COVID-19 in Developing Economies

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13 Pandemics and inequality: Assessing the impact of COVID-19[1]

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This chapter provides evidence on the impact of major epidemics from the past two decades on inequality and job prospects. Our results justify the concern that the COVID-19 pandemic could significantly raise inequality; past events of this kind, even though much smaller in scale, have led to increases in the Gini coefficient, lowered the employment-to-population ratio for those with basic education compared to those with higher education, and pushed people into precarious work in the form of self-employment or in the informal sector.

The COVID-19 pandemic has claimed 350,000 lives according to official statistics as of end-May 2020 and upended the livelihoods of millions. While most, if not all, economic classes are adversely affected by the pandemic, anecdotal evidence suggests that the poor are being disproportionately hurt for a number of reasons. First, they are more prone to getting infected. In New York City, for instance, poor people were found to be less likely to test negative for COVID-19 – in the richest zip code in the city, 65% of people tested negative, while in the poorest zip code fewer than 40% tested negative (Schmitt-Grohe et al. 2020). Second, the poor are more likely to die if they get infected. In the US, mortality rates are higher among low-income people and among minorities, which unfortunately are two groups with quite a bit of overlap. African Americans made up 25% of deaths from COVID-19 in the US though they make up a little under 13% of the US population.[2]

1 The views expressed in this chapter are those of the authors and do not necessarily represent those of the IMF or its member countries. We are grateful to Ayhan Kose for providing some of the data used in this chapter and Daniel Ostry for helpful comments on a previous draft.

2 Source: https://covidtracking.com/race

The poor are also more likely to suffer job loss or have to go in to work rather than being able to work from home – this in turn makes them more prone to getting infected. Poorer people are in jobs where working from home is less likely to be an option; by some estimates, the poorest 20% of the population are in jobs that can be done from home in less than 20% of cases (Avdiu and Nair 2020). Survey data from Japan on COVID-19's effects finds that low-skilled and contingent workers suffered more than highly skilled and regular workers (Kikuchi et al. 2020). Likewise, a study for the UK found that those who could work from home earned on average almost twice as much as those in sectors that had been shut down. This was linked to educational background, as almost half of those with degrees are able to work from home, while just 6% of those in work with no qualifications are able to do so.

In addition to these immediate effects, there are indirect and longer-lasting effects from job loss and other shocks to income. The ILO estimates that 1.25 billion workers, representing nearly 40% 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 households can also suffer an impact on non-labour 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 chapter provides evidence on the impact of pandemics and major epidemics[3] from the past two decades on income inequality, on the employment prospects of people with low education levels (using educational attainment as a proxy for skills) and on informality. 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, lowered the employment-to-population ratio for those with basic education compared to those with higher education, and pushed workers into the informal sector.

This chapter 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 effects on economic activity. In particular, Ma

3 For convenience, we refer to all these events as pandemics.

et al. (2020) examined the same set of episodes considered in our chapter 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 chapter is structured as follows. Section II describes our data and econometric method and presents our results. The last section concludes and outlines avenues for future work on this topic.

The distributional effects of pandemics

We use 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.[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 labour force skill levels". Hence, we use ILO data on employment-to-population ratios for different education levels: advanced, tertiary and basic.[5] Data on self-employment are from the World Bank's World Development Indicators and data on the size of the informal sector are from Elgin et al (2019).

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 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.

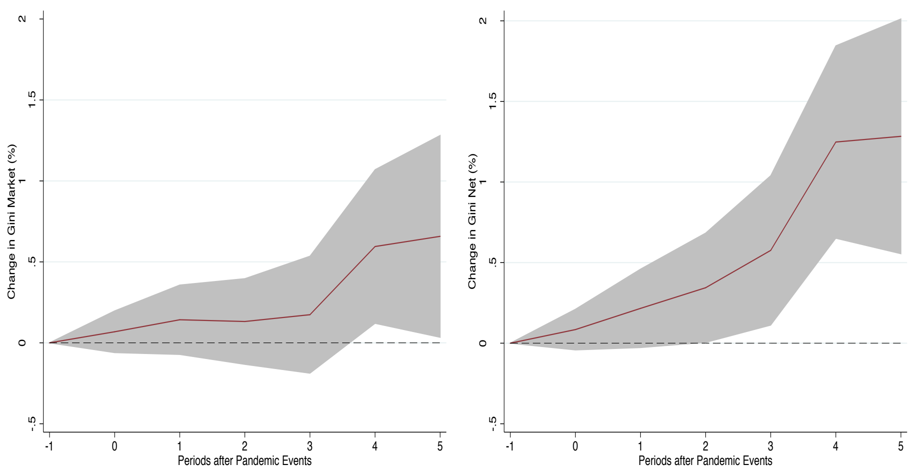
4 See Solt (2009) for details on the construction of this data set.
5 See https://ilostat.ilo.org/resources/methods/description-employment-by-education/ for details.

