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The Impact of COVID-19 on Global Inequality and Poverty

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Abstract

The COVID-19 pandemic has had catastrophic economic and human consequences worldwide. This paper tries to quantify the consequences of the pandemic on global inequality and poverty in 2020. Since face-to-face household survey data collection largely came to a halt during the pandemic, a combination of data sources is used to estimate the impacts on poverty and inequality. This includes actual household survey data, where available, high-frequency phone surveys, and country-level estimates from the literature on the impact of the pandemic on poverty and inequality. The results suggest that the world in 2020 witnessed the largest increase to global inequality and poverty since at least 1990. This paper estimates that COVID-19 increased the global Gini index by 0.7 point and global extreme poverty (using a poverty line of $2.15 per day) by 90 million people compared to counterfactual without the pandemic. These findings are primarily driven by country-level shocks to average incomes and an increase in inequality between countries. Changes to inequality within countries were mixed and relatively modest.

Keywords: Poverty, inequality, COVID-19
JEL codes: D63, I32

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Introduction

Although the COVID-19 pandemic started as a health crisis, the economic shutdowns and downturns that it entailed have had catastrophic economic consequences. The shutdowns also implied a halt to much of the data collection done by national statistical offices, which has led to a lack of information on the magnitude of the economic consequences (United Nations and World Bank 2020). At the country level, it is unclear which parts of the distribution were most hurt by the pandemic. This lack of distributional evidence has made it difficult to understand whether broad-based growth policies should be preferred over policies prioritizing the worst off. At the global level, it is unclear where the economic consequences of the pandemic have been most severe, which matters for targeting of emergency funds across countries for international organizations, international NGOs, and development agencies.

In this paper, we triangulate various data sources available to get a global picture of the impact of the pandemic on inequality and poverty in 2020. We use welfare distributions for 2019 covering 168 countries comprising more than 97% of the world's population from the World Bank's Poverty and Inequality Platform (PIP) as our starting point. To obtain estimates for 2020 we use published traditional household surveys available for 20 countries and tabulated household income statistics available from national statistical offices for a further 8 countries. We complement them with a simulation exercise using High-Frequency Phone Surveys (HFPS) for 37 countries. The HFPSs were conducted in a large number of developing countries to provide a real-time picture on the pandemic. While these surveys do not contain information on households' level of income, they do include information on whether households gained or lost income. We use this information together with household characteristics and sectoral national account data to estimate the pandemic's distributional impact. For 26 countries that do not have any of the above three sources of data, we rely on estimates from simulations published in the literature or provided to us by World Bank teams. For the rest of the world, covering roughly 18% of the global population, we utilize growth in national accounts (disaggregated by economic sector where possible). We combine these various data sources to estimate the global income distribution in 2020.[1] To isolate the impact of the pandemic, we compare our actual 2020 distribution with a counterfactual 2020 distribution which assumes that countries in 2020 experienced no distributional change and the economic growth that was forecasted before the pandemic spread.

This paper provides the first estimates of the impact of the pandemic on global inequality and poverty that explicitly account for the distributional impact of the pandemic. Earlier work on global inequality (such as Deaton 2021) and global poverty (such as Lakner et al. 2022, Valensisi 2020, Sumner et al. 2020) did not account for within-country inequality or used general equilibrium models (Laborde et al. 2021). Several cross-country studies estimate the impact of the

[1] Our global distribution combines income and consumption data. For simplicity, we refer to it as the global income distribution throughout.

pandemic on poverty and inequality within countries (Clark et al. 2021, Lastunen et al. 2021, Lustig et al. 2021, Palomino et al. 2020).

We find that the world in 2020 witnessed the largest single-year increase in global inequality and poverty since 1990, when our study begins. When compared against a counterfactual without COVID-19, we find that the pandemic increased the global Gini index by 0.7 point and pushed an additional 90 million people into extreme poverty---measured as having a daily income or consumption less than $2.15 per capita. Put differently, we observe an increase between 2019 and 2020 by 0.5 Gini points and 71 million poor people. However, the pandemic also prevented a reduction in global inequality of about 0.2 Gini points and 19 million people from moving out of poverty. The net impact of the pandemic is the sum of the two effects. To put this in perspective, the only other marked increase in global inequality and poverty in the last three decades happened during the Asian financial crisis when the global Gini index increased cumulatively by 0.7 point between 1996 and 1999 and global extreme poverty increased by 0.2 percentage point or 37 million people. The pandemic-driven increase in global inequality and poverty reverse declines that have taken three years to accomplish. The uptick in global inequality is driven by increases in inequality between countries, reflecting that the shock to mean welfare was larger in poorer countries. Likewise, the uptick in extreme poverty was driven mostly by shocks to average incomes and not by changes to inequality within countries.

A secondary contribution is to provide annual estimates of global inequality from 1990 to today. Since not every country has a household survey in every year, we have to interpolate and extrapolate household surveys such that we cover all 218 countries in every year. This approach is similar to the methodology used for reporting global poverty by the World Bank (see Prydz et al. 2019 and Ferreira et al. 2016). Previous studies, such as Lakner and Milanovic (2016), Milanovic (2002, 2016, 2021) and Ravallion (2014), on the other hand, used the household surveys directly. As a result, these papers were able to provide estimates only for selected benchmark years (e.g. every 5 years). For instance, Milanovic (2021) has 131 countries in the global distribution benchmarked to 2013, which includes surveys conducted between 2011 and 2015. While our approach requires additional assumptions, it allows us to provide (i) global inequality measures that are consistent with the global poverty measures, and (ii) annual estimates of global inequality.

Our estimates of global inequality measure the inequality between all citizens of the world, following *Concept 3* inequality as defined by Milanovic (2005). In this concept of global inequality, individuals are ranked according to their personal income no matter the country they reside in.[2] Other authors have looked at the cross-country dispersion in GDP per capita – unweighted or weighted by population (*Concept 1* and *2*, respectively, in the Milanovic taxonomy). For example, Deaton (2021), using per capita GDP growth rates, finds that *concept 1* inequality decreased whereas *concept 2* inequality increased. The difference in his findings is due to accounting for population size in the latter concept. These studies do not account for the within-country inequality which is accounted for by our paper. Another difference is that we measure

[2] Anand and Segal (2008) review the evidence on global inequality and its measurement issues. In a recent paper, Kanbur et al. (2022) focus on the future direction of global inequality, in particular between-country differences.

welfare by the household income or expenditure recorded in surveys (similar to Milanovic's earlier work) and do not distribute total income from national accounts like others have done (for a discussion of one such method, see Piketty et al 2018). An advantage of our approach is that our inequality measures are consistent with the global poverty measures produced by the World Bank.

Due to the paucity of household survey data for 2020, despite our best efforts of using alternative data sources, the estimate of inequality and poverty in 2020 must be viewed with a higher level of uncertainty than usual. Even among the countries that conducted traditional household surveys, many were forced to modify the survey design, change the mode of the survey – from face-to-face interviews to phone interviews – or capture one-time transfer payments traditionally not accounted for in household surveys. Neither China nor India, which always play a large role in driving global results, have household survey data for 2020 available yet, further exacerbating uncertainty. The increases in both global inequality and extreme poverty are driven by India and the choice of methodology for data in India plays a large role in the variance of the estimate. Yet, it is important to underscore that the qualitative results are robust to all available data options for India.

The rest of the paper is organized as follows. Section 1 outlines some of the possible mechanisms that could influence the impact of COVID-19 on poverty and inequality. Section 2 explains the data sources we use. Section 3 details our methodology to recover distributions for 2020. Section 4 covers our main results. Section 5 contains some robustness checks. Section 6 concludes.

1. Potential mechanisms

The pandemic, its economic consequences, and the policy responses to these consequences have impacted inequality and poverty across and within countries in a variety of ways. Several channels work in opposite directions, and hence ex-ante the impact of the pandemic on country-level or global inequality and poverty is not clear.

Firstly, the virus itself may have impacted poverty. When household members got ill and in worst cases died because of contracting the virus, they were unable to generate an income, which may have pushed their household into poverty. Other family members may have stopped working to care for the ill, further exacerbating this effect. Across countries, this suggests that the greater the severity of the pandemic, all else equal, the greater the implications for poverty.

Secondly, most countries responded to the pandemic by shutting down parts of the economy. During these shutdowns, individuals of certain occupations were unable to work and earn an income. Some individuals' jobs may not have been directly affected, but with schools and daycares closed, they had to take care of children rather than working. All else equal, the longer and more severe these shutdowns were, the greater the impacts on poverty. Given that the occupations most affected by these shutdowns tend to be low-skilled urban households (Bundervoet et al. 2022), it is likely that this channel will have increased inequality in middle- and high-income countries where low-skilled urban households are among the lowest incomes. In low-income countries, the impact of the economic shutdowns is less clear since subsistence agricultural farmers rather than low-skilled urban workers tend to be in the bottom of the income distribution there.

Thirdly, in response to the economic shutdowns, countries around the world implemented emergency transfers and other mitigating economic mechanisms at a record speed (Gentilini 2020). To the extent that these transfers were targeted towards the poorest, they are likely to have reduced, mitigated, or reversed the impact of the pandemic on inequality and poverty. Given that wealthier countries often have more resources available for such transfers, it is likely that this effect has been greater for high-income countries.

Fourthly, the connectivity of the global economy means that the pandemic will have had consequences on poverty and inequality for a country even if it was not hit by the pandemic, did not shut down parts of its economy, and did not implement any emergency transfers. Countries might have seen a lower demand for goods they normally export, seen remittances go down, and experienced a sharp drop in tourism. All of this contributes to slowing down growth and hence increasing poverty.

Finally, it is important to note that our study ends in 2020. Beyond 2020, different factors have been at play, such as access to vaccines, the elimination of emergency social support, and inflation.

2. Data

Our starting point is the country-level distributions of welfare from the Poverty and Inequality Platform (PIP), which is the World Bank's database of country-level, regional, and global estimates of poverty and inequality.[3] PIP contains more than 2,000 surveys from 169 countries covering 97.7% of the world's population. The data available in PIP are standardized as far as possible but differences exist with regard to the method of data collection, and whether the welfare aggregate is based on income or consumption. PIP reports per capita household income or consumption reported in 2017 purchasing power parities. PIP directly uses survey micro data wherever available and supplements these with binned income data.[4]

[3] In 2022, PovcalNet was replaced by PIP. The data in PIP feeds into the United Nations' monitoring of the first target of the first Sustainable Development Goal, to end extreme poverty. Most of the data in PIP is based on the Global Monitoring Database, which is the World Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty. We use the September 2022 version of PIP.

[4] For 156 of the countries, housing 73% of the world's population, survey micro data are available. For an additional 8 economies (Australia; Canada; Germany; Israel; Japan; the Republic of Korea; Taiwan, China; and the United States), or 8% of the world's population, grouped income data of 400 bins are available. We treat these bins as microdata. Finally, for China, United Arab Emirates, Algeria, and Trinidad and Tobago, constituting about 17% of the world's population, only decile or ventile shares and the overall mean income or consumption is available. For these countries, PIP fits a General Quadratic Lorenz curve or a Beta Lorenz curve, chooses the one that gives the best fit, and uses it to recover a full distribution.

For 2020, the pandemic-induced shutdowns implied that traditional household surveys were largely absent and, where available, were switched to phone-based surveys.[5] At the same time, average growth in national accounts may be a poor proxy of growth in household income or consumption during 2020. For example, the wide-ranging public spending policies may not be fully reflected in the national accounts growth rates or the lockdowns had a very heterogeneous impact across sectors. Therefore, for 2020, we rely on the following sources of data, ranked by order of preference.

First, we use the household survey micro data when available in PIP, which applies to only 20 countries. Second, for 8 countries, we rely on tabulated income statistics that report average income for various quantiles of the income distribution available from national statistical offices (NSOs). Third, in 37 countries, we use the High-Frequency Phone Surveys (HFPSs) that the World Bank has collected in collaboration with NSOs.[6] These surveys are conducted over the phone and are hence less comprehensive than traditional household surveys. In many countries, phone surveys are some of the only national surveys available from 2020. Most of the phone surveys have been reweighted, to at least partially address problems of representativeness (Ambel et al. 2021; Brubaker et al. 2021).[7] Fourth, we use distributional changes available in the literature or made available to us by World Bank teams. Fifth, we use sectoral growth rates from national accounts to capture at least the limited heterogeneity across sectors.[8] Sixth, when none of the above sources are available, we use per capita GDP growth rates from national accounts

[5] Castaneda et al. (2022) discuss the available 2020 surveys and how COVID-19 led to changes in survey methodologies.

[6] At the time of writing, such surveys have been conducted in 85 countries across all developing regions. We only use a subset because some of the countries also conducted a traditional household survey (which we used instead) and because some of the phone surveys do not contain answers to the questions we need.

