race, age, and gender. Third, the human cost of pandemics is also sadly higher in low-income groups, which are more prone to diseases and have often more limited access to health services. These issues need attention.

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TABLE 1: DATA SOURCES AND DESCRIPTIVE STATISTICS

Variable	Source	Obs	Mean	Std. Dev.	No. of Countries
Gini Market	SWIID 8.3	5,472	45.39	6.59	177
Gini Net	SWIID 8.3	5,472	38.38	8.73	177
Top 40% Income Share	WDI	1,444	67.77	6.65	64
Top 20% Income Share	WDI	1,444	46.28	7.83	64
Top 10% Income Share	WDI	1,444	30.85	7.31	64
Bottom 40% Income Share	WDI	1,444	17.12	4.56	64
Bottom 20% Income Share	WDI	1,444	6.31	2.19	64
Bottom 10% Income Share	WDI	1,443	2.44	1.02	64
Employment/Population (E/P) ratios					
E/P ratio – Basic Education	ILO	1,340	42.51	16.22	76
E/P ratio – Non-basic Education	ILO	1,340	57.49	16.22	76
Financial Crises	Laeven and Valencia (2020)	289 episodes			177

TABLE 2: 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 (*100,000)	Average Mortality rate (%)
2003	2	SARS	AUS, CAN, CHE, CHN, DEU, ESP, FRA, GBR, HKG, IDN, IND, IRL, ITA, KOR,, MNG, MYS, NZL, PHL, ROU, RUS, SGP, SWE, THA, TWN, USA, VNM, ZAF	27	774	8,094	9.56	1.25	9.77
2009	4	H1N1	AFG, AGO, ALB, ARG, ARM, AUS, AUT, BDI, BEL, BGD, BGR, BHS, BIH, BLR, BLZ, BOL, BRA, BRB, BTN, BWA, CAN, CHE, CHL, CHN,CIV, CMR, COD, 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, GTM, HND, HRV, HTI, HUN, IDN, IND, IRL, IRN, IRQ, ISL, ISR, ITA, JAM, JOR, JPN, KAZ, KEN, KHM, KNA, KOR, LAO, LBN, LCA, LKA, LSO, LTU, LUX, LVA, MAR, MDA, MDG, MDV, MEX, MKD, MLI, MLT, MNE, MNG, MOZ, MUS, MWI, MYS, NAM, NGA, NIC, NLD, NOR, NPL, NZL, PAK,PAN, PER, PHL, PLW, PNG, POL, PRI, PRT, PRY, QAT, ROU, RUS, RWA, SAU, SDN, SGP, SLB, SLV, STP, SUR, SVK, SVN, SWE, SWZ, SYC, TCD, THA, TJK, TON, TUN, TUR, TUV, TZA, UGA, UKR, URY, USA, VEN, VNM, VUT, WSM, YEM, ZAF, ZMB, ZWE	149	19,091	6,502,779	0.29	122.69	4.02
2012	3	MERS	AUT, CHN, DEU, EGY, FRA, GBR, GRC, IRN, ITA, JOR, KOR, LBN, MYS, NLD, PHL, QAT, SAU, THA, TUN, TUR, USA, YEM	22	572	1,453	39.37	0.24	35.95
2014	8	Ebola	ESP, GBR, ITA, LBR, SLE, USA	6	8,767	24,809	35.34	74.37	16.34
2016	2	Zika	ARG, BOL, BRA, BRB, CAN, CHL, COL, CRI, DOM, ECU, HND, JAM, LCA, PAN, PER, PRI, PRY, SLV, SUR, URY, USA	21	20	198,122	0.01	76.21	0.03
			Total Pandemic and Epidemic Events	**225**					

Sources: WHO, Ma 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 3: IMPACT OF PANDEMICS ON MARKET GINI AND NET GINI COEFFICIENTS

Panel A: Net Gini

	k=0	k=1	k=2	k=3	k=4	k=5
$D_{i,t}$	0.017	0.065	0.135**	0.232***	0.325***	0.414***
	(0.028)	(0.054)	(0.065)	(0.086)	(0.109)	(0.128)
$D_{i,t-1}$	0.038	0.105**	0.237***	0.309***	0.400***	0.534***
	(0.029)	(0.046)	(0.067)	(0.100)	(0.119)	(0.150)
$D_{i,t-2}$	0.037	0.115*	0.233***	0.316***	0.346***	0.401**
	(0.028)	(0.060)	(0.080)	(0.103)	(0.130)	(0.166)
$y_{i,t-1}$	1.629***	2.068***	2.372***	2.510***	2.578***	2.624***
	(0.029)	(0.058)	(0.088)	(0.127)	(0.163)	(0.193)
$y_{i,t-2}$	-0.651***	-1.127***	-1.480***	-1.675***	-1.803***	-1.911***
	(0.029)	(0.056)	(0.083)	(0.119)	(0.152)	(0.181)
Observations	5,110	4,933	4,756	4,579	4,403	4,228
R^2	1.000	0.998	0.997	0.994	0.992	0.990

Panel B: Market Gini

	k=0	k=1	k=2	k=3	k=4	k=5
$D_{i,t}$	0.050	0.113**	0.182***	0.219**	0.314***	0.413***
	(0.036)	(0.052)	(0.070)	(0.090)	(0.119)	(0.152)
$D_{i,t-1}$	0.041	0.111**	0.203***	0.256**	0.335**	0.539***
	(0.034)	(0.055)	(0.078)	(0.111)	(0.134)	(0.186)
$D_{i,t-2}$	0.040	0.070	0.151*	0.214*	0.338**	0.477**
	(0.031)	(0.061)	(0.088)	(0.119)	(0.155)	(0.212)
$y_{i,t-1}$	1.608***	2.053***	2.389***	2.582***	2.734***	2.843***
	(0.031)	(0.059)	(0.089)	(0.120)	(0.154)	(0.182)
$y_{i,t-2}$	-0.625***	-1.099***	-1.473***	-1.710***	-1.910***	-2.072***
	(0.0311)	(0.060)	(0.088)	(0.117)	(0.149)	(0.176)
Observations	5,110	4,933	4,756	4,579	4,403	4,228
R^2	0.999	0.997	0.994	0.989	0.985	0.980

Note: Estimates are obtained using a sample of 177 countries over the period 1960–2019, and based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country *i* in year *t*; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country *i* in year *t*. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A1 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level. Country and time fixed effects included but not reported.

TABLE 4: PANDEMIC DUMMY REGRESSION, POOLED PROBIT ESTIMATOR (AVERAGE MARGINAL EFFECTS)

Probit model of treatment at time *t+1* (pandemic dummy)				
	(1)	(2)	(3)	(4)
Total Health Expenditures	-0.022	-0.031		
	(0.054)	(0.055)		
General government final consumption expenditure (% of GDP)	-0.042	-0.046	-0.030	-0.032
	(0.029)	(0.031)	(0.023)	(0.024)
Age dependency ratio (% of working-age population)	-0.046***	-0.046***	-0.048***	-0.053***
	(0.016)	(0.017)	(0.011)	(0.013)
GDP per capita (constant 2010 US$) (log)	0.965**	0.851**	1.686***	1.648***
	(0.390)	(0.408)	(0.302)	(0.316)
Growth rate of GDP	-0.016	-0.016	-0.014	-0.016
	(0.013)	(0.013)	(0.011)	(0.012)
Mortality rate, adult, (per 1,000 adults)	0.002*	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)
Temperature (Year average)	0.253***	0.298***	0.328***	0.375***
	(0.080)	(0.083)	(0.074)	(0.077)
Gini Disposable - level		-0.0691		-0.002
		(0.0459)		(0.034)
Gini Disposable - change		-0.0215		-0.101
		(0.190)		(0.159)
Observations	1,912	1,850	3,485	3,413

Note: Country fixed effects included but not reported. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

TABLE 5: AVERAGE TREATMENT EFFECT OF PANDEMICS, AIPW ESTIMATES

			PANEL A			
	k=0	k=1	k=2	k=3	k=4	k=5
ATE, restricted $\theta_1^h = \theta_0^h$	0.06***	0.13***	0.25***	0.26***	0.17***	0.25***
	(0.02)	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)
ATE, unrestricted $\theta_1^h \neq \theta_0^h$	0.02	0.16***	0.27***	0.36***	0.38***	0.62***
	(0.02)	(0.04)	(0.05)	(0.06)	(0.08)	(0.08)
Observations	1,826	1,826	1,745	1,630	1,511	1,393
			PANEL B			
	k=0	k=1	k=2	k=3	k=4	k=5
ATE, restricted $\theta_1^h = \theta_0^h$	0.08***	0.15***	0.28***	0.35***	0.38***	0.47***
	(0.01)	(0.03)	(0.04)	(0.05)	(0.06)	(0.06)
ATE, unrestricted $\theta_1^h \neq \theta_0^h$	-0.01	0.09**	0.16***	0.15**	0.13	0.27***
	(0.02)	(0.04)	(0.06)	(0.07)	(0.09)	(0.10)
Observations	3,298	3,298	3,213	3,094	2,971	2,849

Notes:. Empirical sandwich standard errors (clustered by country) in parentheses *** p<0.01, ** p<0.05, * p<0.1. AIPW estimates based on the baseline model as in equation (5). Results for Panels A and B are based on the propensity scores obtained using the model of column 2 and 4 of Table 4, respectively. When imposing $\theta_1^h = \theta_0^h$ (i) the effect of the controls X_t on the outcomes is assumed to be stable across the treated and control subpopulations (i.e. countries experiencing a pandemic event and countries not experiencing a pandemic event); (ii) the expected value of X_t in each subpopulation is assumed to be the same. When imposing $\theta_1^h \neq \theta_0^h$ these assumptions are relaxed. For further details see the methodological section and Jordà and Taylor (2016).

