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Will Covid-19 affect inequality? Evidence from past pandemics[1]

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This paper provides evidence on the impact of major epidemics from the past two decades on income distribution. Our results justify the concern that the current 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 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.

1 The views expressed in this paper are those of the authors and do not necessarily represent those of the IMF or its member countries.

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I. Introduction

Deaths from the Covid-19 pandemic have already exceeded 200,000 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. In the United States, for instance, evidence from a large-scale survey of households suggests that 20 million jobs were lost by early April, far more than were lost over the entire Great Recession of 2008-09 (Coibion, Gorodnichenko and Weber 2020). While the global job loss is more difficult to gauge, the decline in working hours thus far, which is easier to track in real-time, is already equivalent to a decline in 195 million full-time jobs (ILO 2020).

While most, if not all, economic classes are adversely affected by the pandemic in one way or another, it is possible that people in low-income deciles and low-skilled workers may end up being disproportionately hurt. Indeed, there is already anecdotal evidence of the substantial effects of the pandemic on these groups, raising concerns that it will end up raising inequality in many countries. There are direct and fairly immediate effects from low-income groups being more prone to the disease; as one example, 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. Recent analysis from the Kansas City Fed suggests that workers with non-college education have taken the largest hit in the first wave of job losses due to Covid-19 in the United States.[1]

In addition, there are indirect and longer-lasting effects from possible job loss and other shocks to income and diminished employment prospects. The ILO estimates that 1.25 billion workers, representing nearly 40 per cent of the global workforce, are employed in sectors that face high risk of worker displacement. These sectors also have a high proportion of workers in informal employment, with limited access to health services and social protection (ILO 2020). Despite attempts by governments to limit the damage, such workers run a high risk of facing challenges in regaining their livelihoods even after economies start to recover. In many countries, low-income

[1] https://www.kansascityfed.org/en/publications/research/eb/articles/2020/women-take-bigger-hit-job-losses-covid19

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households can also suffer an impact on non-labor income due to decline in remittances as the pandemic affects the livelihoods of migrants. The World Bank estimates that global remittance flows, which fell 5% during the 2009 financial crisis, will fall 20% this year, which would mark the sharpest decline since 1980.

To shed light on such potential impacts of Covid-19, this paper provides evidence on the impact of pandemics and major epidemics[2] from the past two decades on income inequality, income shares of the top and bottom deciles, and the 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 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 deciles of income, and lowered the employment-to-population ratio for those with basic education compared to those with higher education.

This paper relates to two main strands of literature. The first is the literature on the economic effects of pandemics (for recent contributions, see Atkeson 2020; Barro et al. 2020; Eichenbaum et al. 2020; Jorda et al. 2020; Ma et al. 2020). This literature provides evidence of large and persistent effect on economic activity. In particular, Ma et al. (2020) examined the same set of episodes considered in our paper and found that real GDP is 2.6% lower on average across 210 countries in the year the outbreak is officially declared and remains 3% below pre-shock level five years later. The second strand of the literature is on the role of crises and recessions in exacerbating inequality by depressing employment for those most vulnerable, such as less skilled and youth (see de Haan and Sturm 2017 and references therein).

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.

[2] For convenience, we refer to all these events as pandemics.

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II. Data and Econometric Method

Income distribution

Our data on various measures of distribution come from three sources. Table A1 in the Appendix provides summary statistics on the variables used in the analysis.

▪ Gini coefficients are from the Standardized World Income Inequality Database (SWIID), which combines information from the United Nations World Income Database (UNWIDER) and the Luxembourg Income Study (LIS). SWIID provides comparable estimates of market income inequality for 175 countries from 1961 to the present.[3]

▪ 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.[4]

▪ 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.[5]

Pandemic events

Following Ma et al. 2020, we focus on five major events: SARS in 2003; H1N1 in 2009; MERS in 2012; Ebola in 2014; and Zika in 2016. The list of countries in our sample that are affected by each event is given in Table A2 in the Appendix. Among the five events, the most

[3] See Solt (2009) for details on the construction of this data set.