To estimate the distributional impact of pandemics, we follow the method proposed by Jordà (2005). This approach allows us to trace out the dynamic effects of pandemics on several measures of income distribution.[6]

Impacts on Gini coefficients

Figure 1 shows the estimated dynamic response of the Gini coefficient to a pandemic event over the five-year period following the event, together with the 90% confidence interval around the point estimate.

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.

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 Gini coefficient is a very slow-moving variable, these are quantitatively important effects – the effect corresponds to approximately 0.5 standard deviation of the average change of the Gini in the sample.

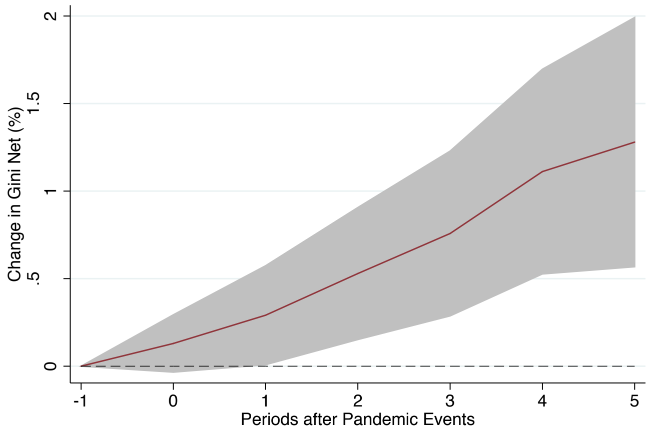
The fact that the impact on the net Gini is larger than that on the market Gini is somewhat surprising and suggests that policies undertaken to address previous pandemics may actually have been regressive, especially in the medium term, though further analysis would be needed to confirm such a conclusion. There is already some evidence from the current experience that suggests that some government programmes set up to target those who need help the most are nevertheless set up in ways that the rich can find a way to benefit from them. For instance, some provisions of the CARES programme in the US have been assessed by the bipartisan Joint Committee on Taxation to be likely to largely benefit the rich (JCT 2020).[7]

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 (ADL) model, 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 globalisation. The results are reported in Figure 3 and are very similar to, and not statistically different from, the baseline.

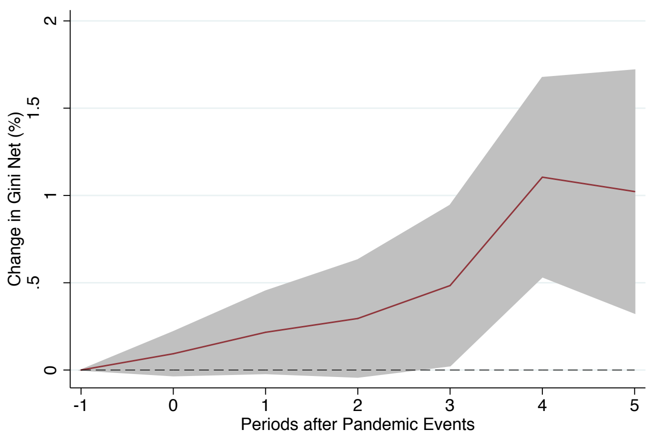
Finally, since the episodes we considered have occurred in the post 2000 period, we replicated the analysis for this restricted sample. The results presented in Figure 4 are fairly similar to that for the full sample period, except that there is some attenuation in the impact.

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



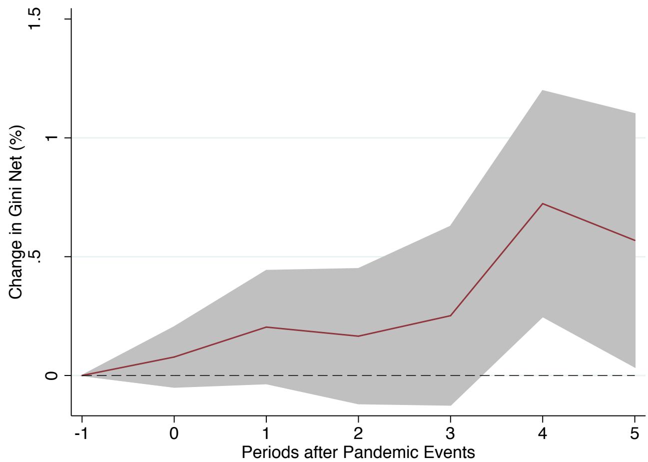
Notes: Impulse response functions are estimated using a sample of 175 countries over the period 1961-2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; t = 0 is the year of the pandemic event. Estimates based on $\Delta y_{i,t} = \alpha_i + \gamma_t + \beta_k(l)D_{i,t} + \varepsilon_{i,t}$. $y_{i,t}$ 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.