TABLE 6: F-TESTS DIFFERENCE

	F-test difference					
	k=0	k=1	k=2	k=3	k=4	k=5
Pandemics vs Financial Crises[a]	0.001	0.895	3.976**	5.807**	7.106***	8.473***
Pandemics vs Recessions[a]	0.075	0.472	1.521	2.794*	3.832*	4.545**
Interaction with Cases-Population ratio[b]	0.159	0.0301	0.295	1.425	2.642	3.575*
Interaction with GDP Growth[b]	0.006	0.615	0.539	2.091	3.142*	3.727*

*** p<0.01, ** p<0.05, * p<0.1. [a] The F-test of the difference between the estimations in the case of Pandemics and Financial Crises (Recessions)—(See Figure 13). [b] The F-test of the difference between the estimations in the case of low and high regime of the interaction variable with the pandemic dummy—(See Figure 17).

TABLE 7: PANDEMICS AND INEQUALITY - IV FIRST STAGE

$log_{10}(1+x)$ transformation

	k=0	k=1	k=2	k=3	k=4	k=5
Instrument	-0.002***	-0.002***	-0.003***	-0.003***	-0.004***	-0.004***
	(-2.770)	(-3.570)	(-3.530)	(-3.840)	(-3.850)	(-4.340)
Observations	4,888	4,725	4,561	4,398	4,235	4,075
Centered R-squared	0.012	0.019	0.020	0.026	0.028	0.040
Kleibergen-Paap_rk_Wald_F_statistic	7.676	12.77	12.45	14.72	14.82	18.86

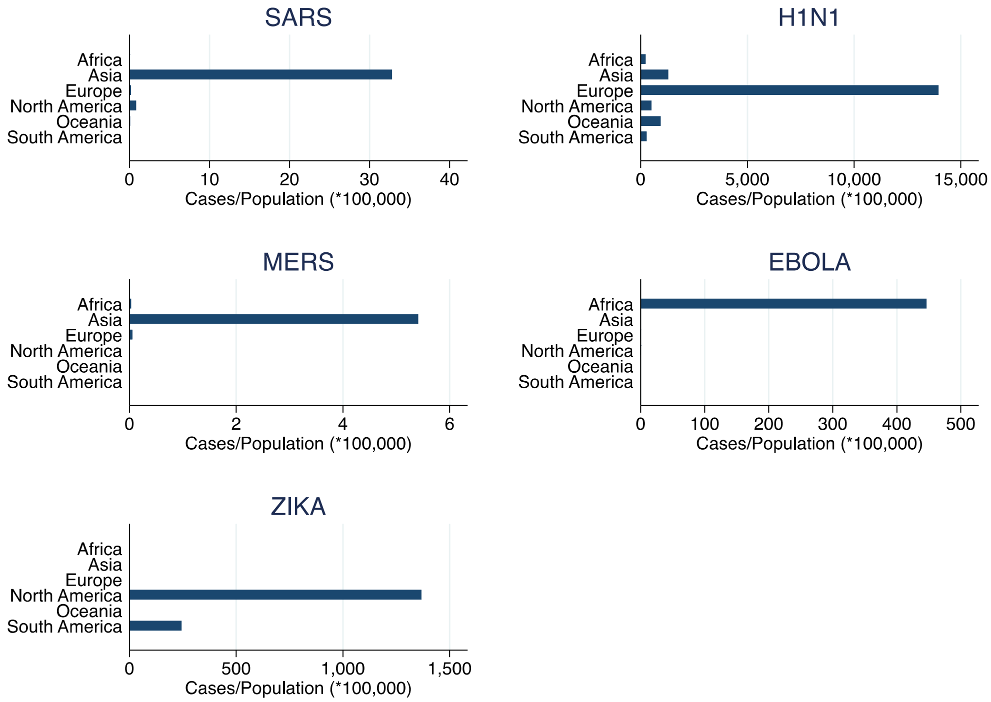
Note: k=0 is the year of the pandemic. k=1,2,3,4,5 are the years after the pandemic event. IV first stage estimates based on equation (1) in the main text. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included but not reported. The Kleibergen–Paap rk Wald F-statistic tests for weak identification.

Inverse Hyperbolic Sine (IHS) transformation

	k=0	k=1	k=2	k=3	k=4	k=5
Instrument	-0.006***	-0.007***	-0.008***	-0.009***	-0.010***	-0.013***
	(-2.780)	(-3.570)	(-3.530)	(-3.830)	(-3.840)	(-4.360)
Observations	4,888	4,725	4,561	4,398	4,235	4,075
Centered R-squared	0.013	0.019	0.020	0.026	0.029	0.038
Kleibergen-Paap_rk_Wald_F_statistic	7.720	12.80	12.46	14.69	14.78	19.00

Note: k=0 is the year of the pandemic. k=1,2,3,4,5 are the years after the pandemic event. IV first stage estimates based on equation (1) in the main text. Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Control variables included but not reported. The Kleibergen–Paap rk Wald F-statistic tests for weak identification.

FIGURE 1: PANDEMIC CASES BY REGIONS



Sources: WHO, Ma 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/;

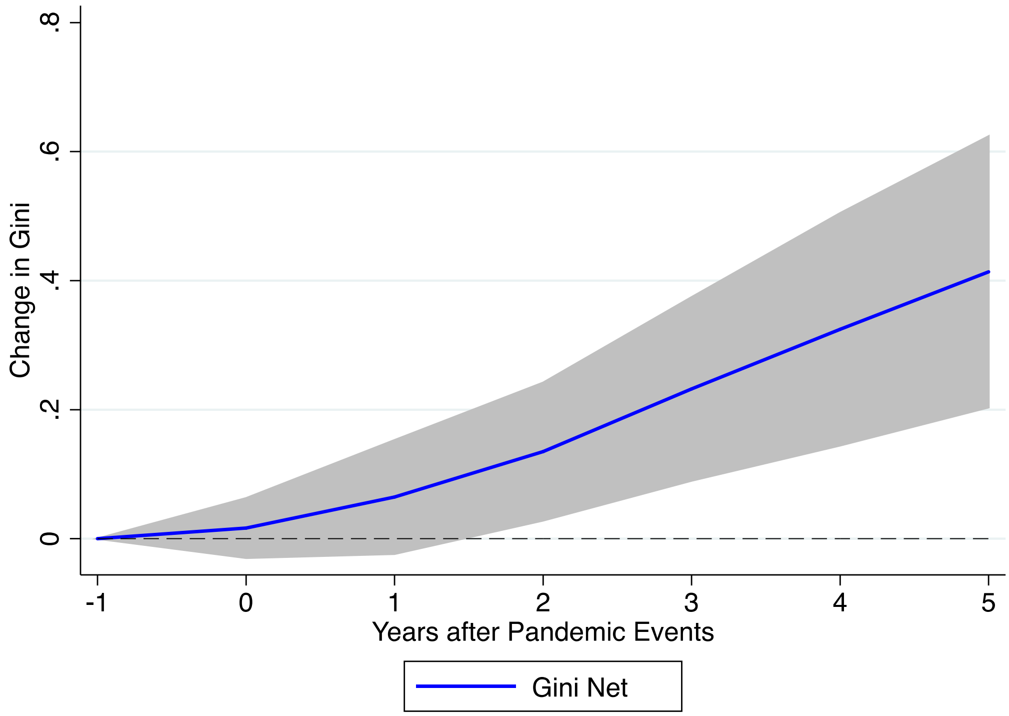
H1N1: https://en.wikipedia.org/wiki/2009_swine_flu_pandemic_by_country and https://www.ecdc.europa.eu/en/seasonal-influenza/2009-influenza-h1n1;

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;