[4] See https://datacatalog.worldbank.org/dataset/world-development-indicators for details.

[5] See https://ilostat.ilo.org/resources/methods/description-employment-by-education/ for details.

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widespread one is H1N1 (Swine Flu Influenza). We construct a dummy variable, the pandemic event, which takes the value 1 when WHO declares a pandemic for the country and 0 otherwise.

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:

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

where $y_{i,t}$ is the log of our distribution variables (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 the pandemic dummy. In the baseline, we do not control for other factors affecting inequality as the date of occurrence of the pandemic event is likely to be exogenous and uncorrelated to these factors and the error term in equation (1).

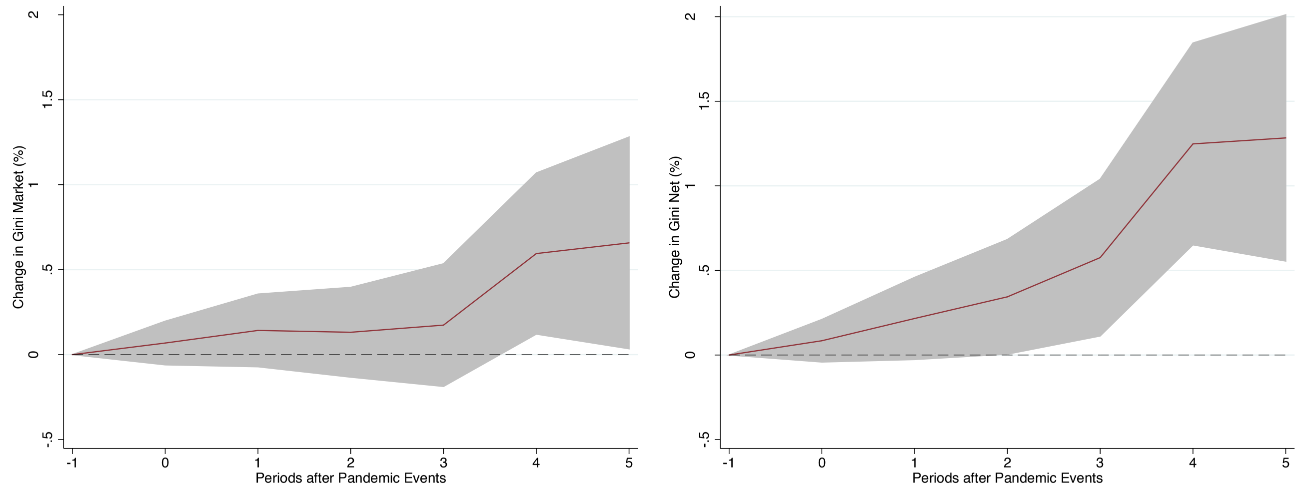
Equation (1) is estimated for an unbalanced panel of 175 countries over the period 1961-2017, for each horizon (year) *k*=0,..,5. Impulse response functions are computed using the estimated coefficients β^k, and the confidence bands associated with the estimated impulse-response functions are obtained 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 1 shows the estimated dynamic response of Ginis to a pandemic event over the five-year period following the event, together with the 90 percent confidence interval around the point estimate. Table 1 reports the associated regressions.

Figure 1. Impact of pandemics on market Gini and net Gini coefficients (%)



Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1961-2017. 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 $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the log of the 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. See Table A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

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Table 1. Impact of pandemics on market Gini and net Gini coefficients