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 (log) level of GDP per capita, the (log) level of GDP per capita squared, 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.

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



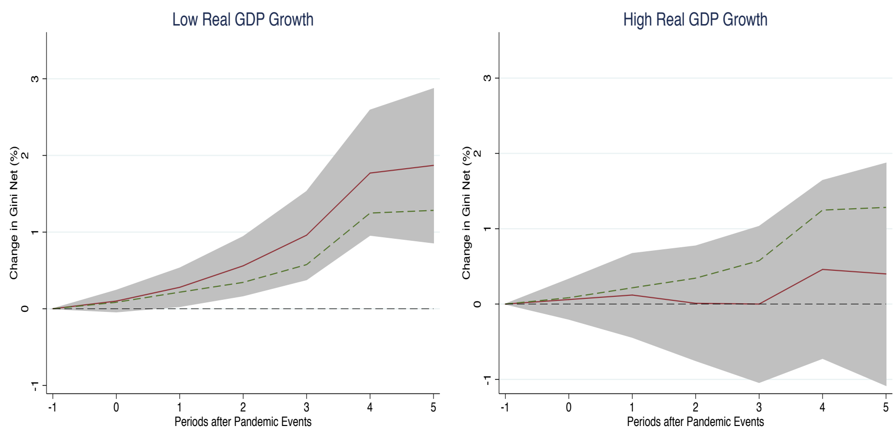
Notes: Impulse response functions are estimated using a sample of 175 countries over the period 2001-2017. The graph shows the response and 90 percent confidence bands. The x-axis shows years (k) after pandemic events; $t = 0$ is the year of the pandemic event. Estimates based on $y_{i,t+k} - y_{i,t-1} = \alpha_i^k + \gamma_t^k + \beta^k D_{i,t} + \theta^k X_{i,t} + \varepsilon_{i,t+k}$. $y_{i,t}$ 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.

Channels of transmission

As shown by Ma et al. (2020), the impact of the five pandemic events on aggregate economic activity varies across episodes and countries. Since changes in economic activity are an important driver of changes in inequality, we examine whether the distributional effect of pandemic events to vary with their impact on economic activity. The results in Figure 5 suggest that this is the case. 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%), while it is not statistically significantly different from zero for episodes associated with high growth.

In addition to output loss, a related channel through which pandemics can affect inequality is adverse impacts on employment prospects. The tragic death toll of the current pandemic 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 US, for instance, more jobs were lost in a few months in 2020 than in entire Great Recession of 2008-09 (Coibion et al. 2020) and globally the decline in working hours is estimated to be equivalent to a decline of 200 million full-time jobs (ILO 2020). 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 US.[8]

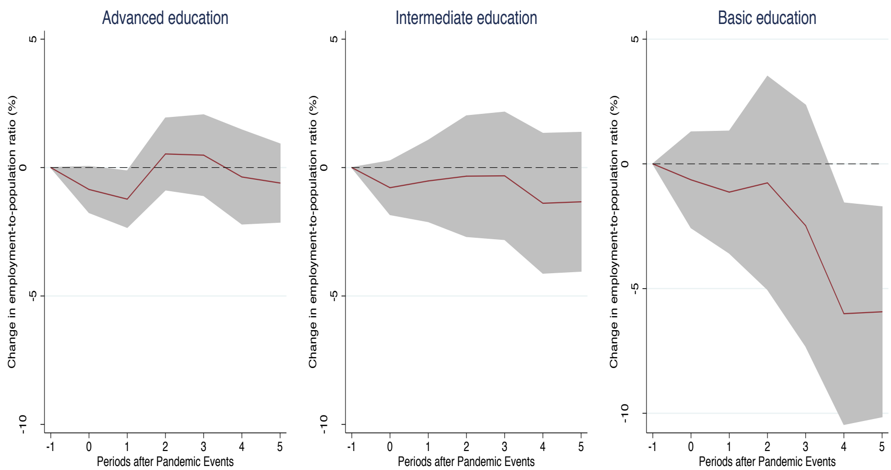
Figure 5 Impact of pandemics on net Gini coefficients: The role of economic conditions associated with pandemic events (%)



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. $F(Z_{i,t})$ 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 ($F(Z_{i,t})$ $\approx$ 1) when z goes to minus infinity) and booms (1 – ($F(Z_{i,t})$ $\approx$ 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.

We investigate whether past pandemics have been followed by job loss and whether the extent of diminished job prospects are higher for some groups of workers, particularly low-skilled workers. Since data on employment by skill levels are difficult to obtain for a large group of countries, we use data on employment-to-population ratios for different education levels; ILO (2020) notes that "statistics on levels of educational attainment remain the best available indicators of labour force skill levels." Figure 6 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% in the medium term.