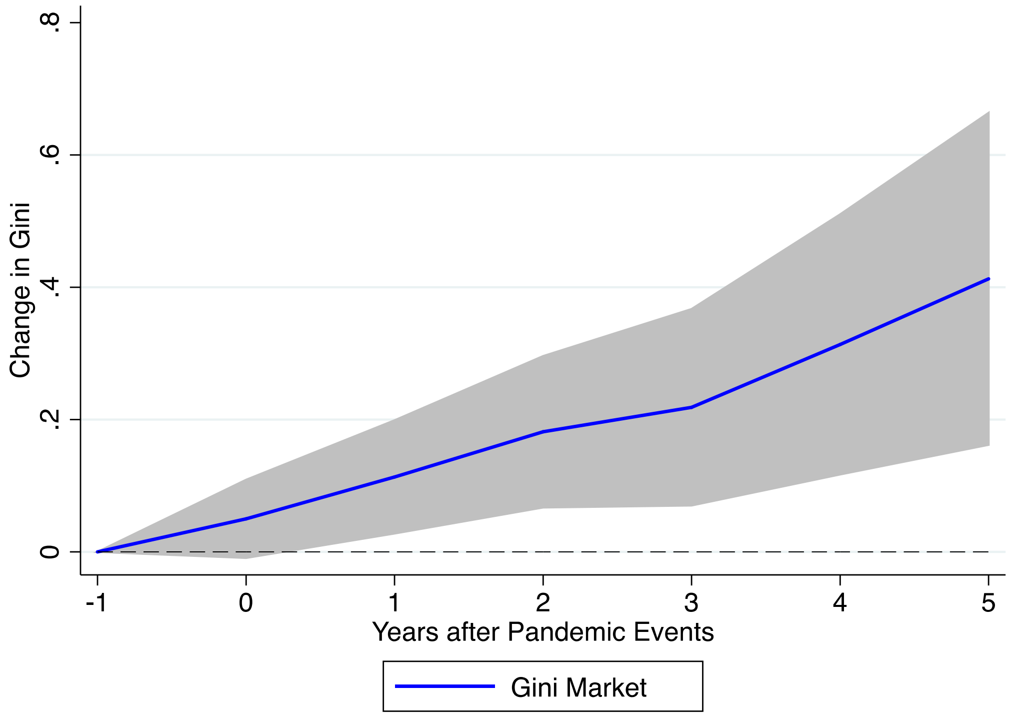
ZIKA: https://www.paho.org/hq/index.php?option=com_content&view=article&id=12390:zika-cumulative-cases&Itemid=42090&lang=en.

FIGURE 2: IMPACT OF PANDEMICS ON NET GINI



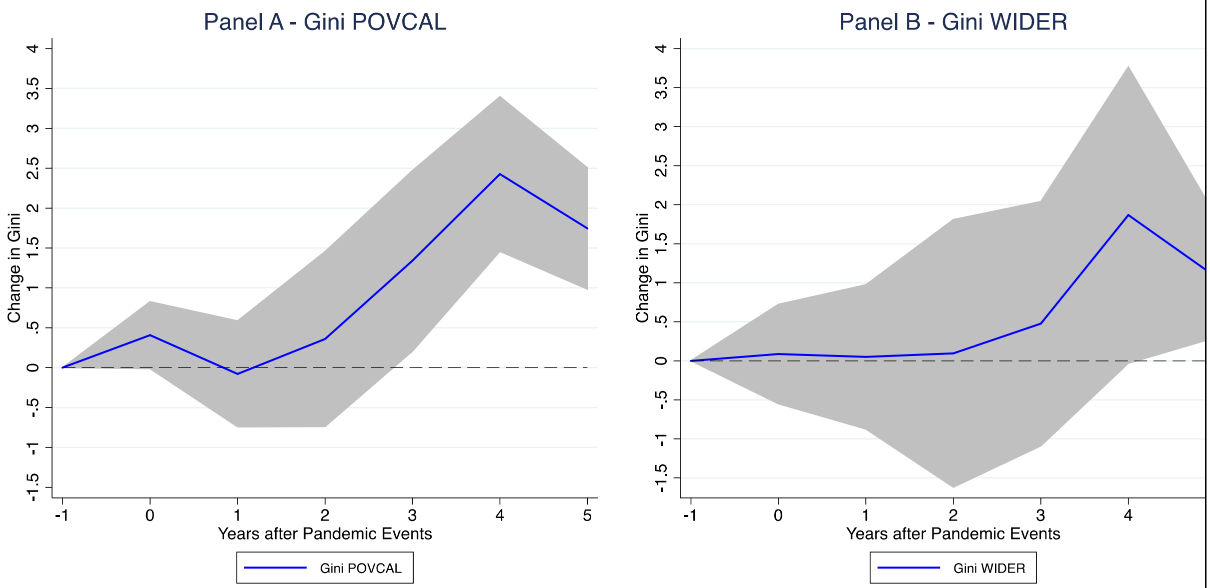
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A1 for the full list of pandemic events.

FIGURE 3: IMPACT OF PANDEMICS ON MARKET GINI



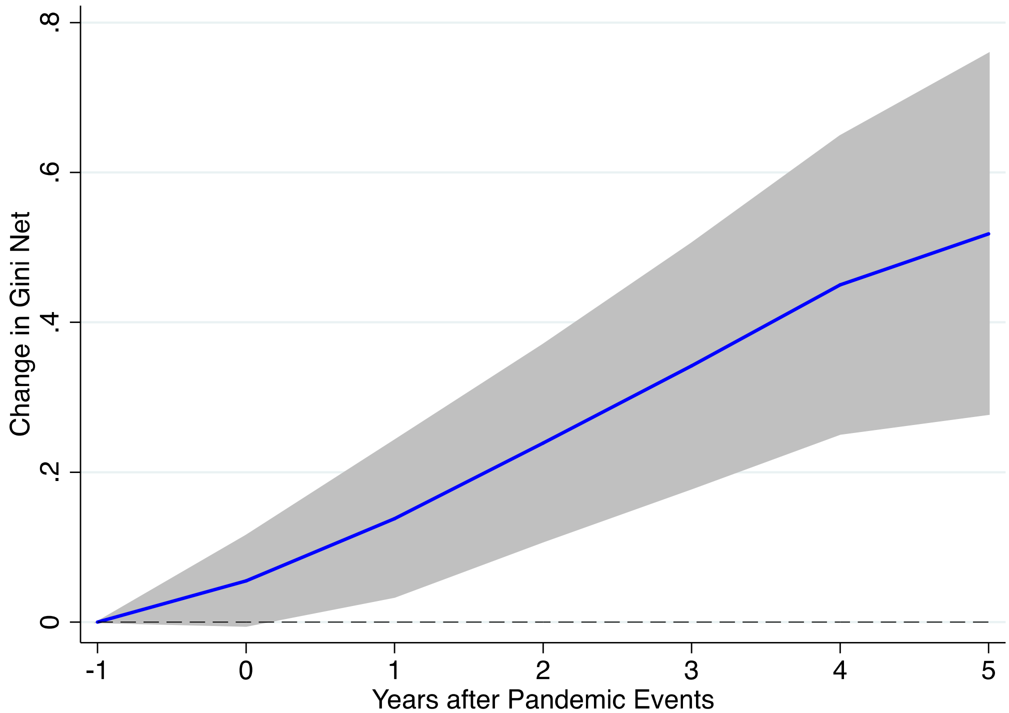
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A2-A3 for the full list of pandemic events.

FIGURE 4: IMPACT OF PANDEMICS ON NET GINI—DIFFERENT MEASURES OF INEQUALITY



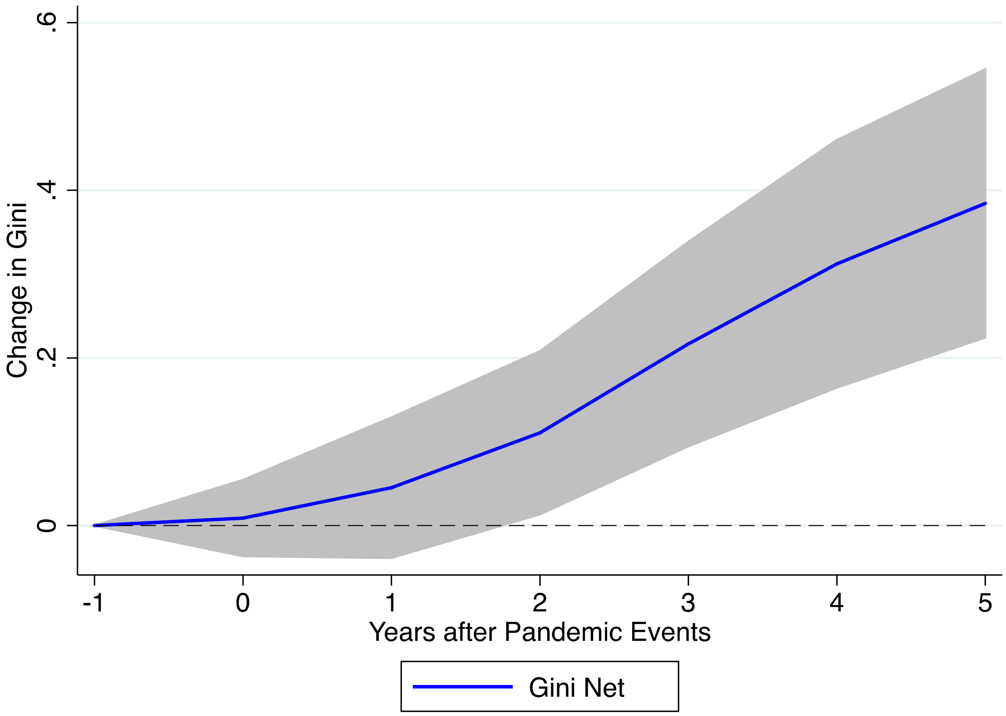
Notes: Impulse response functions are estimated using, alternatively, Gini POVCAL (69 countries – 763 observations) and Gini WIDER (66 countries – 641 observations). The graph shows the responses and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy.