[7] The HFPSs are not nationally representative for a few reasons. First, households without a phone are outside the sampling frame. Second, among the households contacted, a non-negligible share declines to be interviewed. Third, there are many missing values in our key variable of interest, the share of households that have experienced income declines or increases. Fourth, in a few countries, the surveys did not cover the entire country. In the Democratic Republic of the Congo, most notably, the survey only covered Kinshasa, less than 20% of the whole population. It is important to note that reweighting cannot address these issues if the households captured are fundamentally different from households not captured, conditional on covariates. We could further post-stratify the weights based on the missing values of our variable of interest. However, we use these surveys only to get statistics for types of households (e.g. rural households that experienced an income loss with the head-of-household between 31 and 45 years of age, with any secondary schooling, and living in a family of between 2 and 4 people). Since we would have used the same variables to post-stratify and define types, the post-stratification would have only shifted the total weight from some types to others, without affecting the distribution of weights within types.

[8] We use sectoral growth rates data from the April 2022 vintage of the World Bank's Macro and Poverty Outlook (MPO).

thus holding within-country inequality fixed.[9] Seventh, for the 3% of the global population with no micro data in PIP, in line with what the World Bank does for global poverty calculation, we assign the average regional distributions.[10]

Given that one of our main purposes is to study how inequality within countries changed in 2020, we prefer methods that can speak to this over projections using per capita GDP growth rates for all households. For the purpose of studying how poverty changed in 2020, we also prefer methods that model distributional changes. Though projections using per capita growth rates may work well to predict poverty in normal times, there are strong reasons to believe that it is less appropriate in 2020. In many countries, the pandemic impacted households differentially based on their occupation, location, and age, and resulted in a large government response to the crisis (e.g. Bundervoet et al., 2022; Kugler et al., 2021). These events cast doubt on whether a GDP-based projection works well in 2020.

Table 1 reports the share of the population (panel a) and the number of countries (panel b) covered by each data source used in 2020. The data sources are ordered from the most preferred on the left column (survey data) to the least preferred on the right (regional average). We have either survey data or tabulated data for 28 countries (covering 42% of the world's population). Our preferred methods include the first four columns – household surveys, tabulations, phone surveys, and estimates from the literature. This includes 101 countries that cover 82% of the global population.

In addition to the observed 2020 distribution, we also construct a counterfactual 2020 distribution. The income and consumption distributions would have certainly changed in 2020 even in the absence of the COVID-19 pandemic. Hence, the change from 2019 to 2020 captures both the changes due to the pandemic and those changes that would have happened even without the pandemic. For instance, a number of countries in Sub-Saharan Africa were expected to have negative per capita GDP growth before the pandemic. Hence, not all negative income growth in 2020 can be attributed to the pandemic. To estimate the net impact of the pandemic, we construct a counterfactual distribution for 2020 using growth forecasts from before the pandemic.[11] This counterfactual distribution potentially captures all the anticipated changes before the pandemic but not including the pandemic. The difference between the observed 2020 distribution and the counterfactual distribution provides an estimate of the net impact of the pandemic. The counterfactual distribution is further discussed in Section 3.2.

[9] We use per capita GDP growth rates from the World Development Indicators (WDI).

[10] We construct our global data set with grouped data of 1,000 bins of national welfare for each country in 2019 derived using the microdata in PIP. This is then projected to 2020 using the growth rates available from various data sources described in this section.

[11] We use the forecasts that were published in January 2020 in the World Bank's Global Economic Prospects (GEP). It is important to note that the counterfactual projection is distribution neutral.

Table 1a: Population coverage by data source and region (%)

Region	Surveys	NSO	Phone surveys	Literature	Sectoral growth	Nationa l growth	Regional average
East Asia & Pacific	15	72	7	0	0	2	3
Europe & Central Asia	23	7	14	43	12	1	0
Latin America & Caribbean	78	0	5	0	4	7	6
Middle East & North Africa	0	0	4	18	51	15	12
North America	0	100	0	0	0	0	0
South Asia	0	0	0	74	24	0	2
Sub-Saharan Africa	0	0	59	21	18	1	0
World	14	28	13	27	13	2	3

Table 1b: Country coverage by data source and region (number of countries)

Region	Surveys	NSO	Phone survey s	Literature	Sectoral growth	Nationa l growth	Regional average
East Asia & Pacific	2	5	5	0	5	8	13
Europe & Central Asia	6	1	7	21	12	2	9
Latin America & Caribbean	12	0	3	0	5	4	18
Middle East & North Africa	0	0	2	1	7	5	6
North America	0	2	0	0	0	0	1
South Asia	0	0	0	1	6	0	1
Sub-Saharan Africa	0	0	20	3	21	2	2
World	20	8	37	26	56	21	50

Note: This table reports the share of regional population (panel a) and the number of countries (panel b) covered by the various data sources used to derive the 2020 welfare distribution. The sources are ordered with the most preferred on the left to the least preferred on the right.

3. Methodology

We estimate three types of welfare distributions for each country: (a) welfare distributions for 2019 and earlier, (b) a 2020 counterfactual welfare distribution (without the influence of the COVID-19 pandemic), and (c) a 2020 observed welfare distribution. In what follows, we outline the methods to estimate each distribution.

3.1 Estimating the welfare distribution for 2019 and before

Survey data are available for 60 countries (covering 59% of the global population) in 2019. For the rest of the countries that do not have survey data, PIP extrapolates the latest distribution to 2019 assuming all households grow with the real per capita growth rate of Household Final Consumption Expenditure or GDP (see Prydz et al. 2019 for details). This assumes that the only information relevant for projecting older surveys to 2019 is national accounts, and that inequality has not changed since the last survey. Mahler et al. (forthcoming) show that both of these assumptions are relatively accurate.[12]

This approach is possible for 168 countries with data available in PIP at some point in time.[13] For the countries that do not have any prior household surveys, we assume their 2019 distribution equals the 2019 distribution of the geographic region they belong to, using PIP's regional definition. For instance, the 2019 distribution we use for Afghanistan is the population-weighted distribution of the rest of the countries in South Asia. This method is applied to 3% of the world population in 2019.

The distributions for the period between 1990 and 2019 are obtained similarly. In addition, adjacent surveys are interpolated for intervening years that do not have a survey estimate.

3.2 Estimating the counterfactual 2020 welfare distribution

To isolate the impact of the pandemic on poverty and inequality, we construct a counterfactual 2020 welfare distribution that approximates what the income distribution in a country would have looked like in the absence of the COVID-19 pandemic. To that end, we use the January 2020 per capita GDP growth forecasts for 2020 to grow each country's 2019 welfare distributions to 2020. We assume all households grow with the same growth rate within a country, so inequality within a country is held fixed at the 2019 level. Evidence suggests that the pass-through from growth in per capita GDP to growth in the mean consumption in household surveys is less than

[12] The authors show that more complicated methods that try to predict growth in the survey mean and/or changes to inequality yield only slight increases in predictive accuracy.

[13] Note that while there are 169 countries with microdata in PIP, there is no national accounts data for the República Bolivariana de Venezuela after 2014. The República Bolivariana de Venezuela is assigned the regional average distribution between 2014 and 2019.

one (Ravallion 2003, Deaton 2005, Lakner et al. 2022, Prydz et al. 2022). To account for this, we multiply the per capita GDP growth in 2020 by 0.7 for surveys that use a consumption aggregate and 1 for surveys that use an income aggregate, based on the analysis by Mahler et al. (forthcoming).[14] For the roughly 3% of the global population without microdata in PIP, we use the regional average distribution as we did for 2019.

A concern with our counterfactual estimate is that it may be a poor approximation of what would have happened without COVID-19 for several reasons. For one, the growth forecasts may be inaccurate. While we are unable to test this, the growth forecasts are based on all the information available at the beginning of 2020. Second, even if the growth forecasts are accurate, the counterfactual distribution assumes that welfare in household surveys grows in accordance with the growth in real GDP per capita and that inequality remains constant. As shown by Mahler et al. (forthcoming), these two assumptions are on average relatively accurate compared to more sophisticated modeling approaches. Third, other unanticipated events happened in 2020. For example, in countries where environmental disasters hit in 2020, the difference between our 2020 estimates and the counterfactual captures the pandemic as well as the disaster. Given the size of the COVID-19 shock, it is reasonable to assume that most changes between the 2020 growth forecasts and realized growth rates are due to the pandemic.

Our preferred estimates of inequality and poverty are the net impact of the pandemic – that is the difference in 2020 between the counterfactual and the observed distribution (discussed in the next section). However, we also report the change in inequality and poverty from 2019 to 2020, which can be thought of as a gross effect.

3.3 Estimating the observed 2020 welfare distribution

(i) Household surveys

Microdata from household surveys are available for 20 countries in 2020. Twelve of these are in Latin America, a further six in Europe and Central Asia, and two in East Asia. These countries account for 14% of the global population and 78% of the population in Latin America (Table 1). While having a household survey is clearly superior to the other data sources used in 2020, it is important to note that changes in survey design imply that these surveys are subject to greater than usual uncertainty in 2020 (for detail see Castaneda et al. 2022).

[14] An alternative approach would be to anchor the income or consumption from household surveys to national accounts making use of other sources of data (such as tax data from fiscal authorities). For a discussion of such methods, see Piketty et al. (2018) and Lustig (2020). Note also that Lakner et al. (2022) propose a global pass-through rate of 0.85 independent of the welfare measure used. However, they also find a consumption-specific pass-through rate of 0.72. This paper adopts pass-through rates differentiated by welfare aggregate from Mahler et al. (forthcoming) who have an updated sample compared to the previous study.

(ii) Tabulated statistics

For eight countries, we rely on tabulated or grouped data acquired from these countries' NSOs to create the 2020 distribution. This information is typically published in the form of quantile growth rates. In several cases, we need to make important assumptions to match this data to our 2019 distributions. For example, the tabulations might use a different income concept, use an equivalence scale, cover different parts of the year or rank households instead of individuals. See Appendix B for further details.

(iii) High-frequency phone surveys

Our next preferred source of data is the HFPSs. At the time of writing, the HFPSs were conducted in 85 countries resulting in 155 harmonized indicators. We use this method for 37 countries covering 13% of the global population. Note that more than half of these countries are in Sub-Saharan Africa (SSA). For 59% of the population residing in this region, the HFPSs is the only source of information on the income growth of households in 2020. HFPSs are also available for 7 countries in ECA (amounting to 14% of the population in the region), 5 countries in EAP (covering 7% of the regions' population), and 5 countries in LAC and the Middle East and North Africa (MENA) covering 5% and 4% of the respective regional populations.

While the phone surveys provide information on whether households gained or lost income or consumption since the beginning of the pandemic, they do not contain information on households' level of income or consumption, nor do they report the size of the change in income or consumption. To utilize the information in the HFPSs, we need to (a) map the changes in income or consumption from the HFPSs to the 2019 welfare distributions discussed above and (b) estimate the size of the change for each household. We need to make several strong assumptions to use the HFPSs, which in many countries is the only data that were (and will ever be) collected in 2020. It is also important to emphasize that for those countries that use the HFPSs, total growth follows the growth in national accounts (adjusted using a pass-through rate as explained in Section 4.2). The phone surveys are only used to allocate this growth to various groups within the country and thus allow for within-country distributional changes.

The method we employ differs a little based on whether the phone survey collected data on income changes (which was asked for 24 countries) or consumption changes (which was asked for 13) countries, since the consumption question only asks whether consumption did not change or fell (but not whether it increased). The method using income changes is described below. Further details, including the method for consumption changes, are provided in the Appendix.

(a) Mapping the income changes from the phone surveys to the 2019 welfare distribution

In the phone survey, households are asked whether they lost, gained, or experienced no change in their income since the start of the pandemic. Employing a multinomial logit regression for each country separately, we derive probabilities for an *increase*, *decrease*, or *no change* in income based on certain household and demographic characteristics – namely, where they reside (urban or rural area), the number of members in the household, the education of the head of household, and the age of the head of household (Table B.1. reports the coefficients from these regressions).

Then, in the 2019 welfare distribution, we randomly assign each household an increase, decrease, or no change in income based on the probabilities derived from the multinomial logit regression on the phone survey. Suppose that the phone survey revealed that a particular household type in a country had a 75% probability of experiencing an income loss, 20% probability of experiencing no change, and 5% probability of experiencing an income increase. Then, all households in the 2019 welfare vector that are of this type are randomly assigned such that 75% have an income loss in 2020, 20% have no change, etc.

In the robustness checks section, we validate this matching procedure in Nigeria, where the phone survey sample was drawn from the 2019 survey. Therefore, we know which households experienced an income gain, loss, or no change. We show that the results are very similar whether we use the observed matching or the random matching.