Panel A: Market Gini

	k=0	k=1	k=2	k=3	k=4	k=5
$D_{i,t}$	0.0683	0.142	0.132	0.174	0.595**	0.658*
	(0.0781)	(0.130)	(0.161)	(0.219)	(0.288)	(0.379)
$D_{i,t-1}$	0.0545	0.118	0.157	0.383	0.473	0.869*
	(0.0563)	(0.0889)	(0.151)	(0.245)	(0.341)	(0.474)
$D_{i,t-2}$	0.0699	0.106	0.218	0.300	0.671*	0.831
	(0.0685)	(0.137)	(0.218)	(0.305)	(0.399)	(0.532)
$\Delta y_{i,t-1}$	0.550***	0.966***	1.287***	1.456***	1.592***	1.745***
	(0.0457)	(0.0908)	(0.114)	(0.147)	(0.174)	(0.178)
$\Delta y_{i,t-2}$	0.102***	0.162***	0.156*	0.194*	0.218	0.186
	(0.0275)	(0.0612)	(0.0845)	(0.104)	(0.135)	(0.149)
Observations	4,771	4,596	4,421	4,247	4,075	3,906
R^2	0.563	0.576	0.567	0.556	0.559	0.567

Panel B: Net Gini

	k=0	k=1	k=2	k=3	k=4	k=5
$D_{i,t}$	0.0844	0.216	0.344*	0.576**	1.248***	1.283***
	(0.0764)	(0.148)	(0.206)	(0.282)	(0.363)	(0.443)
$D_{i,t-1}$	0.104*	0.303**	0.524**	1.096***	1.186***	1.677***
	(0.0614)	(0.123)	(0.207)	(0.320)	(0.392)	(0.574)
$D_{i,t-2}$	0.145	0.303*	0.659**	0.760**	1.047**	1.125*
	(0.0926)	(0.180)	(0.284)	(0.362)	(0.522)	(0.668)
$\Delta y_{i,t-1}$	0.590***	1.005***	1.336***	1.480***	1.588***	1.689***
	(0.0428)	(0.0896)	(0.121)	(0.168)	(0.192)	(0.216)
$\Delta y_{i,t-2}$	0.0520**	0.0723	-0.00246	-0.0222	-0.0444	-0.0924
	(0.0249)	(0.0586)	(0.0859)	(0.123)	(0.151)	(0.174)
Observations	4,771	4,596	4,421	4,247	4,075	3,906
R^2	0.534	0.521	0.498	0.476	0.473	0.477

Note: Estimates are obtained using a sample of 175 countries over the period 1961-2017, and 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 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. See Table A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.
*** p<0.01, ** p<0.05, * p<0.1. Country and time fixed effects included but not reported.

Pandemics lead to a persistent increase in inequality, with the impact being stronger in the case of the net Gini. Five years after the pandemic, both the market and net Gini are above the pre-shock trends by about 0.75% and 1.25%, respectively. Given that the Ginis are very slow-moving variables, these are quantitatively important effects, particularly since the Gini coefficient changes slowly over time—the effect corresponds to approximately ½ standard deviation of the average change of the Gini in the sample.

The fact that the impact on the net Gini is larger than that on the market Gini is somewhat surprising and suggests that policies undertaken to address previous pandemics may actually have been regressive, especially in the medium term, though further analysis would be needed to confirm such a conclusion.

We have carried out several robustness checks of these findings. Here, we report the main three. First, we used as an alternative regression strategy the autoregressive distributed lag model (ADL), as in Romer and Romer (2010) and Furceri et al. (2019). The results in Figure 2 for the net Gini are very similar to those obtained in the baseline using the local projection method.

The second robustness check is to include several control variables in the regression—such as proxies for the level of economic development, demographics, and measures of trade and financial globalization. The results are reported in Figure 3 and are very similar to, and not statistically different from, the baseline.

Finally, since the episodes we considered have occurred in the post 2000 period, we replicated the analysis for this restricted sample. The results presented in Figure 4 are fairly similar to that for the full sample period, except that there is some attenuation in the impact.