FIGURE 5: IMPACT OF PANDEMICS ON NET GINI—ADL



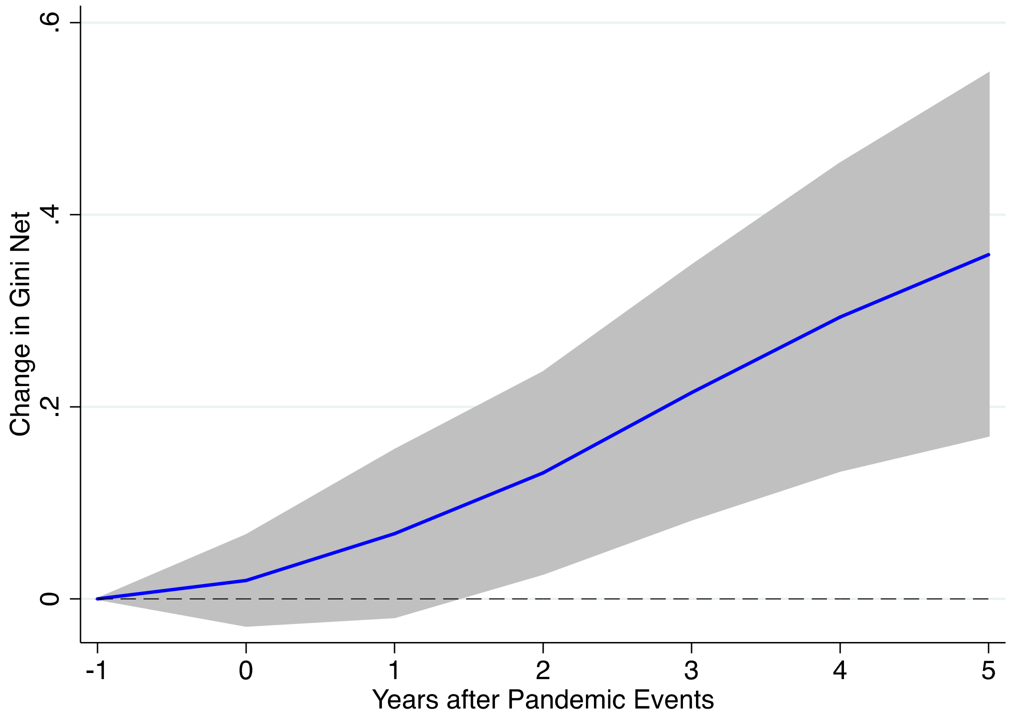
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $\Delta y_{i,t} = \alpha_i + \gamma_t + \beta_k(l)D_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. See Table A2-A3 for the full list of pandemic events.

FIGURE 6: IMPACT OF PANDEMICS ON NET GINI—RESTRICTED SAMPLE (1990-2019)



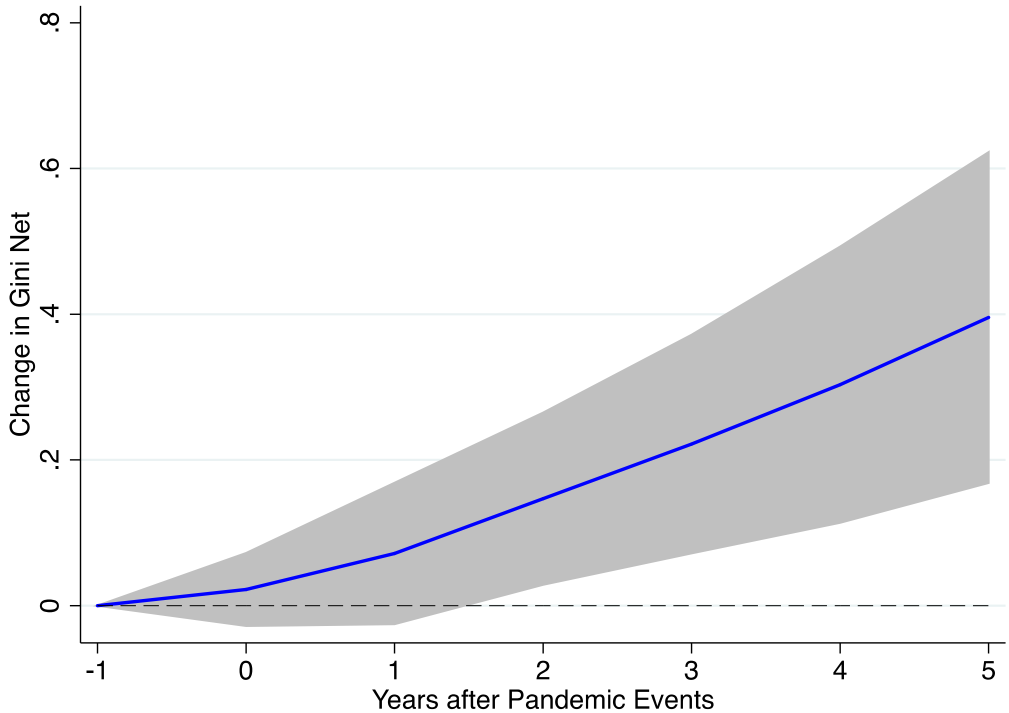
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1990–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A2-A3 for the full list of pandemic events.

FIGURE 7: IMPACT OF PANDEMICS ON NET GINI—ADDITIONAL CONTROLS



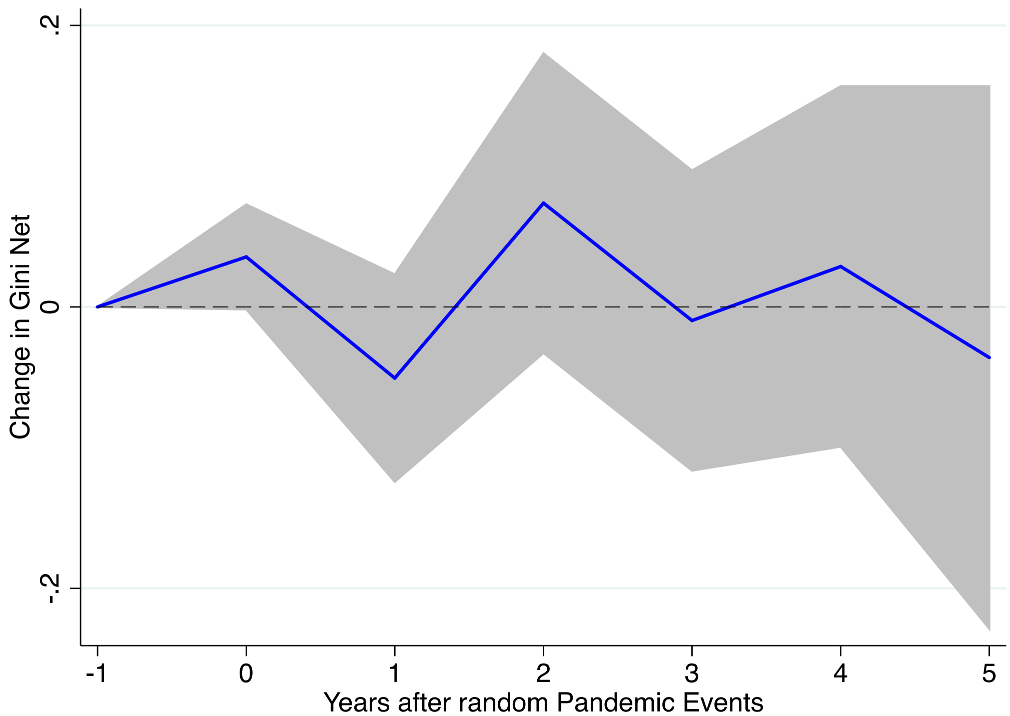
Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1960–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable, two lags of the pandemic dummy, the level of GDP, the level of GDP square, population density, the share of population in urban area, the KOF index of trade globalization and the KOF index of financial globalization. See Table A2-A3 for the full list of pandemic events.