(b) Estimating the size of the income gains and losses

Whereas we now have an approximation of *which* households experienced a gain, loss, or had no change in income in the 2019 distributions, we still do not know the size of the income losses and increases. We need the latter to estimate the 2020 welfare vector.

We first split the sample into rural and urban households. We then allocate sectoral growth rates from national accounts – growth in income from agriculture, industry, and services –to rural and urban areas, which requires several strong assumptions. Growth in the agricultural sector is allocated to rural households. Growth from industry is applied to urban households, which is a reasonable assumption at least in most developing countries (which are the countries for which we use the HFPSs). The service sector is the most difficult to allocate. On the one hand, both urban and rural household benefit from government services such as education and health care services. On the other hand, financial services, retail, ITS and more, are all likely to be predominantly present in urban areas. Even government services are likely to be overrepresented and of greater value in urban areas. In our analysis we use growth in service sector income, but the argument likely carries over from levels of service sector income to its growth. One extreme assumption would be to assign all service sector growth to urban areas. Another option would be to assign the growth according to population weights. We opt for a middle way by assuming that the growth (or more likely, declines) in service income in low- and middle-income countries experienced in 2020 is distributed according to the urban and rural *income* shares. Since urban areas are richer than rural areas, using the income share gives a higher share of service growth to urban areas compared with using population shares. The results are very similar whether income or population shares are used (Table B.4).

These assumptions on sectoral growth pin down the total growth rate for rural and urban areas, but further assumptions are needed to specify the level of the growth and declines. Note that the macro sectoral growth rates in 2020 are largely negative. For households that experienced an increase in income in 2020, we set the size of the increase to match the growth projection prior to COVID-19. Intuitively, if a household managed to grow their income in 2020 (at the same time as mean income was declining), our best guess is the growth rate that was previously projected. With this approach, we will assign each household to one of five different growth rates; two positive growth rates for urban and rural households, two negative growth rates for urban and rural households, and a zero growth rate. In the robustness section we show that our results do not change notably if we add random noise to the growth rates.

(iv) Estimates from the literature

For 26 countries (covering 27% of the global population) we use estimates of distributional changes due to the COVID-19 pandemic available from various studies – including published papers and calculations available from teams in the World Bank. These studies (with the exception of India) are not based on new data collected in 2020, but instead use an econometric model to predict the distributional impact using a household survey from an earlier year. Like with the tabulated data, we often use quantile-specific growth rates from these studies and need to make strong assumptions to apply them to our data. In the case of India, we use estimates from Roy and van der Weide (2022). See Appendix B for further details.

(v) Countries without any other data

For 127 countries, we were unable to use any of the sources presented thus far. Many of these countries are small, such that these countries together account for roughly 18% of the global population. For this group of countries we use three other methods in the following order of preference.

Use sectoral national accounts growth rates. As with the HFPSs, we use the sectoral national accounts growth rates to estimate urban and rural growth rates. We apply those growth rates to the 2019 distribution, such that households could only experience two different growth rates in 2020. By design, this will only capture a small fraction of the within-country inequality changes that happened in 2020. This method is applied to 56 countries covering 13% of the global population (half the population in the Middle East, nearly a quarter in South Asia, and close to a fifth in Sub-Saharan Africa).

Apply national growth rates. For some countries we lack sectoral national accounts or information on whether a household resides in an urban or rural area. For those countries, we apply the growth rate in real GDP per capita to all households, which means that we do not allow for any within-country distributional changes. We use this method in 21 countries covering 2% of the global population.

Use the regional distribution. Finally, for close to 3% of the world's population (50 countries), we have no prior household survey data. For those countries, we generate the 2020 distribution in the same way as we generated the 2019 distribution: by applying the regional distribution to those countries. This follows the methods used by PIP for countries without data.

4. Results

In what follows, we first report within-country changes in poverty and inequality comparing across the four preferred methods – actual household survey data, data from NSOs, data from phone surveys, and data from the literature.[15] Then, we report the changes in global inequality and poverty. Finally, we look at the drivers of these global changes.

4.1 Impact of COVID-19 on inequality and poverty within countries

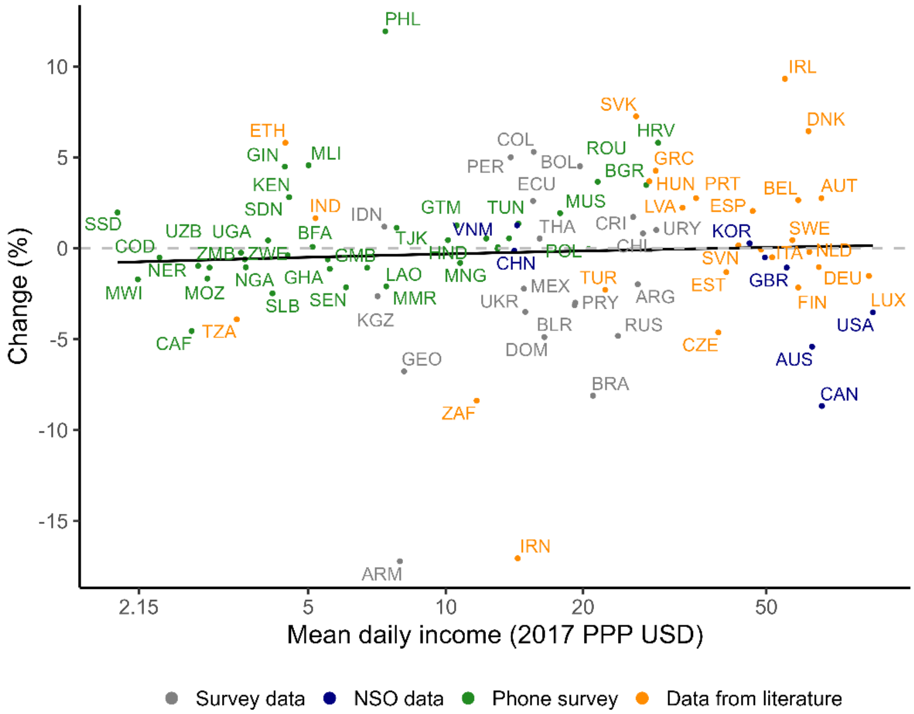
Figure 1 shows the net percent change in the Gini index in 2020 for all countries with data from our four preferred methods. The net impact is calculated as the difference between the Gini index in the observed 2020 distribution and the counterfactual distribution.[16] The countries are ranked according to their mean income or consumption expenditure on the horizontal axis. In general, changes in the Gini index in 2020 are mixed and, for most countries, small. Note that some of the larger declines in the Gini – for instance in the US, Canada, Australia, Brazil, and South Africa – can be linked to the wide-ranging social assistance programs that were implemented in 2020. Across countries, inequality is just as likely to increase (in 43 countries) as decrease (in 48 countries).

Whereas the changes in inequality were mixed, extreme poverty has largely been increasing (Figure 2). We find large increases in extreme poverty for countries that already had high poverty rates. This could either be because these countries experienced larger shocks to average incomes, or because they have more people just above the international poverty line. India experienced the largest increases in the extreme poverty rate, which appears to be for both of these reasons. South Africa and Brazil, two countries that had substantial pandemic support (see World Bank 2022), report the largest declines in poverty.

[15] This does not include the last group of countries which relies only on national accounts growth rates or the regional average. While the sectoral growth rates allow for some distributional effects, these are very limited.

[16] Note that the change from 2019 to 2020 is equivalent to the net COVID-19 impact on within-country inequality because the country inequality is held fixed at the 2019 level for the counterfactual distribution. This does not apply to the global Gini which depends on both within- and between-country differences.

Figure 1: Change in within-country inequality from 2019 to 2020



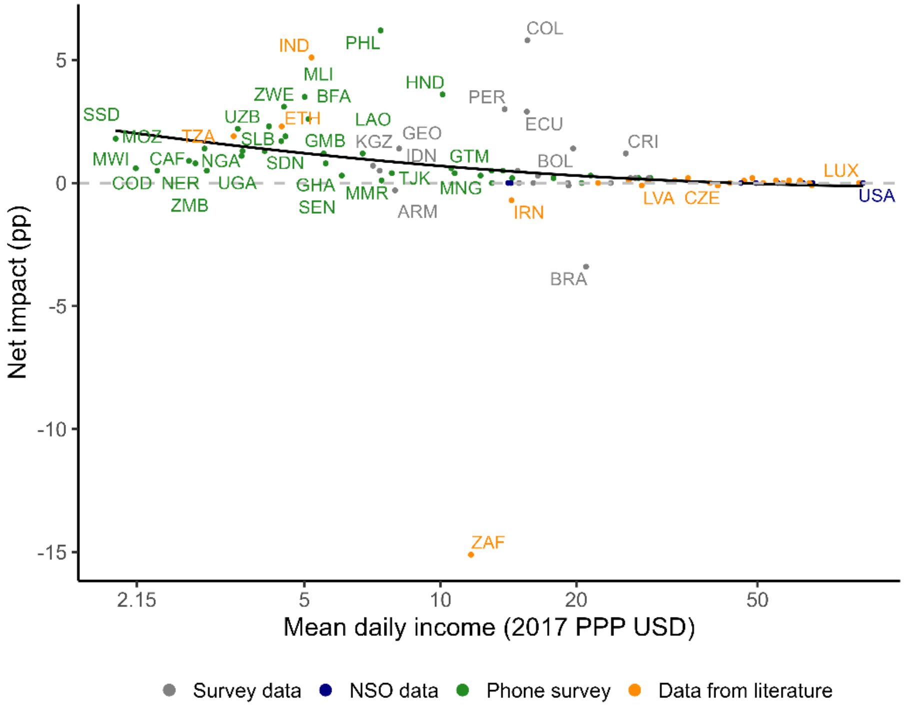
Note: This figure reports the change in the Gini index from 2019 to 2020. Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. Map B.1 shows the spatial distribution of these estimates. The solid line is fitted using a quadratic specification. See Table B.3a for the inequality estimates for the countries using phone surveys.

The net impact on extreme poverty is small for upper-middle-income and high-income countries, as not many people in those countries live close to the international poverty line (IPL) of $2.15-a-day. To gauge the impact of the negative growth shocks on incomes in the lower part of respective country distributions, we use the World Bank's societal poverty line (SPL).[17] This is a variant of a relative poverty line, which varies with mean income. We anchor the SPL to 2019, i.e. we calculate this line for each country in 2019 and hold it fixed for 2020. Hence, this approximates a country-relevant absolute poverty threshold. It also avoids the paradoxical result where the relative poverty rate can decline despite a large reduction in the mean.[18]

[17] Using the cross-country relationship between national poverty lines and average incomes, Jolliffe and Prydz (2019) defined the World Bank's SPL as $max(\$1.90, \$1.00 + 0.5 * Median)$ with the 2011 PPPs. Jolliffe et al. (2022) updated the line to $max(\$2.15, \$1.15 + 0.5 * Median)$ with the 2017 PPPs, which is used in this paper.

[18] Typically, a relative poverty line is a fixed fraction of the median. Hence a decline in the median would lower the poverty line. Depending on the shape of the distribution, this could lead to a decline in poverty despite a fall in average incomes.

Figure 2: Net impact on extreme poverty due to COVID-19 in 2020, by country

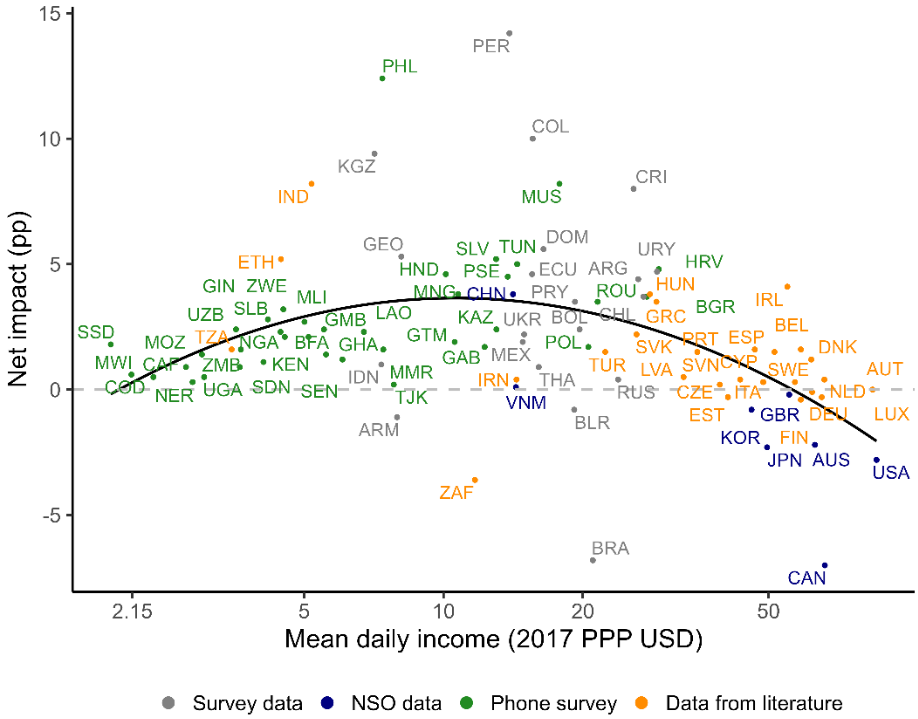


Note: This figure reports the net percentage points impact in extreme poverty – i.e., those living below the $2.15-a-day poverty line -- in 2020 due to the pandemic (i.e. comparing the 2020 estimate with the counterfactual 2020 estimate). Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. The solid line is fitted using a quadratic specification. Map B.2 shows the spatial distribution of these estimates. Figure B.1 shows the same plot using 2019 instead of the counterfactual 2020 as the baseline. See Table B.3b for the poverty estimates for the countries using phone surveys.