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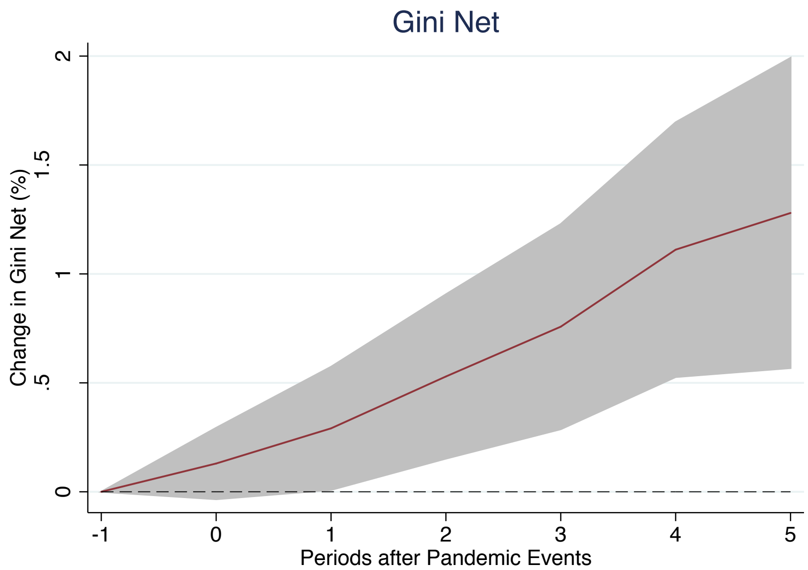
Figure 2. Impact of pandemics on net Gini coefficients (%)—ADL



Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1961-2017. 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 $\Delta y_{i,t} = \alpha_i + \gamma_t + \beta_k(l)D_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ is the log of 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 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

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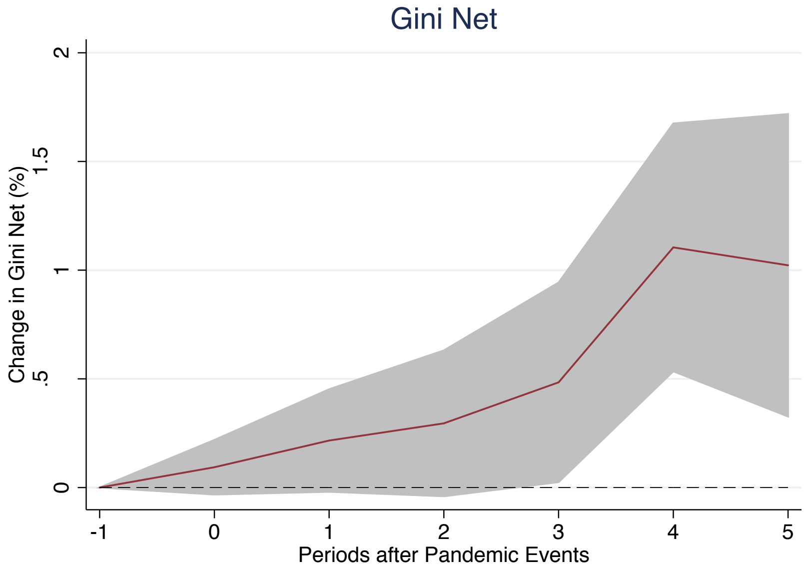
Figure 3. Impact of pandemics on net Gini coefficients (%)—Additional controls



Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1961-2017. 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 $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the log of the 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, 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 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

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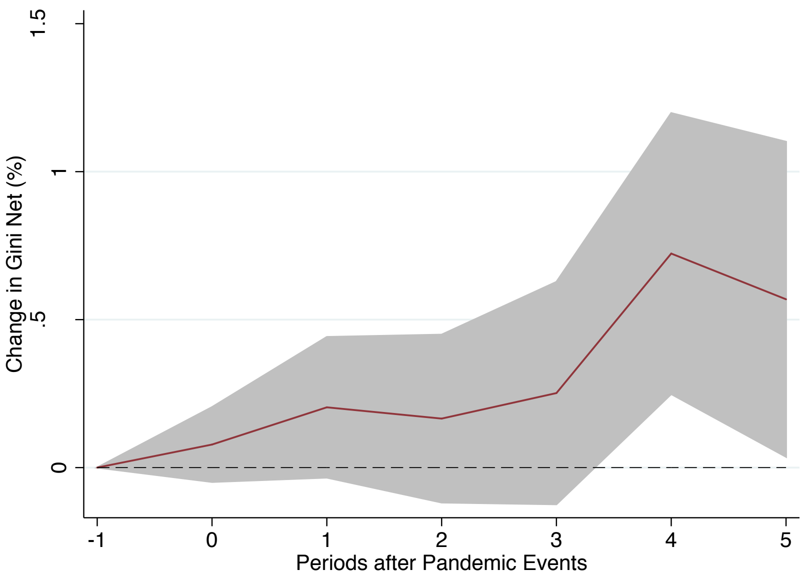
Figure 4. Impact of pandemics on net Gini coefficients (%)—Restricted sample (2000-17)