FIGURE 8: IMPACT OF PANDEMICS ON NET GINI—ADDING COUNTRY-SPECIFIC TIME TRENDS AS CONTROL



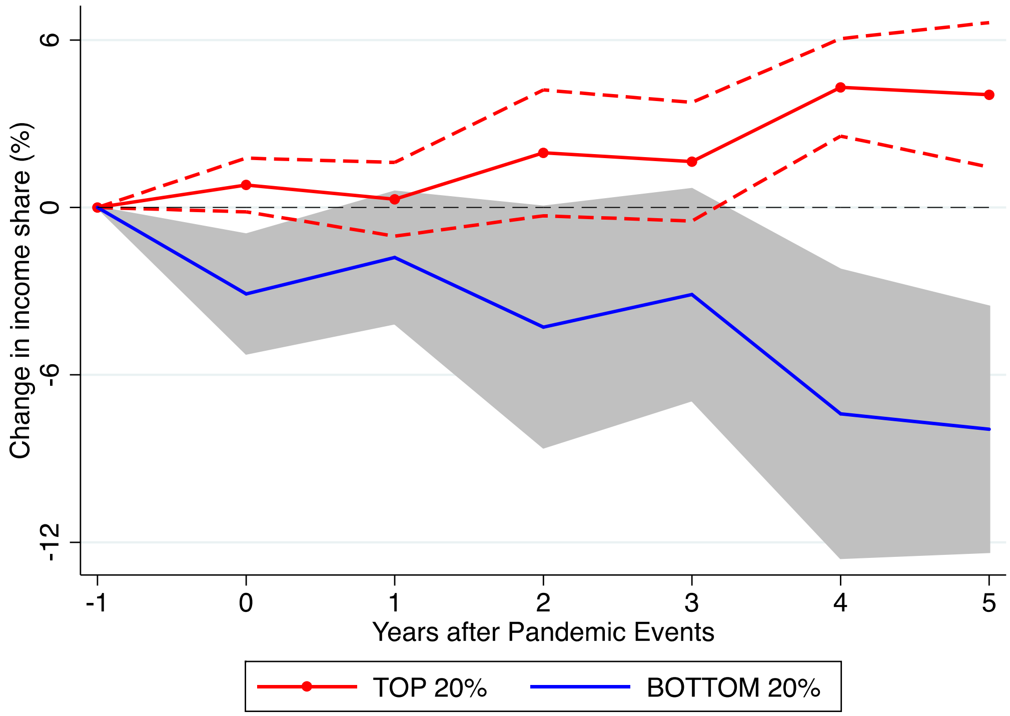
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable, two lags of the pandemic dummy and country-specific time trends. See Table A2-A3 for the full list of pandemic events.

FIGURE 9: IMPACT OF PANDEMICS ON NET GINI—PLACEBO TEST



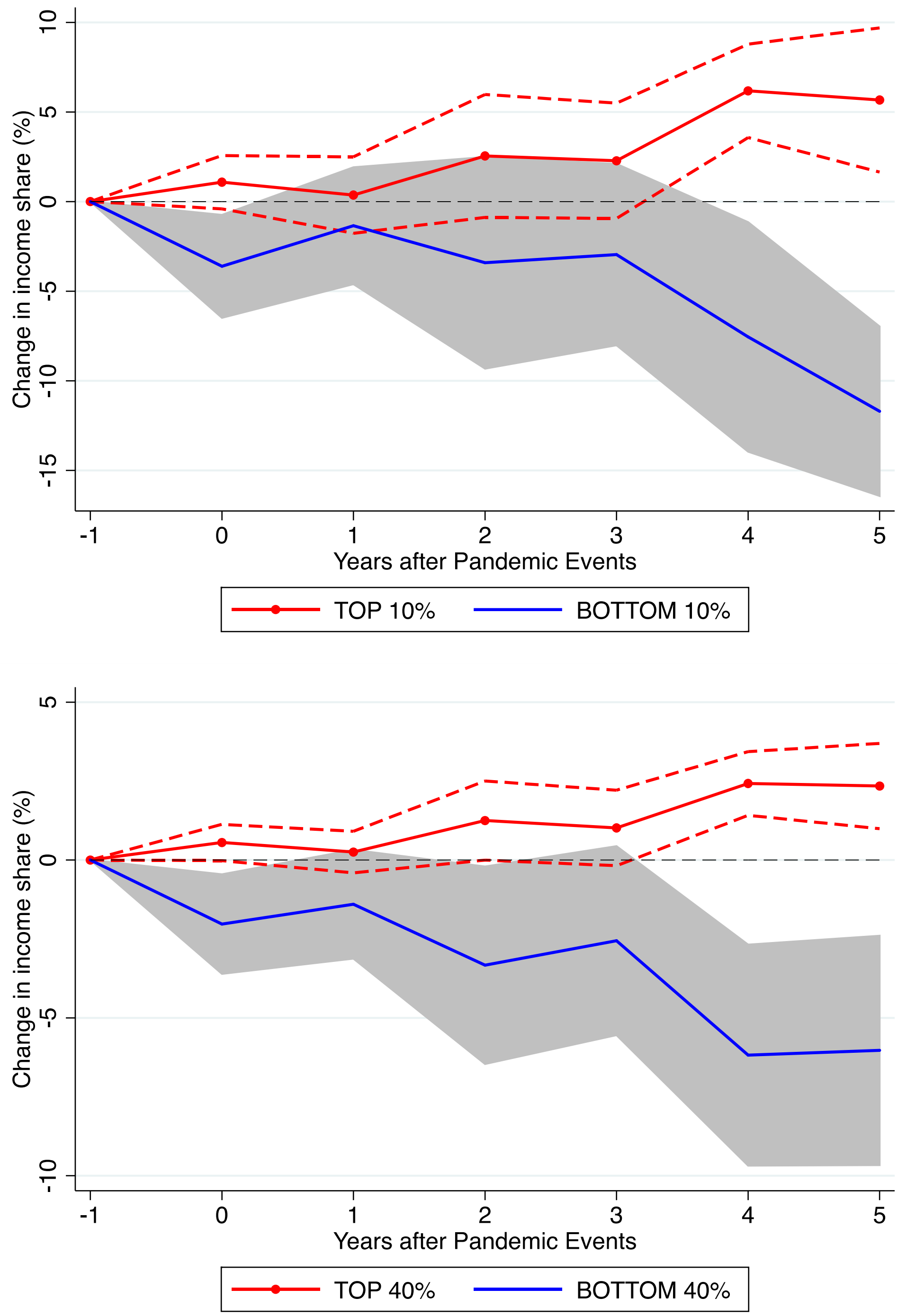
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. The placebo test is conducted estimating the impulse responses attributing the values of our measure of the shock, $D_{i,t}$, randomly, across the whole sample.

FIGURE 10: IMPACT OF PANDEMICS ON SHARES OF INCOME



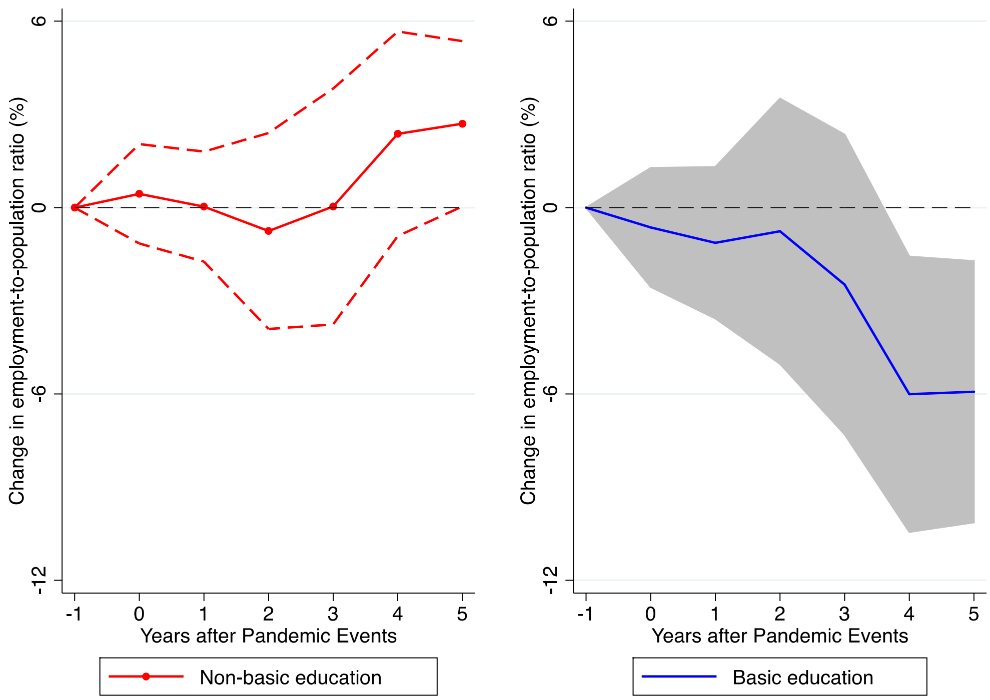
Notes: Impulse response functions are estimated using a sample of 64 countries over the period 1981–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates are based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the log of the income share held by the top (bottom) 20 percent for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and the pandemic dummy. See Table A1 for the full list of pandemic events.