Figure 3 reports the net impacts for poverty using these country-specific absolute poverty rates using the anchored-SPL in 2019. We find that the middle-income group of countries had larger negative impacts on welfare compared to both the bottom and the top of the distribution of countries. We find that poverty in high-income countries decreased in several wealthy countries in 2020, most likely due to the social protection measures in place. This pattern across countries is robust to using other country-specific absolute poverty thresholds. Figure B.3 reports the same using income-group specific poverty lines – i.e., $.2.15-a-day line for low-income countries, $3.65-a-day line for lower-middle income countries, and $6.85-a-day line for the rest.[19]

[19] These are the three absolute poverty lines used by the World Bank since the adoption of the 2017 PPPs. Jolliffe et al. (2022) derive these lines as the median of the national poverty lines among low-income countries ($.2.15), lower-middle income countries ($3.65) and upper-middle income countries ($6.85).

Figure 3: Net impact on societal poverty due to COVID-19 in 2020, by country

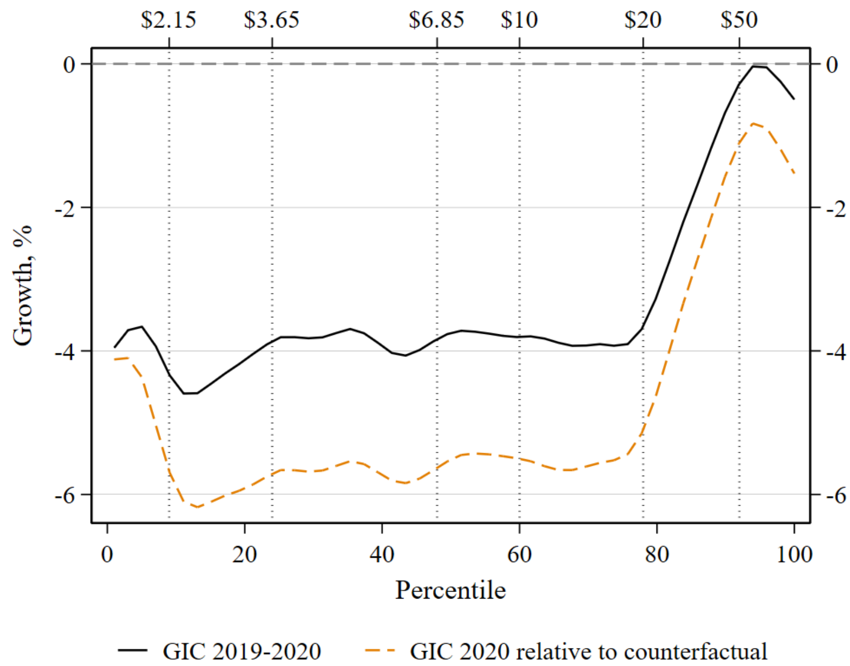


Note: This figure reports the net percentage points impact in absolute poverty in 2020 due to the pandemic (i.e. comparing the 2020 estimate with the counterfactual 2020 estimate) using the World Bank's societal poverty line (SPL) anchored to 2019. The anchored-SPL for each country is calculated as the maximum of \$2.15 or \$1.15 + ½ x median daily income in 2019. Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. The fitted line uses a quadratic specification. Map B.3 shows the spatial distribution of these estimates. Figure B.2 shows a similar plot using the 2019 distribution as the baseline instead of the counterfactual 2020 distribution. Figure B.3 reports poverty using income-group-specific absolute poverty lines.

4.2 Impact of COVID-19 on global inequality and poverty

Next, we aggregate our various distributions for 2019 and 2020 and look at the impact of COVID-19 on the global distribution. Figure 4 shows the global growth incidence curve (GIC) when comparing 2020 with our counterfactual estimates for 2020 (dashed line) and with 2019 (solid line). On average, every percentile of the global income distribution experienced a negative income shock in 2020. The largest shocks were reported for those that live approximately below the 80th percentile of the global income distribution. This highlights the global nature of the COVID-19 pandemic shock. Those in the top 20 percentiles fared relatively better with those in the top 10 percentiles experiencing the smallest shocks. The positive slope of the GIC suggests that global inequality in 2020 has increased due to the pandemic.

Figure 4: Global growth incidence curve



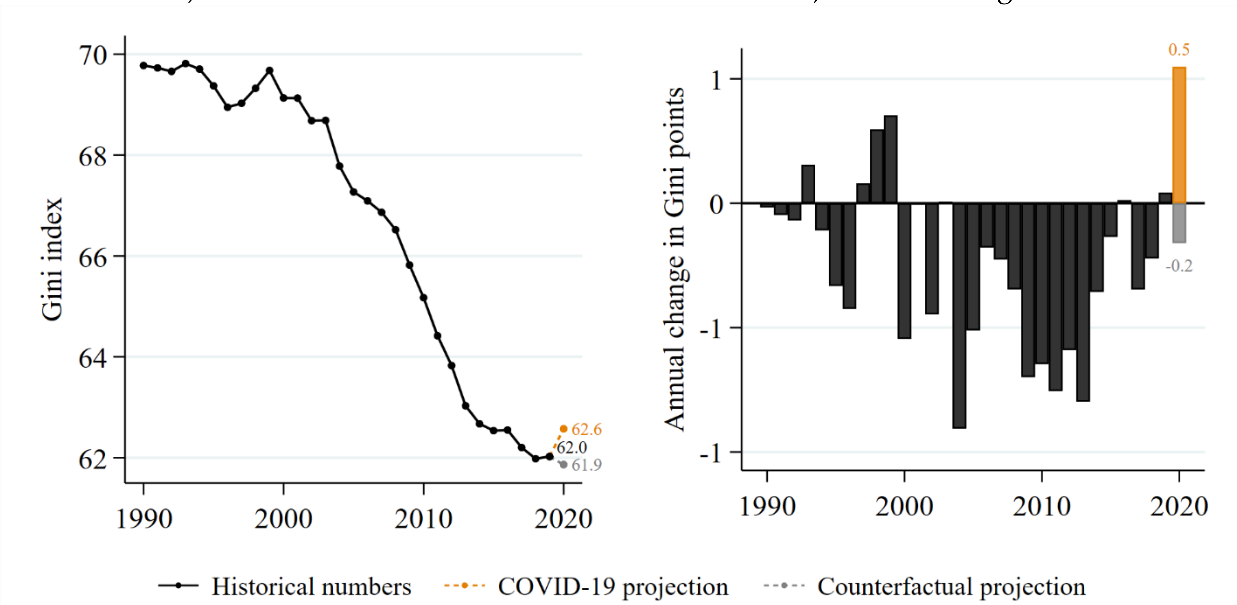
Note: The figure shows an anonymous global growth incidence curve (GIC) comparing the 2020 distribution with the counterfactual 2020 distribution (dashed line) and 2019 (solid line). The bottom horizontal axis ranks the global population into welfare percentiles from the poorest (left) to the richest (right). The *GIC, 2019-2020* reports the change in welfare from 2019 to 2020, and *GIC 2020, relative to counterfactual* reports the difference between the observed 2020 distribution and the counterfactual 2020 distribution.

We evaluate the impact of the pandemic on global inequality more directly by looking at the global Gini index over time in Figure 5.[20] We estimate that the global Gini index increased to 62.57 points in 2020 from 62.0 points in 2019 – close to a 1% increase -- and that the net impact of the pandemic is an increase in global inequality of 0.7 Gini point. This is the first time in the past two decades that the Gini index has had a marked increase and is the largest single-year increase in the past three decades. The increase due to the COVID-19 pandemic is equivalent to the cumulative increase from 1996 to 1999, mostly driven by the Asian financial crisis, of 0.7 Gini point or 1.1%. As is evident from the figure, the decrease in global inequality was slowing in the last 5 years. From 2014 to 2019, the global Gini index had an average annual decline of 0.13 point. At that rate, it will take more than five years to reverse the increase in the Gini index experienced in 2020 due to the COVID-19 pandemic.

[20] Table B.5 shows that our estimates are very close to earlier estimates in the literature.

Figure 5: Global inequality from 1990 to 2020

a) Level of Gini b) Annual change in Gini



Note: This chart shows the global Gini index and its annual change (in Gini points) from 1990 to 2020, using the global distributions in PIP for the *Historical numbers* and the simulations conducted in this study for 2020. The net COVID-19 impact includes both the increase from 2019 to 2020 (the *COVID-19 projection*) and what would have happened to the global Gini in the absence of the pandemic (the *Counterfactual projection*). Table B.5a compares the Gini and GE(0) estimates to those previously reported in the literature.

Table 2 reports the change in share of income held by the top 10%, middle 40%, and the bottom 50% of the global income distribution. Without the crisis, we expected the middle 40% and the bottom 50% to increase their share of income slightly from 40.2% to 40.3% and 10.9% to 11% respectively. The crisis reverses the expected gains for both these groups. Due to the pandemic, we estimate that the top 10% income group increase their income share from 48.8% to 49.8%. The net impact of the pandemic will be to increase the share of income held by the top decile by around 1 percentage point and reduce the income shares of the middle 40% and the bottom 50% by half a percentage point.[21]

[21] Using a different methodology, the World Income Database reports the top 10% income share to have increased from 52.2% to 52.3% and the bottom 50% income share to have decreased from 8.5% to 8.4% (Chancel et al., 2022). They do not find any change to the income of the middle 40% of their global distribution. See also Table B.5b.

Table 2: Income share (%) of the global top 10%, middle 40%, and bottom 50%

	2019	2020		Net COVID-19 impact, pp
		Counterfactual	COVID-19	
Top 10%	48.84	48.67	49.81	1.14
Middle 40%	40.23	40.34	39.79	-0.55
Bottom 50%	10.92	10.99	10.41	-0.58

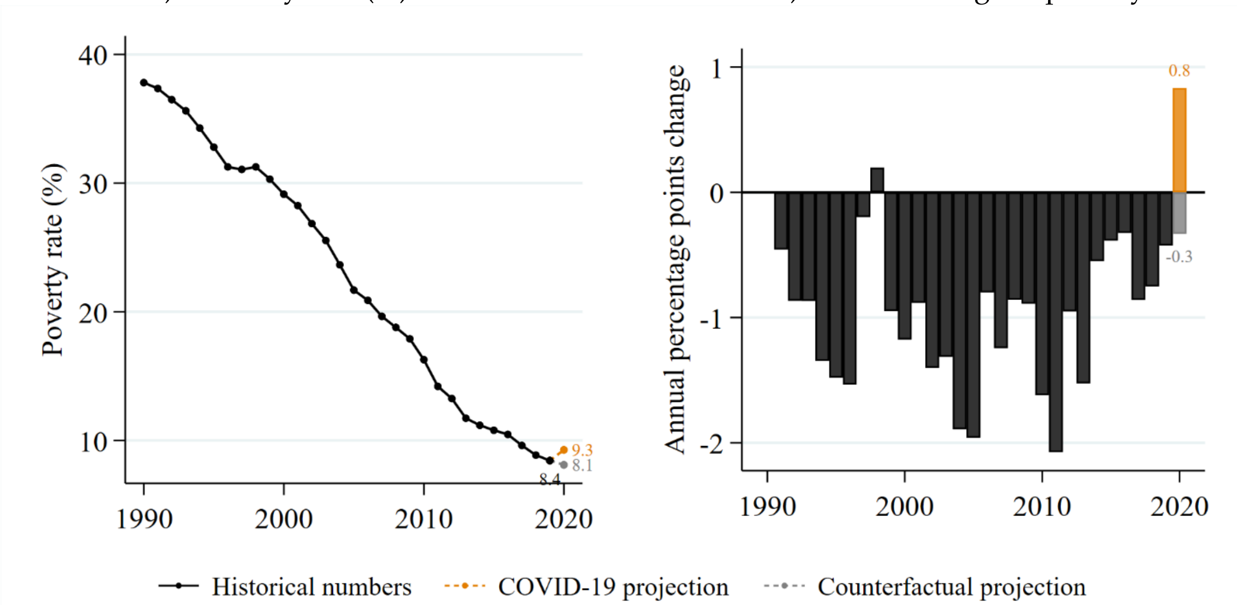
Note: This table reports the share of global income held by various income groups. The last column reports the net impact on the income share in percentage points due to COVID-19. *Net COVID-19 impact* is calculated as the difference between 2020 distribution with COVID-19 and counterfactual distribution.