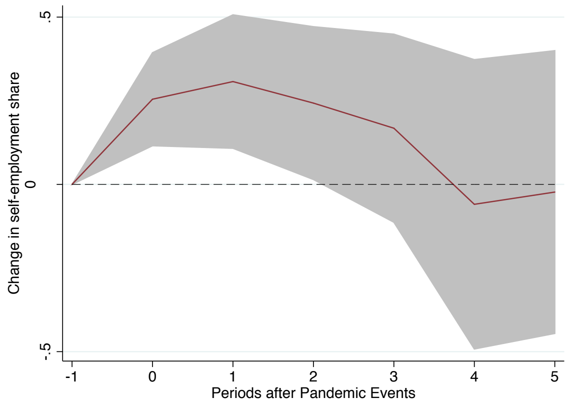
Figure 6 Impact of pandemics on employment-to-population ratio, by education level



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.

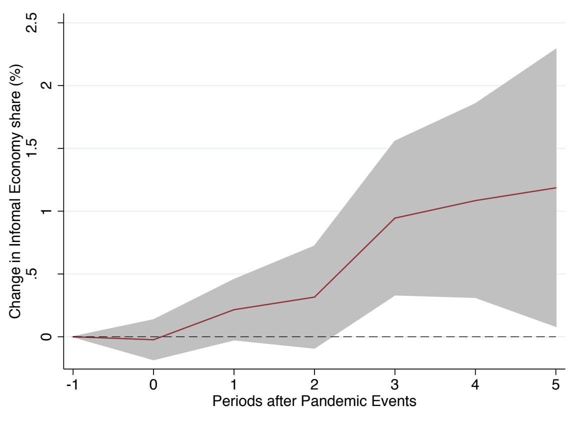
Our evidence thus far pertains largely to those in wage-paying jobs in the formal sector of the economy. However, various forms of self-employment and informality are pervasive in many developing economies. It is estimated that informal employment accounts for about 70% of employment and 35% of GDP in a typical developing economy, compared with about 15% of GDP in advanced economies (World Bank 2019). As Elgin et al (2019) note, "while offering the advantage of flexible employment under some circumstances", these more precarious forms on employment are "associated with a wide range of adverse economic outcomes" including low productivity and limited fiscal resources. It is likely that by adversely affecting the prospects for market work, pandemics drive more activity into precarious work. To test this conjecture, we use data on self-employment from the World Bank and on the size of the informal sector from Elgin et al. (2019) to see how these sectors change following a pandemic. As shown in Figure 7, there is a statistically significant increase in the share of self-employment for about three years following an epidemic. The increase in the size of the informal economy is even more longer-lasting and also statistically significant (Figure 8).

Figure 7 The effect of pandemics on self-employment



Note: Impulse response functions are estimated using a sample of 177 countries over the period 1991-2017. 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 share of self-employed to total employment 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 8 The effect of pandemics on informal economy



Note: Impulse response functions are estimated using a sample of 158 countries over the period 1950-2016. 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 size of the informal sector according to Elgin et al. (2019) 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.

Conclusions

A recent poll of top economists found that the vast majority felt the COVID-19 pandemic will worsen inequality, in part through its disproportionate impact on low-skilled workers (IGM 2020). Our evidence supports concerns about the adverse distributional impacts of pandemics. We find that major epidemics in this century have raised income inequality, hurt employment prospects of those with only a basic education while scarcely affecting employment of people with advanced degrees, and pushed people into precarious work.

While the pandemic is having an adverse effect on almost everyone in society, policies need to pay specific attention to preventing scarring effects on the livelihoods of the least advantaged in society. Absent strenuous and targeted attempts, we are again likely to see an increase in inequality, which was already "one of the most complex and vexing challenges in the global economy" (Georgieva 2020). In concrete terms, what can be done? Unemployment benefits and access to health benefits and sick leave are useful for all in dealing with the effects of the pandemic but particularly so for poorer segments of society who lack a stock of savings and are thus living hand-to-mouth. Where informality is pervasive, cash transfers may be the best response. Expanding social assistance systems, introducing new transfers, boosting public work programmes to offer job opportunities, giving financing opportunities to sustain employment – all are likely to be part of the policy mix to take the edge off the devastating distributional consequences from the pandemic.

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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
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
Size of the informal sector (DGE estimates on informal output in percent of official GDP)	Elgin et al. (2019)	8,021	34.84	14.40	158
Self-employed (% of total employment)	WDI	4,778	43.66	27.93	177

Source: Based on Ma and others (2020).

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	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, 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).