FIGURE 11: IMPACT OF PANDEMICS ON SHARES OF INCOME, BY DECILES – ROBUSTNESS CHECKS



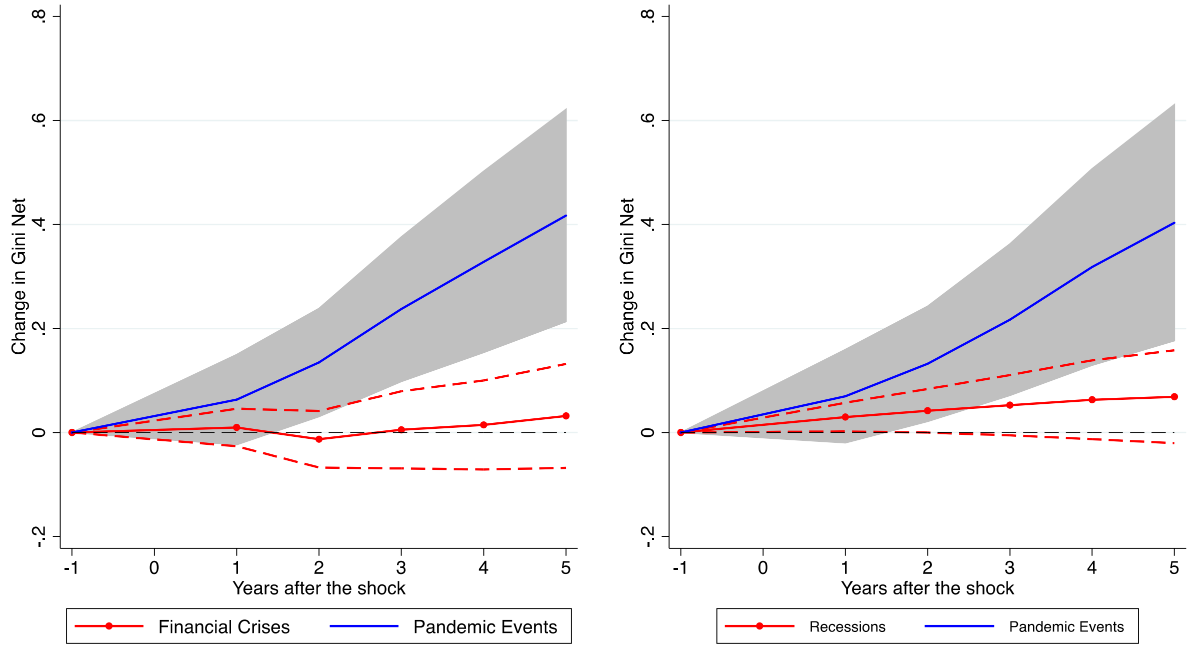
Notes: Impulse response functions are estimated using a sample of 64 countries over the period 1981–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates are based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is, in turn, the log of the income share held by the top (bottom) 10 percent (40 percent) for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A1 for the full list of pandemic events.

FIGURE 12: IMPACT OF PANDEMICS ON EMPLOYMENT-TO-POPULATION RATIO, BY EDUCATION LEVEL



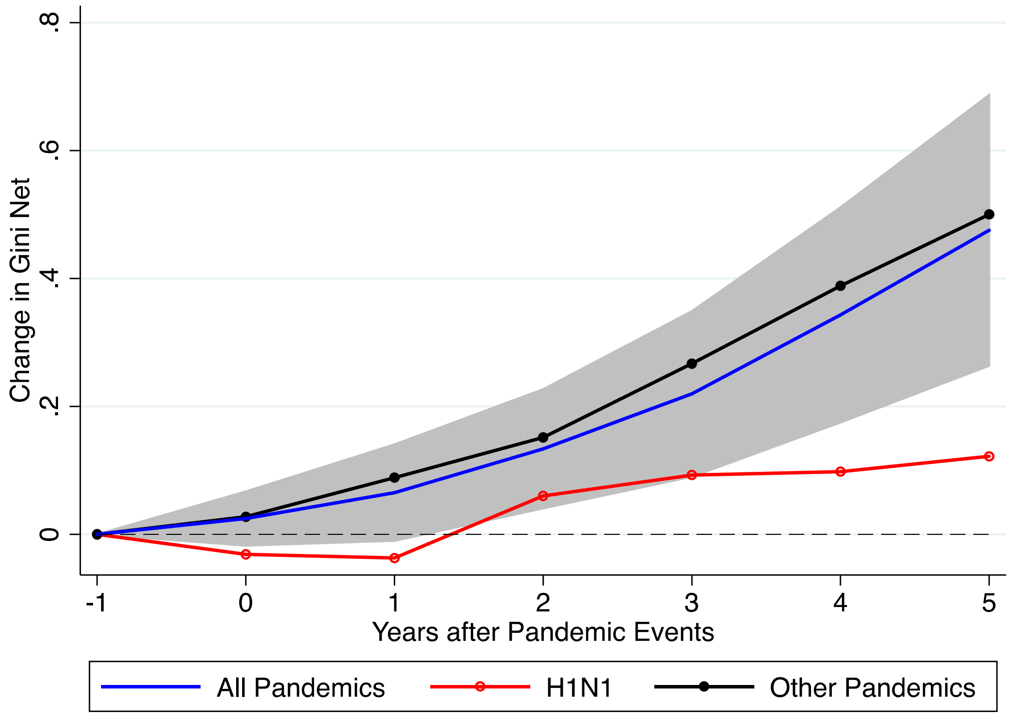
Notes: Impulse response functions are estimated using a sample of 76 countries over the period 1990–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates are based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is, in turn, the log of employment-to-population ratio by education level for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and the pandemic dummy. See Table A1 for the full list of pandemic events.

FIGURE 13: IMPACT OF PANDEMICS VS. FINANCIAL CRISES AND OTHER RECESSIONS



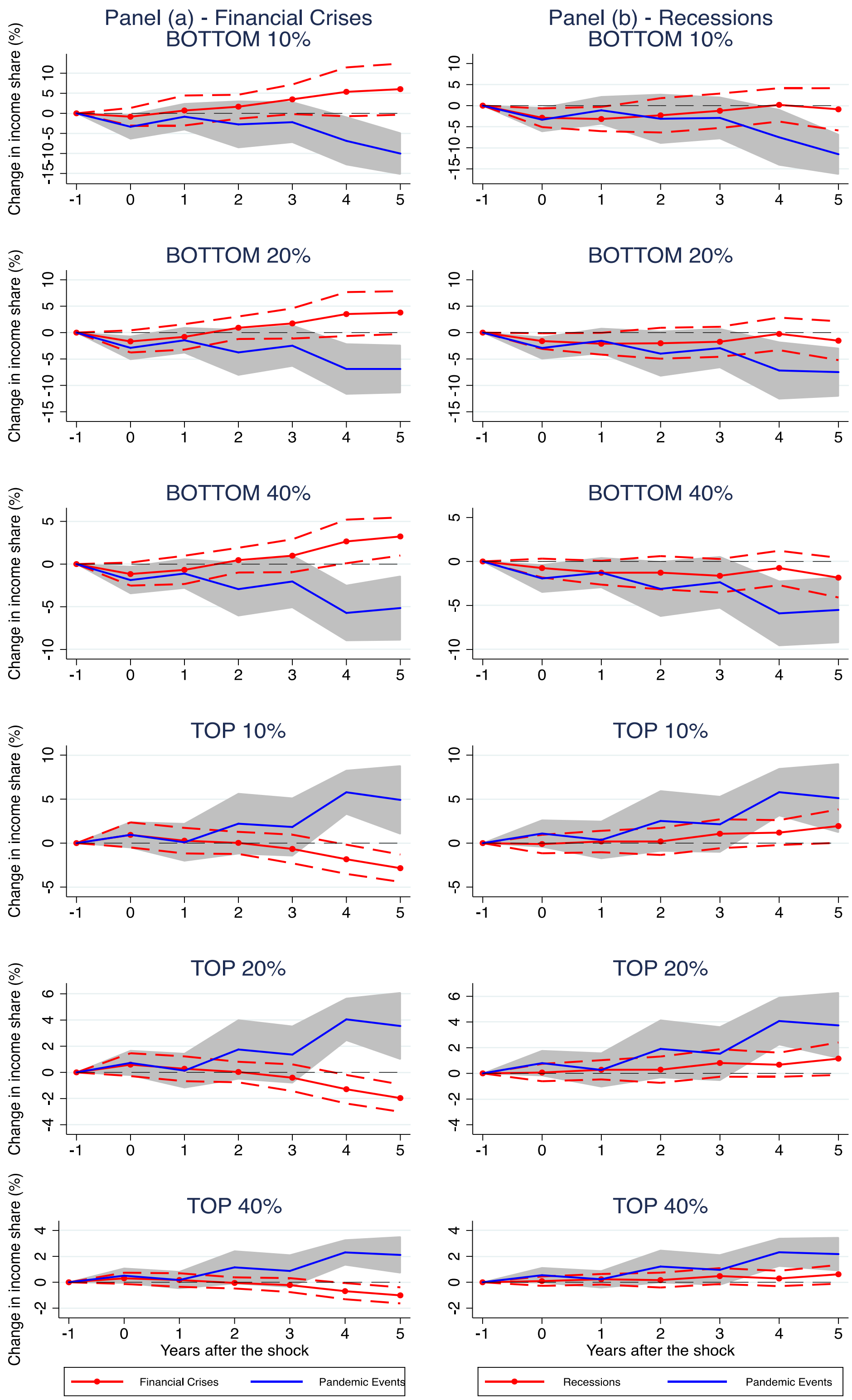
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019 (1970–2017 in the case of financial crises). The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \vartheta^k C_{i,t} + \theta^k M_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t; $C_{i,t}$ is a dummy variable denoting, alternatively, the year of occurrence of a financial crisis or a year of negative growth, $M_{i,t}$ is a vector that includes two lags of the dependent variable and the pandemic dummy plus two lags of the financial crisis (recession). See Table A1 for the full list of pandemic events. The F-tests for the difference between the estimations in the case of Pandemics and Financial Crises (Recessions) are shown in Table 6.