Turning to poverty, we use the same global distribution just focusing on its lower tail. Figure 6 shows the global extreme poverty rate from 1990 to 2020 and the year-on-year change in the poverty rate from 1991 to 2020. We find that global extreme poverty increased for the first time in over two decades in 2020. There have been only two episodes of increases in poverty in the last 30 years. Poverty increased by around 0.2 percentage point (37 million people) in the year following the Asian financial crisis (i.e., 1997-98). We expect 0.8 percentage point (or 71 million people) to have moved into poverty in 2020 compared to 2019 due to the COVID-19 pandemic. The latter increase is not only larger in magnitude, but also much larger in relative terms. This is because the stock of extreme poor 20 years ago was nearly 2.5-times larger than the 648 million estimated for 2019. In relative terms, the change in the number of poor from 2019 to 2020 represents a 10% increase, whereas the increase from 1997 to 1998 was about 0.6%. The net COVID-19-induced poverty impact includes the additional 0.3 percentage points (or around 19 million people) who would have otherwise escaped poverty in 2020 had there been no pandemic. In total, this means we estimate the net COVID-19-induced poor to be 1.2 percentage points (or 90 million people) in 2020.[22]

[22] The 2019-2020 observed change is equivalent to 0.83 percentage points and the counterfactual change is 0.34 percentage points adding to a net impact of 1.16 percentage points. Any discrepancy from Figure 6 is due to rounding.

Figure 6: Global poverty from 1990 to 2020

a) Poverty rate (%) b) Annual change in poverty



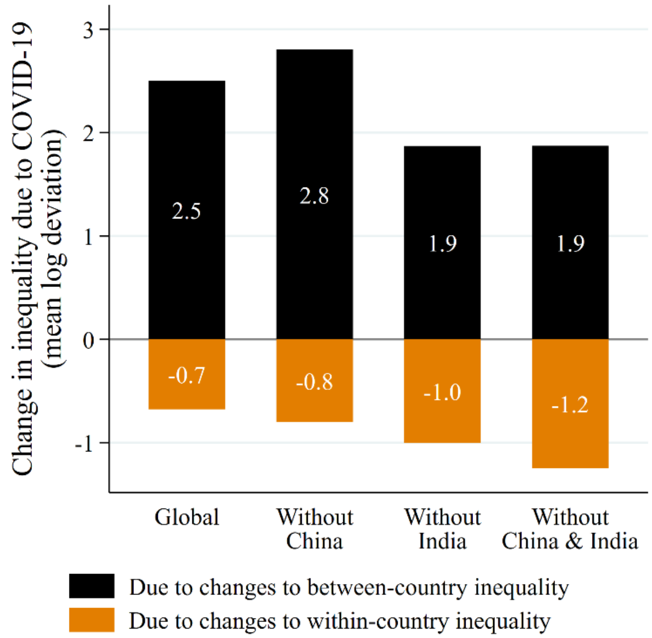
Note: Using the $2.15-a-day line, this chart shows the global poverty rate (panel a) and the annual percentage point change in the global poverty rate (panel b) from 1990 to 2020. It uses the global distributions in PIP for the historical series and the simulations conducted in this study for 2020. The net COVID-19 impact includes both those that entered poverty in 2020 (the *COVID-19 projection*) and those that would have escaped poverty in the absence of the pandemic (the *Counterfactual projection*).

4.3 Decomposing the changes in inequality and poverty

The increase in global inequality can be driven by an increase in inequality between countries or an increase in inequality within countries. Similarly, the increase in global poverty can be driven by shocks to the average income of countries or the increasing inequality within countries. In this section, we explore which of these channels are driving our findings.

Figure 7 disaggregates the increase in global inequality into within-country changes and between-country changes. We use the Mean Log Deviation (MLD) as it allows for total inequality to be additively decomposed into these two parts. We estimate the net impact in COVID-19-induced inequality in 2020 to be 1.8 points and that this increase was driven by increasing differences across countries. Changes to inequality within countries actually decreased overall global inequality by 0.7 point. Another way to think about this is that had the pandemic hit all individuals within a country equally, the MLD would increase by 2.5 points instead of 1.8. Since global inequality (and poverty) are population-weighted statistics, developments in populous countries, such as China and India, naturally have a large effect. Considering the world without China leaves the results almost unchanged, while the large negative shock to India's economy is an important driver behind the increase in between-country inequality. If we exclude India from the world, the overall inequality for this subsample of countries would still increase by 0.9 point compared to the 1.8 points increase for the global sample. Yet even without India (and/or China), we find that inequality increased globally with inequality between countries being the driver for the increase in overall inequality.

Figure 7: Disaggregation of global inequality into within and between countries

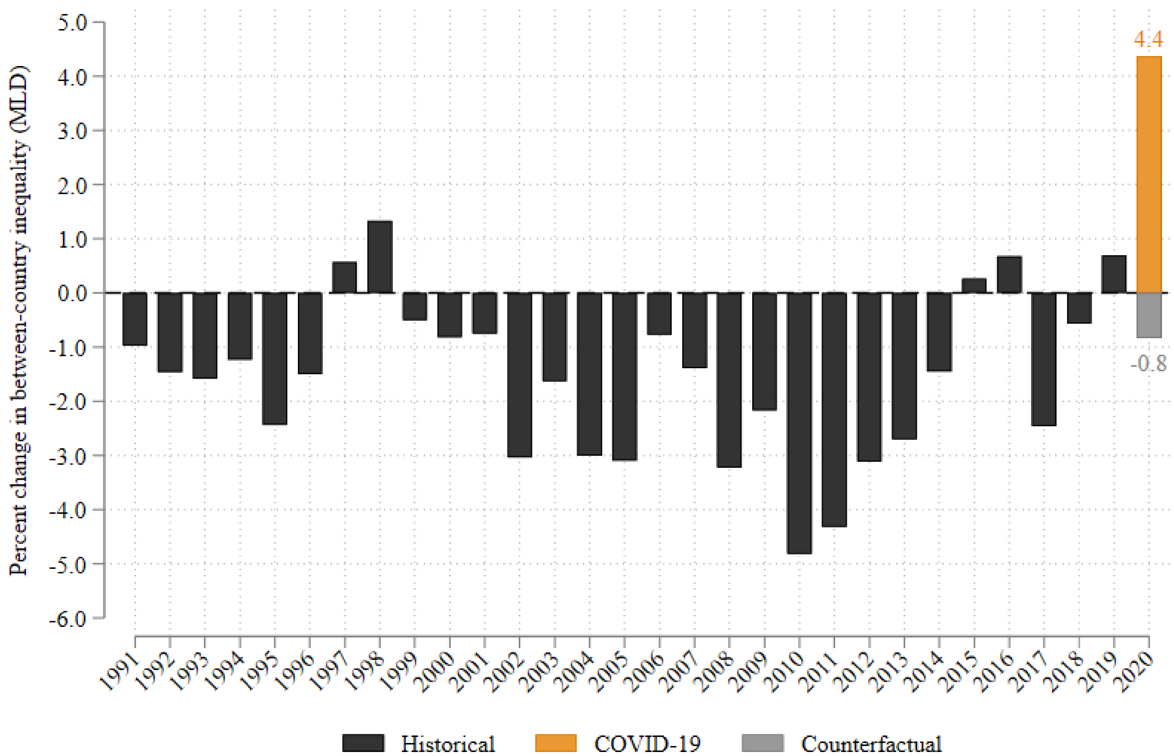


Note: This figure disaggregates the net impact on global inequality due to the pandemic into between- and within-country components. Global inequality is measured using the mean log deviation (scaled up by 100). The disaggregation of the total is shown for the global estimate with and without China and India. A version looking at the changes from 2019 to 2020 is presented in Figure B.4.

This is the first time since the fall of the Berlin Wall that income inequality between countries has risen. Figure 8 reports the change in income differences across countries, calculated as the annual change in the between-country portion of the MLD, from 1991 to 2020.

We find a continuous catch-up of the lower and middle-income countries to the richer countries over the last nearly three decades. There were increases in global between-country inequality in 5 of the 29 years before the pandemic with the most notable increase coinciding with the Asian financial crisis when between-country inequality increased by 0.6% in 1997 and by another 1.3% in 1998. The income differences between countries had decreased by an aggregate 37% between 1990 and 2019. A significant portion of this overall decrease happened in the period after the start of the global financial crisis. Recently, however, the convergence between countries had slowed down considerably. The average annual decline in the MLD between countries in the last five years before the pandemic was 0.3% compared to an average annual reduction of 1.8% from 1991 to 2014. We estimate to see the largest increase in the between-country inequality in at least three decades due to the COVID-19 pandemic. The inequality between countries is estimated to increase by 4.4% in 2020 compared to 2019. In other words, over 12% of the decline in inequality between countries experienced in slightly under three decades from 1990 to 2019 will be wiped out due to the pandemic. This does not include the 0.8% reduction in global between-country inequality expected for 2020 before the pandemic.

Figure 8: Percent change in inequality between countries from 1991 to 2020



Note: This figure reports the annual changes in inequality between countries using the Mean Log Deviation from between 1990 and 2020.

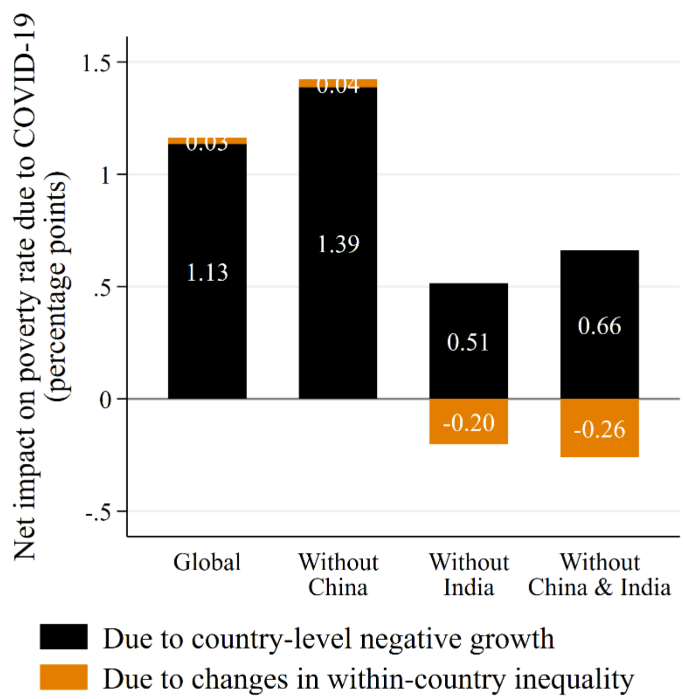
Turning to global poverty, Figure 9 disaggregates the COVID-19-induced net impact on extreme poverty in 2020 by country-level shocks and changes in within-country inequality.[23] We find that almost all the increase in extreme poverty can be attributed to the average negative shocks to household incomes and not to the differential income shocks within-countries. If rather than using differential growth rates across households within a country, we had applied the same

[23] We disaggregate the net impact in extreme poverty by first shifting the counterfactual 2020 distribution to match the mean of the observed 2020 distribution. Comparing this shifted distribution to the counterfactual distribution gives the effect of country-level shocks. The difference between the shifted distribution and the observed 2020 distribution gives the impact of changes to within-country inequality.

average growth rate to each household, the net impact in extreme poverty would have been to 1.13 percentage points instead of 1.16 percentage points – or 92 million net COVID-19 poor instead of 90 million.

Once again, India is the main driver of the result. Without India, the increase in global poverty would have been 0.3 percentage point. Yet, our qualitative finding remains without India (and/or China): global poverty increased in 2020 mostly due to negative shocks to average incomes while within-country changes played a mitigating role in many countries. In fact, in Figure 10 we show that the cross-country decompositions are very similar. The changes to country-level poverty were for the most part driven by negative aggregate shocks and less so by changes in inequality. This is the case whether we use the $2.15-a-day poverty line or country-specific absolute poverty lines.