Notes: Impulse response functions are estimated using a sample of 175 countries over the period 2001-2017. 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 $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ is the log of the 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. See Table A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

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Heterogeneity across episodes depend on the economic impact of pandemics

As shown by Ma et al. (2020), the impact of pandemic events on economic activity is likely to vary both across episodes and countries. To examine how this heterogeneity in the economic effects affects the distributional consequences of pandemics, we estimated the following equation:

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

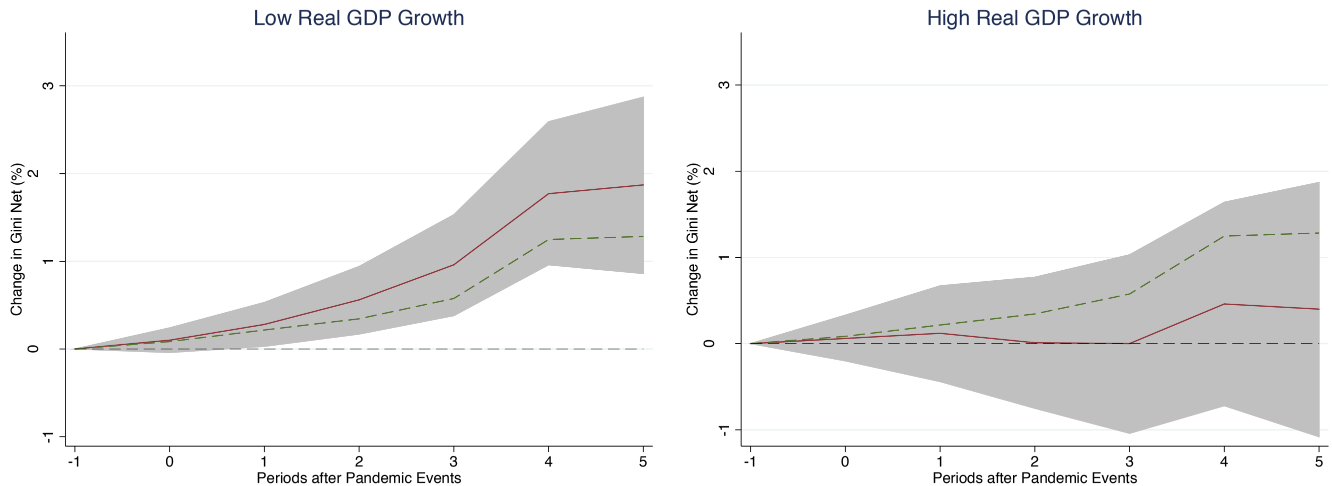
$$\text{with } F(z_{it}) = \frac{exp^{-\gamma z_{it}}}{(exp^{-\gamma z_{it}})}, \quad \gamma = 3.5 \tag{2}$$

where z is an indicator of the state of the economy normalized to have zero mean and a unit variance. The indicator of the state of the economy considered in the analysis is GDP growth. The weights assigned to each regime vary between 0 and 1 according to the weighting function $F(.)$, so that $F(z_{it})$ can be interpreted as the probability of being in a given state of the economy. The coefficients β_L^k and β_H^k capture the distributional impact of a pandemic event at each horizon k in cases of pandemics associated with extreme recessions ($F(z_{it}) \approx 1$ when z goes to minus infinity) and booms ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively.[6] We choose $\gamma = 3.5$, following Tenreyro and Thwaites (2016).