FIGURE 14: IMPACT OF PANDEMICS ON NET GINI, BY PANDEMICS – ROBUSTNESS CHECKS



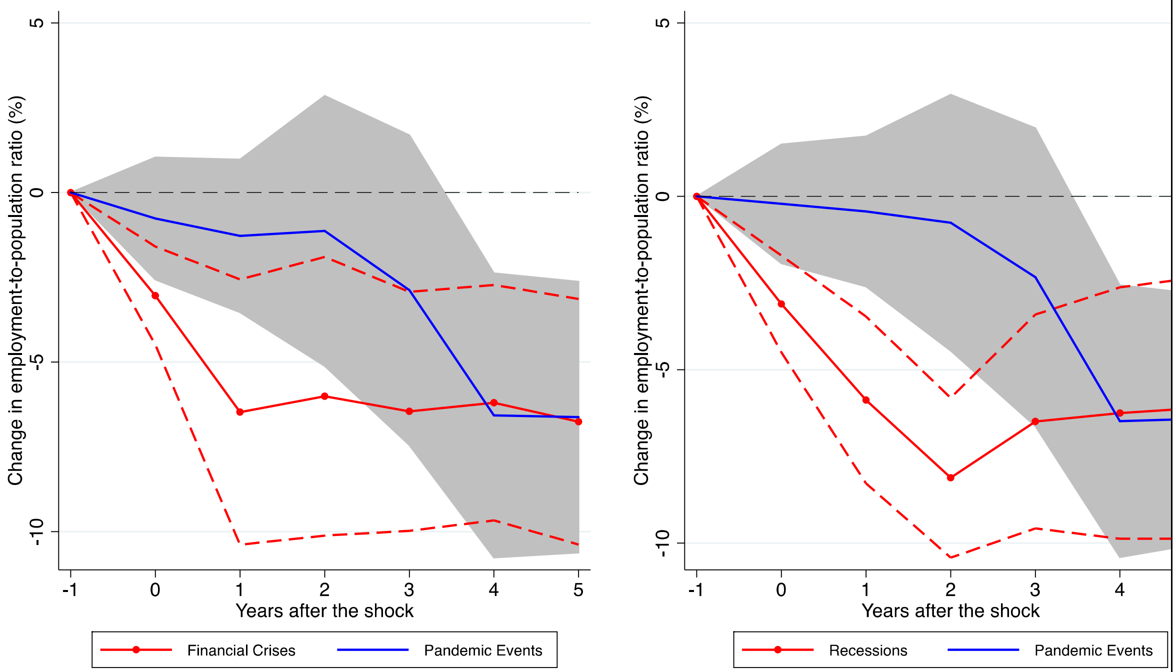
Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t. $X_{i,t}$ is a vector that includes two lags of the dependent variable and two lags of the pandemic dummy. See Table A1 for the full list of pandemic events.

FIGURE 15: IMPACT OF PANDEMICS, FINANCIAL CRISES AND RECESSIONS ON SHARES OF INCOME, BY DECILES



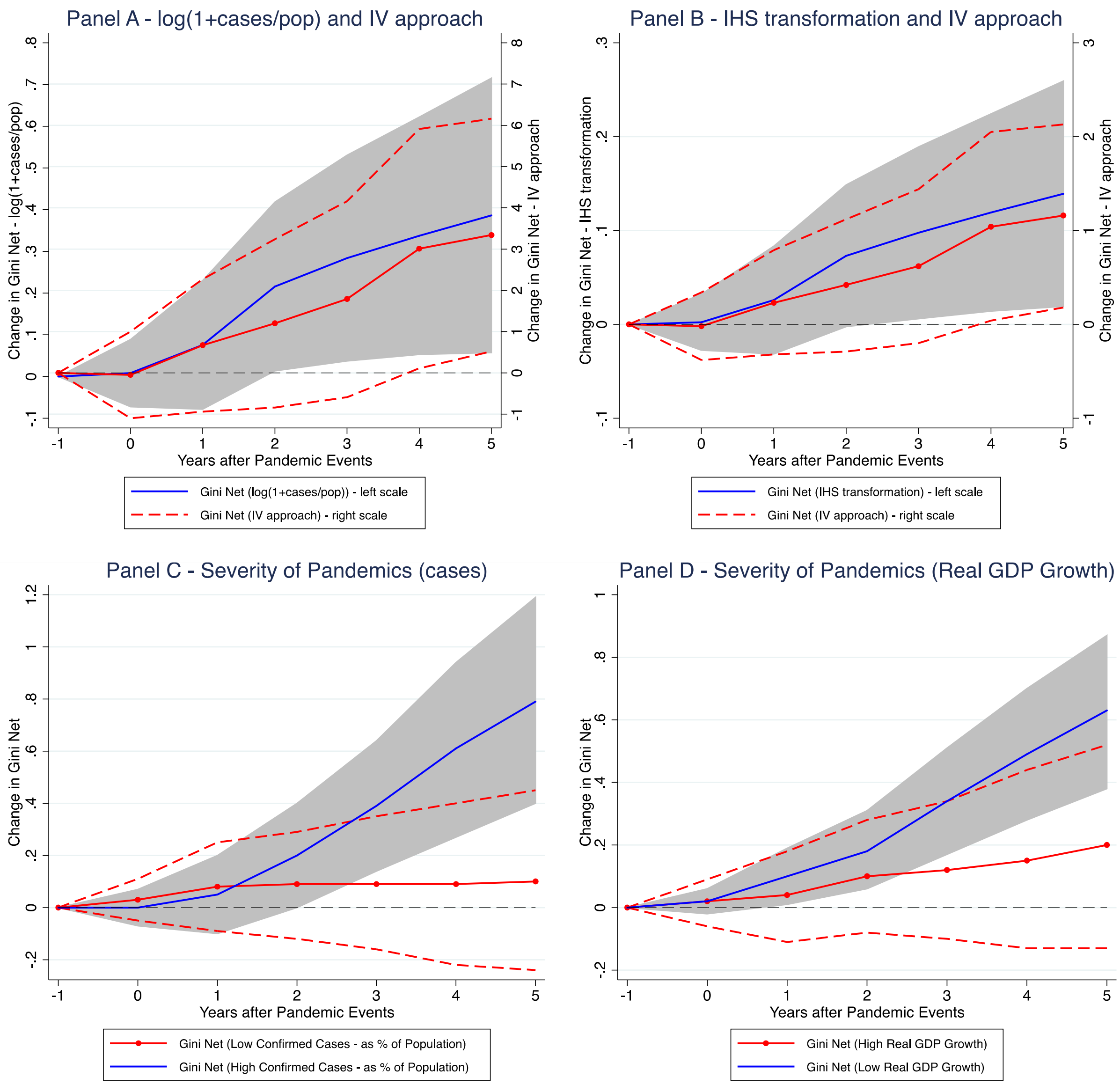
Notes: Impulse response functions are estimated using a sample of 64 countries over the period 1981–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events (financial crises or recessions); t = 0 is the year of the pandemic event (financial crisis or recession). Estimates based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \vartheta^k C_{i,t} + \theta^k M_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is, in turn, the log of the income share held by the top (bottom) 10%, 20%, or 40% for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t; $C_{i,t}$ is a dummy variable denoting, alternatively, the year of occurrence of a financial crisis or a year of negative growth, $M_{i,t}$ is a vector that includes two lags of the dependent variable, two lags of the pandemic dummy plus two lags of the financial crisis (recession). See Table A1 for the full list of pandemic events.

FIGURE 16: IMPACT OF PANDEMICS, FINANCIAL CRISES AND RECESSIONS ON E/P RATIO – BASIC EDUCATION



Notes: Impulse response functions are estimated using a sample of 76 countries over the period 1990–2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events (financial crises or recessions); t = 0 is the year of the pandemic event (financial crisis or recession). Estimates based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \vartheta^k C_{i,t} + \theta^k M_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is, in turn, the log of employment-to-population ratio by education level for country i in year t; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country i in year t; $C_{i,t}$ is a dummy variable denoting, alternatively, the year of occurrence of a financial crisis or a year of negative growth, $M_{i,t}$ is a vector that includes two lags of the dependent variable, two lags of the pandemic dummy plus two lags of the financial crisis (recession). See Table 1 for the full list of pandemic events.