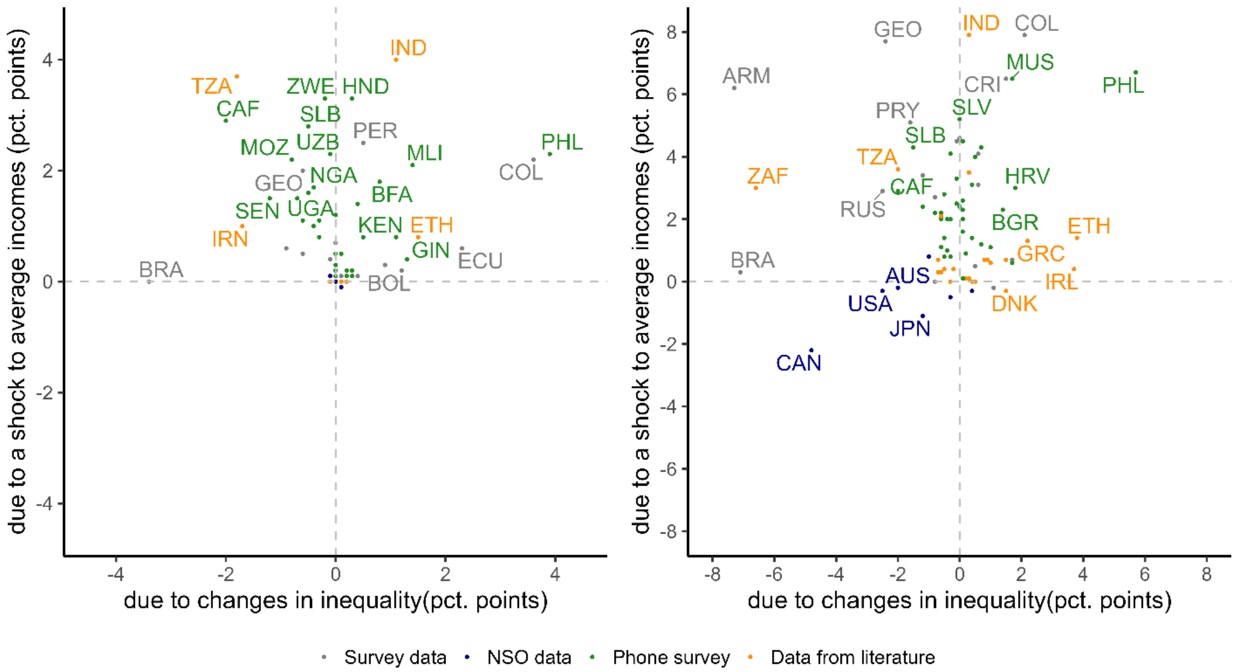
Figure 9: Disaggregation of global extreme poverty into growth and inequality components



Note: This figure disaggregates the net impact on the global extreme poverty rate in 2020 due to COVID into changes due to negative income shocks and within-country inequality. The disaggregation of the total is shown for the global estimate with and without China and India. A version looking at the changes from 2019 to 2020 is presented in Figure B.5.

Figure 10: Disaggregation of the net impact on poverty into growth and inequality component

a) Net impact on extreme poverty   b) Net impact on anchored-SPL



Note: This figure disaggregates the net impact on absolute poverty in 2020 caused by the pandemic into negative income shocks and within-country inequality changes for each country. Panel a reports the changes in extreme poverty – i.e. those living in less than $2.15-a-day – and panel b shows the changes in the anchored-SPL line in 2019. See also Figure 3. Only countries where we have data with one of the four preferred methods are included. South Africa is excluded from panel a since it is an outlier. A version looking at the changes from 2019 to 2020 is presented in Figure B.6.

5. Robustness checks

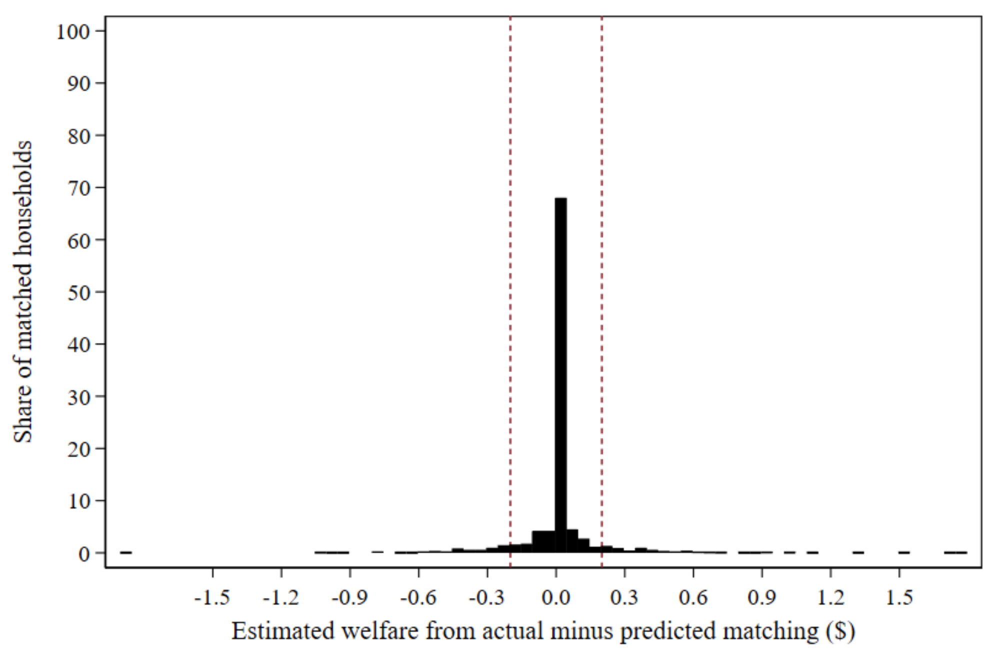
In this section we offer some robustness checks to our estimated inequality and poverty changes from the high-frequency phone surveys. These checks test the validity of the assumptions underpinning our simulations. First, we will look at data from Nigeria to check whether our assumptions regarding which households received an income loss, gain, or no change affect the estimates of inequality and poverty. Second, we will test the assumption of using the same growth rate for particular groups of households – i.e., rural households with income decreases, rural households with income increases, urban households with income decreases, and urban households with income increases. Third, in the group of countries that have actual household survey data, we can compare the survey-based estimates with estimates using the distribution-neutral projections and the HFPSs.

5.1 Allocating households to income gains, losses, or no change

Nigeria is the only country where we can match the households in the phone surveys to an underlying household survey, namely the Generalized Household Survey (GHS). The phone survey sample for Nigeria is a third of the sample of the 2018/19 GHS. There are 1,963 households in the phone survey of which 97 households do not report a change in total income (the variable used to predict income change probabilities from HFPS). For the remaining 1,866 households, we compare the welfare statistics from the actual income change (actual matching) and those using our random assignment (predicted matching). Note that in both cases we keep the method to distribute the growth rate in national accounts the same. In essence, we are testing whether our method of predicting which household receives an increase, decrease, or no change in income influences the poverty and inequality statistics.

Figure 11 reports the difference in estimated welfare between the actual and predicted matching for the 1,866 households. Using the predicted approach, we were able to closely match more than 60% of households with the direction of the income changes that they reported in the phone survey. Hence, for those households the difference in estimated welfare between the two approaches is zero. For 96% of households, the differences in welfare generated using the two approaches were within 5 cents, and the mean difference for all households is $0.0006.

Figure 11: Distribution of welfare differences between actual and predicted matching in Nigeria



Note: *Predicted matching* estimates poverty and inequality in 2020 using the methodology discussed in Section 3.3. *Actual matching* maps income changes reported by each household in the phone surveys to the underlying 2019 distribution. Both methods rely on sectoral growth rates to estimate the size of the household income shock.

Though we do not exactly match the households to an income increase, decline, or no change, this need not matter for our inequality and poverty estimates. Suppose for example there are two households that live on $2.20 a day, one of these experienced an income drop of 10 cents, and the other experienced no change in income. Even if we assign the wrong household an income drop of 10 cents, the implications on poverty and inequality would not change.

We find that the estimated inequality and poverty from the two approaches are only marginally different. Table 3 reports the poverty estimates in panel A and inequality estimates in panel B. The actual match yields a poverty estimate that is 0.18 percentage point lower and an inequality estimate that is less than 0.01 Gini point (in a scale of 0 - 100) higher. Hence, for Nigeria, we find no evidence of significant differences in measured inequality and poverty between using our predicted matching method and the actual matched households.

Table 3: Comparison of actual and predicted matching for Nigeria

	Number of Households	2019	2020		Net COVID-19 impact, pp	Change 2019-2020, pp
			Counterfactual	COVID-19		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Poverty rate (%)						
Actual matching	1,866	30.5	30.5	31.8	1.34	1.37
Predicted matching	1,866		30.5	31.7	1.16	1.19
(B) Gini index (x100)						
Actual matching	1,866	34.2	34.3	34.0	-0.23	-0.19
Predicted matching	1,866		34.3	34.0	-0.24	-0.20

Note: *Predicted matching* estimates poverty and inequality in 2020 using the methodology discussed in Section 3.3. *Actual matching* maps income changes reported by each household in the phone surveys to the underlying 2019 distribution. Both methods rely on sectoral growth rates to estimate the size of household income shock. *Net COVID-19 impact* is the difference between the 2020 distribution with COVID-19 and counterfactual distribution.

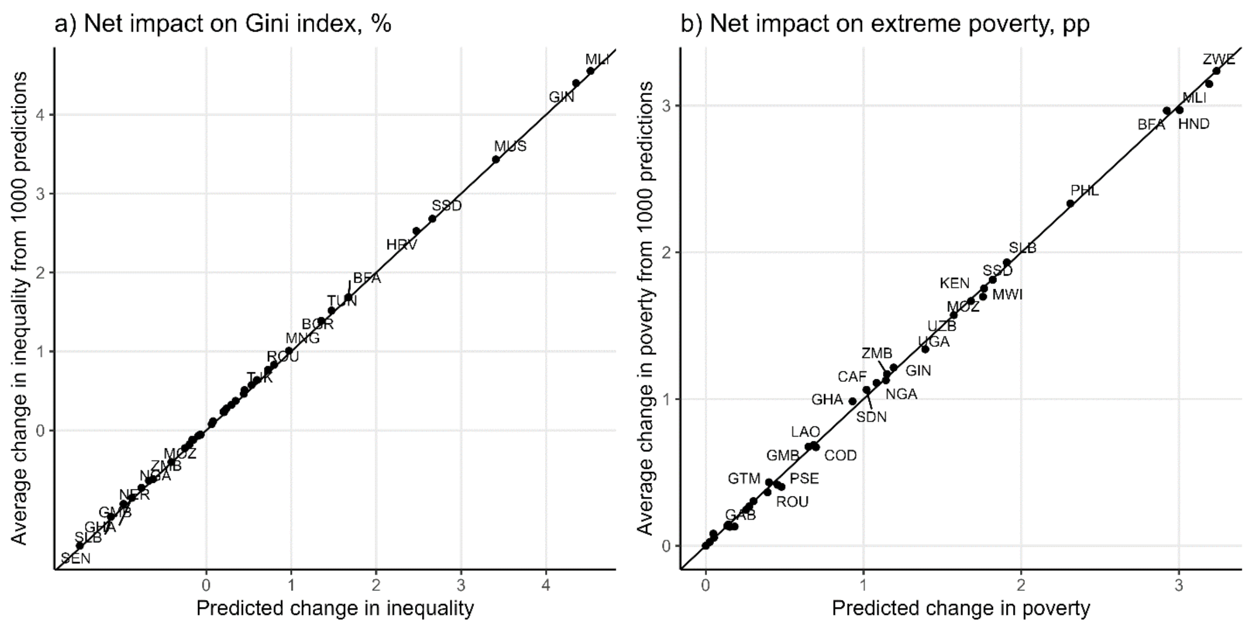
5.2 Random allocation of growth rates

In our simulation, we assigned the same growth rates within five groups of households. These five groups were identified from the income loss, gain, and no change probabilities in rural and urban areas. Our method requires that the growth rates of these five groups aggregate to the growth in per capita GDP. However, within a group, there are infinitely many combinations of growth rates that would allow us to match growth in per capita GDP. In what follows, we will relax our assumption that within each group all households have the same growth and test how alternative growth realizations impact the poverty and inequality estimates.

To that end, we generate 1,000 different growth rates for each household that each randomly adds noise to our baseline growth rates. We do so by first generating a maximum noise parameter, $\pm b$, to add to our baseline growth rates. We limit that bandwidth to 10 percentage points, and across the 1,000 simulations assume that $b \sim U(0,5)$. Then, we assign the i^{th} household a growth rate $g_{t,i}^{area} = g_t^{area} + k_i$, where $k_i \in U(-b, b)$ and $area \in \{rur+, rur-, urb+, urb-\}$. For instance, for $b = 2$ and $g_t^{area} = 3.2\%$, the applied growth rates, $g_{t,i}^{area}$, would be uniformly distributed between 1.2% and 5.2% with mean 3.2%.