The results in Figure 5 show that the distributional effect of pandemic events varies with their impact on economic activity. In particular, for episodes associated with significant economic contractions, the effect is statistically significant and larger than the average effect (the medium-term effect on Gini increases from 1.25 to about 2 percent), while it is not statistically significantly different from zero for episodes associated with high growth.

[6] $F(z_{it})$=0.5 is the cutoff between weak and strong economic activity.

Figure 5. Impact of pandemics on net Gini coefficients (%)—The role of economic conditions associated with pandemic events



Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1961-2017. 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. The dotted green line denotes the average (unconditional) effect reported in Figure 1. The redlines denote the estimates for pandemic events associated with very low and high growth. Estimates based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + F(z_{it})[\beta_L^k D_{i,t} + \theta_L^k X_{i,t}] + (1 - F(z_{it}))[\beta_H^k D_{i,t} + \theta_H^k X_{i,t}] + \varepsilon_{i,t+k}$. $y_{i,t}$ is the log of 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 state of the economy. The coefficients β_L^k and β_H^k capture the distributional impact of a pandemic event at each horizon k in cases of pandemics associated with extreme recessions ($F(z_{it}) \approx 1$ when z goes to minus infinity) and booms ($1 - F(z_{it}) \approx 1$ when z goes to plus infinity), respectively. See Table A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level

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Impact on other indicators of distribution

To shed some light on the channels through which pandemics affect inequality, we explored the impact of pandemic events on income shares and employment outcomes for various educational groups. Due to data limitations, these results are for a much smaller set of countries than those for the Gini results.

The results for the impact of pandemics on the shares of income by decile are shown in Figure 6. It is evident that the impact is to raise the shares of the upper-income deciles and reduce those of the lower-income deciles. The impacts are quantitatively significant. For instance, in our sample, 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 only 6 percent; five years after the pandemic, this share falls further to 5.5 percent.

Figure 7 shows the vastly disparate impact that pandemics have on the employment of people with different levels of educational attainment. Those with advanced or intermediate 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.

IV. Conclusion

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

This 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 policies aimed at protecting the most vulnerable, the pandemic could end up exerting a significant adverse 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 education. In addition, the result that the inequality effect increases with the negative effect of pandemic events on economic activity suggests that the distributional consequences of Covid-19 may be larger than those in previous pandemic episodes, all else equal.

Our results leave several questions open 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 conditions as well as the stringency of containment measures. Second, there is growing evidence that the economic effects of Covid-19 may also vary between different segments of the population in terms of 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.