FIGURE 17: IMPACT OF PANDEMICS ON NET GINI—THE ROLE OF THE SEVERITY OF THE PANDEMIC



Notes: Impulse response functions are estimated using a sample of 177 countries over the period 1960–2019. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. For Panel A, estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + \beta^k cases_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$, where $cases_{i,t}$ is alternatively $cases = log_{10}(1 + x)$ or $cases = ln(x + (x^2 + 1)^{1/2})$ with $x = \left(\frac{1000 \cdot confirmed\_cases_{i,t}}{population_{i,t}}\right)$. The instrumental variable (IV) approach consists of interacting an exogenous time-varying global term—the date of the initial pandemic outbreak in the world—and a country-specific terms exogenous to economic outcomes—such as average temperature (see Table 7 for first-stage estimate). For Panels B and C estimates based on $y_{i,t+k} = \alpha_i^k + \gamma_t^k + F(z_{it})[\beta_L^k D_{i,t} + \theta_L^k X_{i,t}] + (1 - F(z_{it}))[\beta_H^k D_{i,t} + \theta_H^k X_{i,t}] + \varepsilon_{i,t+k}$. $y_{i,t}$ is the Gini coefficient for country *i* in year *t*; α_i are country fixed effects; γ_t are time fixed effects; $D_{i,t}$ is a dummy variable indicating a pandemic event that affects country *i* in year *t*. $X_{i,t}$ is a vector that includes two lags of the dependent variable and the pandemic dummy. $F(z_{it})$ is an indicator function of the severity of the pandemic. The coefficients β_L^k and β_H^k capture the distributional impact of a pandemic event at each horizon *k* in cases of extremely severe pandemics ($F(z_{it}) \approx 1$ when *z* goes to minus infinity) and weak pandemics ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively. The F-tests for the difference between the estimations in the case of low and high regime of the interaction variable with the pandemic dummy are shown in Table 6. See Table A1 for the full list of pandemic events.

Table A1: List of Pandemic and Epidemic Episodes

Country	Event	Number of cases	Number of deaths	Country	Event	Number of cases	Number of deaths
AFG	H1N1	853	17	EGY	MERS	1	0
AGO	H1N1	37	0	ESP	SARS	1	0
ALB	H1N1	426	12	ESP	H1N1	1538	300
ARG	H1N1	11458	626	ESP	EBOLA	1	0
ARG	ZIKA	278	0	EST	H1N1	738	21
ARM	H1N1	119	3	ETH	H1N1	19	0
AUS	SARS	6	0	FIN	H1N1	6122	56
AUS	H1N1	37484	187	FJI	H1N1	234	0
AUT	H1N1	964	40	FRA	SARS	7	1
AUT	MERS	1	0	FRA	H1N1	1980000	344
BDI	H1N1	7	0	FRA	MERS	2	1
BEL	H1N1	76973	19	FSM	H1N1	82	0
BGD	H1N1	1015	7	GAB	H1N1	4	0
BGR	H1N1	766	40	GBR	SARS	4	0
BHS	H1N1	29	4	GBR	H1N1	28456	474
BIH	H1N1	714	13	GBR	MERS	4	3
BLR	H1N1	102	88	GBR	EBOLA	1	0
BLZ	H1N1	49	0	GEO	H1N1	1300	33
BOL	H1N1	2310	59	GHA	H1N1	676	3
BOL	ZIKA	811	0	GIN	H1N1	3	0
BRA	H1N1	58178	2135	GRC	H1N1	17977	149
BRA	ZIKA	137288	11	GRC	MERS	1	1
BRB	H1N1	154	3	GTM	H1N1	1170	24
BRB	ZIKA	150	0	HKG	SARS	1755	299
BTN	H1N1	91	0	HKG	H1N1	33109	80
BWA	H1N1	31	0	HND	H1N1	560	18
CAN	SARS	251	43	HND	ZIKA	308	0
CAN	H1N1	25828	429	HRV	H1N1	50255	26
CHE	SARS	1	0	HTI	H1N1	91	0
CHE	H1N1	11221	18	HUN	H1N1	283	134
CHL	H1N1	12258	156	IDN	SARS	2	0
CHN	SARS	5327	349	IDN	H1N1	1098	10
CHN	H1N1	120940	800	IND	SARS	3	0
CHN	MERS	1	0	IND	H1N1	33783	2024
CIV	H1N1	9	0	IRL	SARS	1	0
CMR	H1N1	4	0	IRL	H1N1	3189	26
COD	H1N1	222	0	IRN	H1N1	3672	147
COG	H1N1	21	0	IRN	MERS	6	2
COL	H1N1	4310	272	IRQ	H1N1	2880	42
COL	ZIKA	9927	0	ISL	H1N1	676	2
CPV	H1N1	118	0	ISR	H1N1	4330	94
CRI	H1N1	1867	67	ITA	SARS	4	0
CRI	ZIKA	2008	0	ITA	H1N1	3064933	244
CYP	H1N1	297	10	ITA	MERS	1	0
CZE	H1N1	2445	102	ITA	EBOLA	1	0
DEU	SARS	9	0	JAM	H1N1	191	7
DEU	H1N1	222360	258	JAM	ZIKA	203	0
DEU	MERS	3	2	JOR	H1N1	3033	19
DJI	H1N1	9	0	JOR	MERS	25	8
DMA	H1N1	36	0	JPN	H1N1	11636	198
DNK	H1N1	651	33	KAZ	H1N1	17	0
DOM	H1N1	491	23	KEN	H1N1	417	0
DOM	ZIKA	335	0	KHM	H1N1	531	6
DZA	H1N1	916	57	KNA	H1N1	6	2
ECU	H1N1	2251	200	KOR	SARS	3	0
ECU	ZIKA	2397	0	KOR	H1N1	107939	250
EGY	H1N1	15812	278	KOR	MERS	185	36

Country	Event	Number of cases	Number of deaths	Country	Event	Number of cases	Number of deaths
LBN	H1N1	1838	5	ROU	H1N1	7006	122
LBN	MERS	1	0	RUS	SARS	1	0
LBR	EBOLA	10678	4810	RUS	H1N1	25339	604
LCA	H1N1	55	1	RWA	H1N1	482	0
LCA	ZIKA	50	0	SAU	H1N1	14500	128
LKA	H1N1	642	48	SAU	MERS	1195	510
LSO	H1N1	65	0	SDN	H1N1	145	5
LTU	H1N1	68	23	SEN	H1N1	325	0
LUX	H1N1	333	3	SGP	SARS	238	33
LVA	H1N1	1253	34	SGP	H1N1	1217	21
MAR	H1N1	2890	64	SLB	H1N1	4	1
MDA	H1N1	2524	46	SLV	H1N1	834	33
MDG	H1N1	877	3	SLV	ZIKA	51	0
MDV	H1N1	35	1	SLE	EBOLA	14124	3956
MEX	H1N1	70715	1316	STP	H1N1	66	2
MEX	ZIKA	11805	0	SVK	H1N1	955	56
MKD	H1N1	2600	26	SUR	H1N1	110	2
MLI	H1N1	29	0	SUR	ZIKA	724	4
MLT	H1N1	718	5	SVN	H1N1	990	19
MNE	H1N1	119	7	SWE	SARS	5	0
MNG	SARS	9	0	SWE	H1N1	10985	29
MNG	H1N1	1259	30	SWZ	H1N1	5	0
MOZ	H1N1	57	2	SYC	H1N1	33	0
MRT	H1N1	15	0	TCD	H1N1	1	0
MUS	H1N1	69	8	THA	SARS	9	2
MYS	SARS	5	2	THA	H1N1	31902	249
MYS	H1N1	12210	92	THA	MERS	1	0
MYS	MERS	1	1	TJK	H1N1	16	0
NAM	H1N1	75	1	TON	H1N1	20	1
NER	H1N1	49	0	TUN	H1N1	1200	24
NGA	H1N1	11	2	TUN	MERS	3	1
NIC	H1N1	2172	11	TUR	H1N1	12316	656
NLD	H1N1	1473	62	TUR	MERS	1	1
NLD	MERS	2	0	TUV	H1N1	23	0
NOR	H1N1	12654	29	TWN	SARS	346	37
NPL	H1N1	172	3	TWN	H1N1	5474	48
NZL	SARS	1	0	TZA	H1N1	770	1
NZL	H1N1	3199	50	UGA	H1N1	263	0
PAK	H1N1	253	25	UKR	H1N1	494	213
PAN	H1N1	813	12	URY	H1N1	550	33
PAN	ZIKA	1253	0	USA	SARS	27	0
PER	H1N1	9165	223	USA	H1N1	113690	3433
PER	ZIKA	1530	0	USA	MERS	2	0
PHL	SARS	14	2	USA	EBOLA	4	1
PHL	H1N1	5212	32	USA	ZIKA	227	0
PHL	MERS	3	0	VEN	H1N1	2187	135
PLW	H1N1	47	0	VNM	SARS	63	5
PNG	H1N1	12	0	VNM	H1N1	11186	58
POL	H1N1	2024	181	VUT	H1N1	3	0
PRI	ZIKA	40562	5	WSM	H1N1	138	2
PRT	H1N1	166922	122	YEM	H1N1	5038	31
PRY	H1N1	855	54	YEM	MERS	1	1
PRY	ZIKA	20	0	ZAF	SARS	1	1
QAT	H1N1	550	10	ZAF	H1N1	12640	93
QAT	MERS	13	5	ZMB	H1N1	726	0
ROU	SARS	1	0	ZWE	H1N1	1318	0

Note: The table shows countries and events included in our sample—observations with data on income inequality—for which at least one case of infection has been reported.