From these, we generate 1,000 different distributions for each country and calculate the impact of COVID-19 on inequality and poverty 1,000 different times. Figure 12 shows the correlation between the mean of these 1,000 estimates and our baseline estimates using identical growth rates. We find both inequality and poverty impacts are scattered closely around the 45-degree line. This implies that our approach of using five fixed growth rates does not bias upward or downward the estimates of inequality and poverty.

Figure 12: Impact of COVID-19 on inequality and poverty using fixed and randomized growth



Note: The figure compares the estimated net impact of the pandemic on the Gini index (panel a) and extreme poverty rate (panel b) reported in this paper (x-axis) versus the average impact from 1000 simulations where a random shock is assigned to each household's growth rate (y-axis). Distribution of the estimates from the 1000 simulations by country are available in Figure B.7 and B.8.

5.3 Comparing poverty estimates for countries with actual household surveys

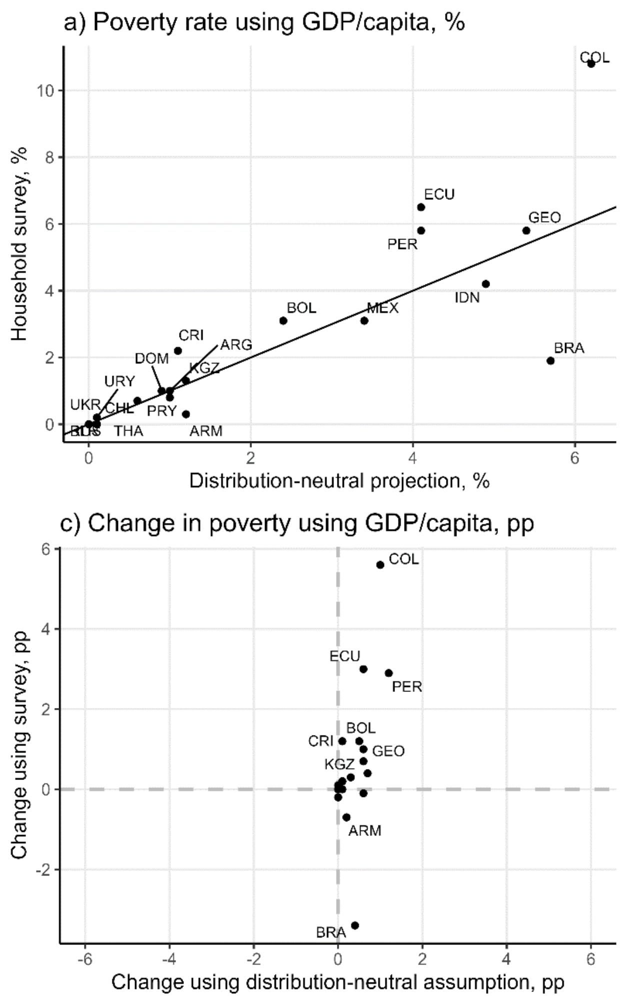
At the time of this writing, household survey micro data for 2020 is available for only 20 countries of which 12 are in LAC with the remaining countries in EAP and ECA. For these countries, it is possible to compare the poverty estimates using the survey microdata with (i) poverty derived using per capita GDP growth-based distribution-neutral projections, and (ii) for a subset of 13 countries, poverty derived using HFPS. Comparing the estimates based on distribution-neutral and phone survey-based projections with the actual survey micro data-based poverty estimates will give us some sense how these estimates might differ. However, given the limited number of countries and the issues discussed above with the actual household surveys themselves, it is not clear how generalizable the results of the findings to other countries will be.

Panel a of figure 13 shows the correlation of the poverty rate calculated using the actual survey data and poverty derived using per capita GDP growth-based distribution-neutral projection. For 13 countries, panel b compares the change in poverty using survey data with poverty using phone surveys. Panel c shows the percentage points change in extreme poverty from 2019 to 2020 using the two sources in panel a, and panel d compares the change in poverty for the sources in panel b.

The figure shows that for most countries in the sample, the change in poverty derived from survey micro data is fairly close to estimates derived using per capita GDP growth and phone surveys. Poverty derived using survey data is on average 0.25 percentage point higher compared to projections based on per capita GDP growth and 0.72 percentage point higher compared to projections based on phone surveys. The correlation coefficient of poverty changes is 0.60 between survey data and per capita GDP growth-based projection, and 0.62 between survey data and phone survey-based projection. Yet there are clear outliers. The change in poverty is 4.5 percentage points higher in Colombia in survey data compared to per capita GDP growth-based projection and 4.8 percentage points higher compared to phone survey-based projection. On the other extreme, survey data estimates a 3.8 percentage point lower poverty in Brazil compared to the per capita GDP growth projection. The lower poverty in Brazil in the survey data can be explained by the extraordinarily large social protection measures implemented during the pandemic (see Castanada et al. 2022).

The poverty rate and size of increases in poverty using the distribution-neutral per capita GDP projection are similar to those using phone surveys. These are reported in Figure B.9. This similarity in estimated poverty is due to the similar magnitude of changes in growth between those calculated using per capita GDP and those calculated using sectoral growth rates, which are used in the phone survey simulations. The fact that the magnitude of the changes is similar and the phone surveys potentially provide additional signal on the distributional changes is an added benefit of using the phone surveys in conjunction with the sectoral growth rates compared to the distribution-neutral per capital GDP growth rates.

Figure 13: Poverty rates and changes using actual household surveys, distribution neutral projection, and phone surveys



Note: This chart compares the poverty rates (top panels) and the 2019-2020 change in poverty rate (bottom panels) calculated using household survey data and per capita GDP growth in the left panels, and household survey data and phone survey data in the right panels. Figure B.9 compares the projected estimates using phone survey and per capita GDP. HFPS – high-frequency phone survey; pp – percentage points.

6. Conclusion

In this paper, we have estimated the impact of COVID-19 on global inequality and poverty in 2020. Due to sparsity of income and consumption data for 2020 from traditional household surveys, we have relied on a combination of alternative data sources. In particular, we use household survey data available for 20 countries; for a further 8 countries, we use tabulated income data reported by national statistical offices; next, for 37 low- and middle-income countries, we use information from High-Frequency Phone Surveys together with pre-pandemic welfare vectors and sectoral growth rates to model the impact of the pandemic along the countries' income distribution; for a further 26 countries, we rely on data from country studies in the literature. Finally, for countries without the aforementioned data sources, we rely on per capita growth observed in national accounts.

We find that the pandemic caused the largest single-year increase in global inequality and poverty since at least 1990. On both fronts, the pandemic erases at least three years of progress. Concretely, we find that the global Gini index in 2020 increased by 0.7 point (or around 1%) compared to 2019 and that the number of people living below the international poverty line of $2.15-a-day PPP USD increased by 90 million people. The increase in poverty is driven by the countrywide economic shocks that almost all countries experienced. The increase in the Gini is driven by poorer countries facing larger economic shocks from the pandemic. Changes to inequality within countries, on the other hand, counteracted the increases to global inequality and poverty as many countries, particularly populous ones, experienced a decline in inequality. If the pandemic had hit all people within countries equally, its impact on global inequality would have been even larger. In low-income countries, this is likely due to the pandemic not hitting rural areas (where the poor predominantly live) as forcefully, while in high-income countries this is likely due to the extensive social protection programs implemented in 2020.

All our results relate to household disposable income or consumption expenditure for 2020. It is likely that with other measures of welfare, or with the same measure of welfare beyond 2020, the results would be different. Our results, for example do not speak to what happened to wealth inequality or health inequality during 2020. Our results also do not speak to what happened in 2021 and beyond, where data is even more sparce. It is likely that inequality in vaccine access and take-up between countries allowed wealthier countries to recover faster, reinforcing the increase in between-country inequality experienced in 2020. It is also likely that some wealthy countries stopped their emergency social protection programs in 2021, leading to increases in within-country inequality.

7. References

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Appendix A: Methodological details

A.1 Tabulations by National Statistical Offices

For Australia, we use data on income growth by quintile from Table 2 of Australian Bureau of Statistics (2021) and apply these growth rates to the 2019 welfare vector for Australia. The data from the Australian Bureau of Statistics reflects gross equivalized income while the 2019 welfare vector we use reflects per capita disposable income, creating an inconsistency between our 2019 and 2020 welfare vectors. The Australian Bureau of Statistics (2021) only makes growth rates available comparing the second half of 2020 with the second half of 2019. We do not have data from the first half of 2020.

For Canada, we rely on growth rates of disposable income by quintile for 2020 (Statistics Canada 2022). Though the growth rates use equivalence scales, we apply them to our 2019 welfare vector that is per capita based. The growth rates are nominal, so we deflate them all with the CPI.

In China we rely on growth rates in per capita disposable income of rural/urban households by quintile (Table 6-3 and 6-12 in National Bureau of Statistics of China 2022). We face two challenges when using this information: (1) the quintiles are created at the household level in contrast to our 2019 welfare vector for China which is at the individual level, and (2) we use consumption data for China, for which no quintile tabulation is published. We ignore the first issue and match the growth rates implied by each quintile to the 2019 distribution for China. Since the National Bureau of Statistics of China (2021) publishes *mean* growth rates of consumption by urban/rural areas, we subsequently scale the urban/rural vectors to match the growth rates in consumption in 2020. We thus assume that the differences in growth rates along the distribution are the same whether income or consumption is used.

For Japan, we use quintile-level data on the growth in disposable income per capita from Table 22-1 of the 2021 and 2022 Statistical Yearbook (Statistics Japan 2022). The quintiles rank households, not individuals, and are only available for "workers' households" and hence lack data for a certain part of the population.

For the Republic of Korea, we rely on annual growth rates in disposable income by quintile from Statistics Korea (2021). These growth rates are reported four times for each quarter of 2020, each comparing the income to the same quarter of the previous year. We factor data in from all four quarters.

For the United Kingdom, we use information on mean disposable income by decile from Table 14 of Office of National Statistics (2022). The means are expressed in UK fiscal years rather than calendar years. We create quarterly decile means by scaling the fiscal year means in a manner such that the overall quarterly growth rate in real disposable income from Office of National Statistics (2022b) is respected, and then convert these quarterly means to calendar averages.

For the United States, we use data on the household-level changes in post-tax income shares by quintile and for the median household (Table C-1 and C-3 in Shrider et al. 2021). To apply this data, we assume that the changes also apply at the individual level, i.e. that the growth in median household post-tax income and individual post-tax income is identical. Then we take the 2019 welfare vector and change each quintile's income share to match the published change. Subsequently, we grow the entire distribution such that the change in median welfare equals the published change.

For Vietnam, we rely on growth rates in consumption per capita by decile between the 2018 and 2020 Vietnam Household Living Standards Survey (VHLSS). We apply those growth rates to the 2018 distribution we have for Vietnam in PIP, which is from to the 2018 VHLSS.

A.2 Estimates from the literature

For 21 countries, we use Eurostat's flash estimates of income inequality and poverty, which are based on a microsimulation building on the work of Rastrigina et al. (2016). These flash estimates contain lower and upper limits of five points on a growth incidence curve. We take the midpoint of those two limits and linearly interpolate between them to generate a full growth incidence curve. Though these estimates are based on adult equivalent income, we apply them to our 2019 welfare vector which is in per capita terms.

For South Africa, we use the results from Barnes et al. (2021). This study contains decile growth rates comparing April-June 2020 with March 2020 and uses a measure of disposable income. To use these results, we assume that disposable incomes did not change after June and apply three-fourth of the April-June growth rates to the 2019 welfare vector (essentially assuming no change to welfare from 2019 to March 2020). We also ignore the fact that the 2019 welfare vector is based on consumption rather than disposable income.

For the Islamic Republic of Iran, we have decile specific growth rates reported in per capita terms that simulate the impact of the pandemic from the 2018/19 survey from Rodriguez and Atamanov (2021). We apply these growth rates to our distribution for the Islamic Republic of Iran for 2019. For Türkiye, we have percentile specific simulated per capita growth rates in income from 2019 to 2020 from Baez and Celik (2021). We collapse these to ventile specific growth rates to smoothen out some variance and apply them to our 2019 vector, noting that the 2019 vector is based on a consumption aggregate rather than an income aggregate. For Ethiopia, from Wieser et al. (2022) we have predicted consumption levels from a survey-to-survey imputation from the 2018/19 household survey to a high frequency phone survey carried out in 2020. We convert these predictions to per capita percentile growth rates from 2018/19 to 2020 and apply them to our 2019 vector for Ethiopia. For Tanzania, we use estimates of the growth in mean disposable income due to the pandemic by income quartile from Lastunen et al. (2021). The growth rates are relative to a counterfactual dataset created to reflect the situation right before the pandemic started. We apply these growth rates to our 2019 distribution, noting that the 2019 distribution is based on a consumption aggregate.