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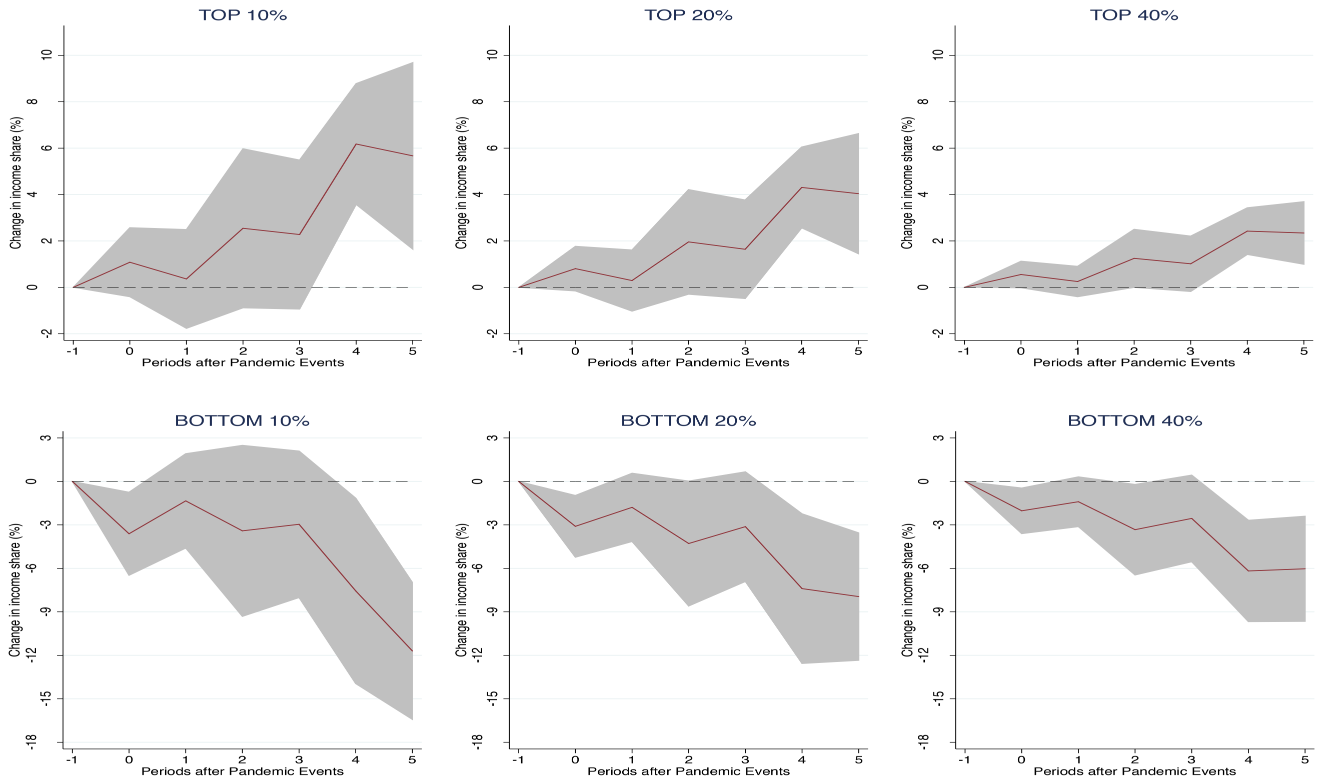
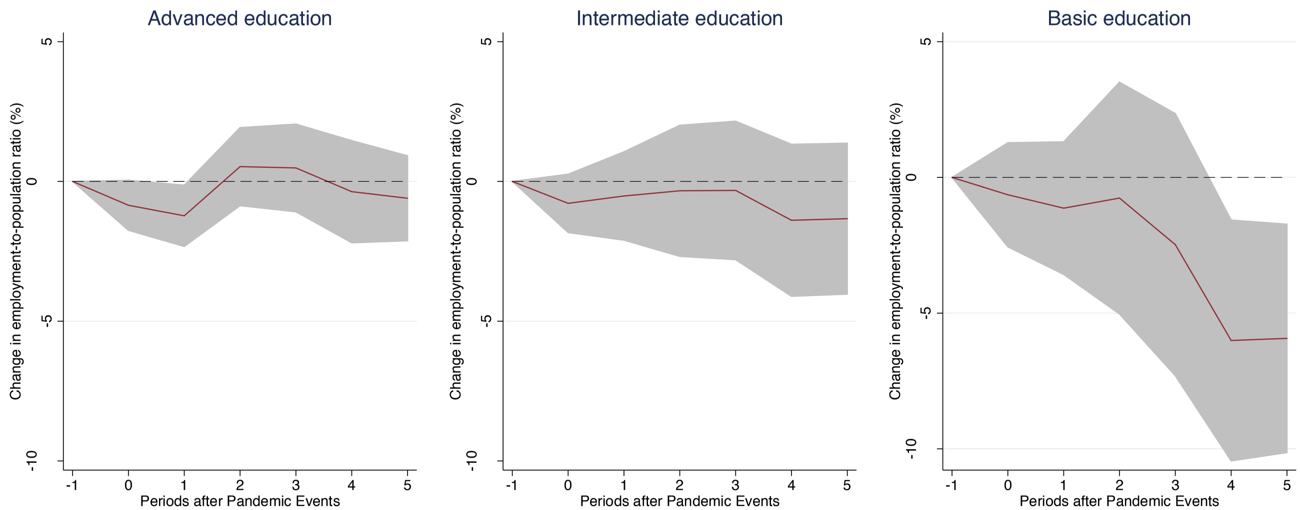
Figure 6. Impact of pandemics on shares of income, by deciles



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; 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) 20% (10%) 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 A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

Figure 7. 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 A2 for the full list of pandemic events. Standard errors in parentheses are clustered at the country level.

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References

Atkeson, A. (2020): "What Will Be the Economic Impact of COVID-19 in the US? Rough Estimates of Disease Scenarios," NBER Working Paper No. 26867.

Barro, R. J., J. F. Ursua, and J. Weng (2020). "The Coronavirus and the Great Influenza Pandemic: Lessons from the "Spanish Flu" for the Coronavirus's Potential Effects on Mortality and Economic Activity," NBER Working Paper No. 26866.

Coibion, O. Y. Gorodnichenko and M. Weber (2020). "Labour markets during the Covid-19 crisis: A preliminary view. NBER Working Paper No. 27017

De Haan, Jackob, and Jan-Egert Sturm (2017). "Finance and Income Inequality: A Review and New Evidence." *European Journal of Political Economy,* 50, 171-195.

Eichenbaum, M. S., S. Rebelo, and M. Trabandt (2020): "The Macroeconomics of Epidemics," NBER Working Paper No. 26882.

Furceri, D., P. Loungani and J.O. Ostry, 2019. The Aggregate and Distributional Effects of Financial Globalization: Evidence from Macro and Sectoral Data, *Journal of Money, Credit and Banking*, 51, 163-198.

ILO (2020). ILO Monitor 2nd edition: COVID-19 and the world of work.

Jordà, O. (2005): "Estimation and inference of impulse responses by local projections," ` American Economic Review, 95, 161–182.

Jordà, O. S.R. Singh and A.M. Taylor (2020). "Pandemics: Long-Run Effects",Covid Economics, 1, 1-15.

Ma, C., J. Rogers and S. Zhou (2020) "Global Financial Effects". Covid Economics, 5, 56-78.
Schmitt-Grohé, S. K. Teoh and M. Uribe (2020). "COVID-19: Testing Inequality in New York City", Covid Economics, 8, 27-43.

Romer, C. D. and D.H. Romer (2010). "The Macroeconomic Effects of Tax Changes: Estimates Based on a New Measure of Fiscal Shocks." American Economic Review, 100(3), 763-801.

Tenreyro, S. and G. Thwaites (2016). "Pushing on a String: US Monetary Policy Is Less Powerful in Recessions." *American Economic Journal: Macroeconomics,* 8 (4): 43-74.

World Bank (2020). Poverty and Distributional Impacts of COVID-19: Potential Channels of Impact and Mitigating Policies BRIEF APRIL 16, 2020, World Bank.

APPENDIX

Table A1. Data Sources and Descriptive Statistics

Variable	Source	Obs	Mean	Std. Dev.	No. of Countries
Gini Market	SWIID 8.2	5,305	45.28	6.59	175
Gini Net	SWIID 8.2	5,305	38.33	8.76	175
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 – Intermediate Education	ILO	1,333	61.03	9.23	76
E/P ratio – Advanced Education	ILO	1,338	75.14	7.60	76

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Table A2. List of Pandemic and Epidemic Episodes

Starting year	Event Name	Affected Countries	Number of countries
2003	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
2009	N1H1	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, 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	148
2012	MERS	AUT, CHN, DEU, EGY, FRA, GBR, GRC, IRN, ITA, JOR, KOR, LBN, MYS, NLD, PHL, QAT, SAU, THA, TUN, TUR, USA, YEM	22
2014	Ebola	ESP, GBR, ITA, LBR, USA	5
2016	Zika	ARG, BOL, BRA, CAN, CHL, COL, CRI, DOM, ECU, HND, LCA, PAN, PER, PRI, PRY, SLV, URY, USA	18
		Total Pandemic and Epidemic Events	**220**

Source: Based on Ma and others (2020).

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