(i) India

The estimates for India underpinning the 2020 global inequality and poverty estimates are based on Roy and van der Weide (2022).[1] Depending on the data sources used, there exists a wide range of estimates of growth shocks in 2020 for India. This, combined with the large population, means that the global estimates of inequality and poverty are sensitive to the choice of estimate used for India. Below, we outline the derivation of the 2020 COVID-19 welfare distribution for India used in the current study and report alternate estimates based on other growth rates reported for India.

The last official household survey released for India dates back to 2011/12. Roy and van der Weide (2022) use various methods to create a comparable time trend using the Consumer Pyramid Household Survey (CPHS) which is a private survey collected in more recent years. Their *approach 1* uses survey-to-survey imputation techniques to estimate consumption in the CPHS using a set of (non-monetary) household characteristics that are common to both the CPHS and the 2011/12 National Sample Survey (NSS). This approach is similar to poverty mapping methods (Elbers et al., 2003) and does not exploit the consumption data that the CPHS collects. In contrast, *approach 2* converts the observed CPHS consumption into NSS-type consumption in an attempt to account for the differences between the two aggregates (e.g. questionnaire design, sampling design).

The World Bank's Poverty and Inequality Platform (PIP) uses the CPHS data adjusted using approach 2 for years 2015/16, 2016/17, 2017/18, 2018/19, and 2019/20, which we follow in the present study.[2] However, estimates based on approach 2 are not yet available for 2020/2021. Estimates here are based on approach 1 using the surveys conducted face to face (see Annex 1G of World Bank 2022 for a discussion on the construction of estimates for 2020/21).

Our preferred estimate of the growth rate in consumption for India for 2020 is based on a comparison of the CPHS distributions derived using approach 1 from Roy and van der Weide (2022) for 2019/20 and 2020/21, or more specifically the growth rate from 2019/20 to 2020. To be used for this study, the 2020/21 estimate needs to be converted from fiscal year (FY) to calendar year (CY) estimate. We calculate the $CY2020_1$ (calendar year 2020 based on approach 1) distribution of consumption using the standard method used to interpolate poverty estimates in PIP. The method forward and backward extrapolates the two estimates to 2020 using growth rates from national accounts, and calculates a weighted average of the two, amounting to the following:

$$CY2020_{1,i} = \frac{1}{4} \times FY2019_{1,i} \times (1 + g_{2019.25-2020}) + \frac{3}{4} \times FY2020_{1,i} \; / \; (1 + g_{2020-2020.25})$$

[1] The estimates for 2020/2021 are available from the authors and will be included in the next iteration of their working paper. Also see Annex 1G of World Bank (2022) for a detailed discussion of the 2020/21 estimates.

[2] Each round follows the Indian fiscal year, which starts in April of a given year and ends in March of the following calendar year.

where i represents each household and g the growth observed in per capita household final consumption expenditure reported in World Development Indicators.[3] For details on the interpolation methodology, see Prydz et al. (2019).

We then collapse the $FY2019_1$ and $CY2020_1$ consumption vectors into 1,000 equally weighted quantiles in each distribution and estimate the growth for each quantile. Finally, we use these quantile growth rates to grow the $FY2019_{pip}$ distribution (2019 FY distribution for India used in PIP, which his based on approach 2) to derive the $CY2020_{covid}$ distribution for India. This paper reports estimates of inequality and poverty based on the $CY2019_{pip}$ and $CY2020_{covid}$ change in India. Our approach makes two assumptions: First, we need to interpolate to get from fiscal years to calendar years. This is a standard PIP assumption whenever data do not line up with calendar years. Second, we assume that the growth rates estimated using approach 1 can be applied to the approach 2 distribution (using 1,000 quantiles). This seems to be a reasonable assumption given that Roy and van der Weide (2022) show that despite differences in poverty levels, the trend in the poverty rate is very similar across the two approaches. Once estimates from approach 2 become available, this assumption can be tested, and our estimates can be updated.

Table A.1 reports the 2020 estimates of poverty using various growth rates for 2020. Using the distribution-neutral per capita GDP growth from national accounts results in an extreme poverty rate of 11% which would mean a global poverty headcount rate of 8.8%.[4] Using unadjusted growth rates from the CPHS (as published by Gupta et al., 2021) instead would result in a poverty rate of 16.2% in India implying a poverty rate of 9.8% globally amounting to a net impact of 130 million additional poor. The preferred approach in this paper also employs the CPHS but with the adjustments suggested by Roy and van der Weide (2022). This results in a poverty rate in India of 13.4% implying a poverty rate of 9.3% globally and a net pandemic impact of 90 million additional poor in 2020 globally.

[3] Given that 25% of the fieldwork for the 2019/20 round took place in 2020, we assign it the time 2019.25. To find the growth between the 2019/20 survey and 2020, $g_{2019.25-2020}$, we first calculate per capita household final consumption expenditure (HFCE) at 2019.25 as a weighted average of the 2019 and 2020 HFCE, with 75% of the weight given to 2019. Upon that, we calculate the growth in HFCE from 2019.25 to 2020. A similar procedure is used with the growth from 2020 to the 2020/21 round.

[4] In this comparison, we only switch the estimate for India to per capita GDP growth, while keeping the approach for all other countries as in the baseline. If instead we used per capita GDP growth for all countries, the global poverty rate would be 9%. For poverty at various poverty thresholds using distribution-neutral projections, see Table B.6.

Table A.1: Various projections for India, 2020

	India			Global		
	Poverty rate (%)	Change 2019-2020 (million)	Net COVID-19 impact (million)	Poverty rate (%)	Change 2019-2020 (million)	Net COVID-19 impact (million)
1. GDP per capita projection	11.0	23	37	8.8	38	57
2. Roy and van der Weide (2022)	13.4	56	70	9.3	71	90
3. Gupta et al. (2021)	16.2	94	109	9.8	109	130

Note: The *net COVID-19 impact* refers to the difference between the 2020 distribution with COVID-19 and the counterfactual distribution.

A.3 High-frequency phone surveys

(i) Surveys reporting income changes

As explained in the main text, the phone surveys provide information on whether households gained or lost income, but they do not report the size of the income change. This part of the Appendix provides the details on the methods we have used to apply the HFPSs.

We consider three non-overlapping groups of households in each residential area (rural or urban): those that experienced an increase, decrease, or no change in income. We can express total growth of rural households as a function of the growth rate of rural households with an increase, decrease, and no change in income, g_t^{rur+}, g_t^{rur-}, and, g_t^{rur0}, and their shares of total rural income, s_{t-1}^{rur+} , s_{t-1}^{rur-} , and s_{t-1}^{rur0}:

$$(1R)\ g_t^{rur} = g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} + g_t^{rur0} s_{t-1}^{rur0}.$$

Likewise, the urban growth can be expressed as:

$$(1U)\ g_t^{urb} = g_t^{urb+} s_{t-1}^{urb+} + g_t{}^{urb-} s_{t-1}^{urb-} + g_t^{urb0} s_{t-1}^{urb0}.$$

By construction, $g^{rur0} = g^{urb0} = 0$, and hence we can simplify (1R) and (1U) to:

$$(1R')\ g_t^{rur} = g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} \quad \text{and} \quad (1U')\ g_t^{urb} = g_t^{urb+} s_{t-1}^{urb+} + g_t{}^{urb-} s_{t-1}^{urb-}.$$

The income shares (s_{t-1}^{rur+}, s_{t-1}^{rur-}, etc.) can be estimated from the 2019 distributions.[5] However, g_t^{rur+}, g_t^{rur-}, g_t^{urb+}, and g_t^{urb-}, as well as growth in rural and urban areas (the left-hand sides) are unknown.

As explained in the main text, we use sectoral growth rates from national accounts to estimate these growth rates. Denoting the contribution to growth from agriculture, industry, and services as $g_t^{c,agr}$, $g_t^{c,ind}$, and $g_t^{c,ser}$, the total growth (g_t^{nat}) is given by $g_t^{nat} = g_t^{c,agr} + g_t^{c,ind} + g_t^{c,ser}$. Note that the contribution to growth from agriculture $g_t^{c,agr} = g_t^{agr} s_{t-1}^{agr}$, where g_t^{agr} is the growth in the agricultural sector and s_{t-1}^{agr} is the share of total income from agriculture, and likewise for other sectors.

We assume that growth in agricultural income accrues to rural households. Similarly, industrial growth is allocated to urban households. The growth in service income is split using the rural and urban l income shares from 2019. In other words, the rural contribution to national growth is given by $g_t^{c,rur} = g_t^{c,agr} + \theta\, g_t^{c,ser}$ and the urban contribution is given by $g_t^{c,urb} = g_t^{c,ind} + (1-\theta) g_t^{c,ser}$, where $\theta = s_{t-1}^{rur}$. We can then rewrite equations (1R') and (1U'):

$$(2R)\ g_t^{c,rur} = g_t^{c,agr} + \theta g^{c,ser} = (g_t^{rur+} s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-}) \times s_{t-1}^{rur}$$

$$(2U)\ g_t^{c,urb} = g_t^{c,ind} + (1-\theta) g_t^{c,ser} = \left(g_t^{urb+} s_{t-1}^{urb+} + g_t^{urb-} s_{t-1}^{urb-}\right) \times s_{t-1}^{urb}$$

The growth rate of rural (urban) households experiencing an income decline or increase (e.g. g_t^{rur+} and g_t^{rur-}) are still unknown. For households that experienced an increase in income in 2020, we set the size of the increase to match the growth projection prior to COVID-19. We refer to those growth rates by adding a 'preCOVID' subscript. The growth estimate still refers to 2020, but it was published before COVID-19 spread. This means we assume that

$$g_t^{rur+} = g_{t,preCOVID}^{c,agr} + \theta g_{t,preCOVID}^{c,ser} \text{ and } g_t^{urb+} = g_{t,preCOVID}^{c,ind} + \theta g_{t,preCOVID}^{c,ser}$$

We now have only one unknown in equations (2R) and (2U), g_t^{rur-} and g_t^{urb-}, and can find these by rearranging the equations:

$$g_t^{c,agr} + \theta g_t^{c,ser} = \left\{ \left(g_{t,preCOVID}^{c,agr} + \theta g_{t,preCOVID}^{c,ser}\right) s_{t-1}^{rur+} + g_t^{rur-} s_{t-1}^{rur-} \right\} \times s_{t-1}^{rur} \leftrightarrow$$

$$(3R)\ g_t^{rur-} = \frac{\left(g_t^{c,agr} + \theta g_t^{c,ser}\right)/s_{t-1}^{rur} - \left(g_{t,preCOVID}^{c,agr} + \theta g_{t,preCOVID}^{c,ser}\right) s_{t-1}^{rur+}}{s_{t-1}^{rur-}}.$$

Similar calculations for urban households' yield

$$(3U)\ g_t^{urb-} = \frac{\left(g_t^{c,ind} + (1-\theta) g_t^{c,ser}\right)/s_{t-1}^{urb} - \left(g_{t,preCOVID}^{c,ind} + (1-\theta) g_{t,preCOVID}^{c,ser}\right) s_{t-1}^{urb+}}{s_{t-1}^{urb-}}.$$

[5] As described in the main text, the observations in the 2019 distribution are assigned to the three income change categories (income growth, decline or no change) using a multinomial logit regression estimated on the HFPS.

To get some intuition for these equations, suppose all growth rates are negative, except for the preCOVID growth rates. The income declines of rural households are then driven by three factors (with a similar intuition for urban households):

1. [The first half in the numerator of (3R)]: The more agricultural and service sector income declined, the greater will be the income decline for rural households that have been assigned an income loss.
2. [The second half of the numerator in (3R)]: The greater growth in agriculture and services expected before COVID-19, and the more rural households experiencing income increases, the larger drops rural households assigned to an income loss will have. The reason for this is that the total growth needs to match national accounts. When there are more households that experience an income increase and/or their incomes grow by more, the larger has to be the decline such that it adds up to the same overall growth.
3. [The denominator of (3R)]: If more rural households experience a decrease in incomes, the loss per rural household will be smaller. If many households experienced declines, their rate of decline needs to be smaller to add up to the same total decline.

(ii) Surveys reporting consumption changes

For surveys that only report a consumption loss variable, we observe households with either a loss (-) in consumption or with no loss (*) in consumption. We follow a similar approach as outlined above to estimate growth rate for the households that experienced a loss in consumption. Following Equation (1R), we can write the growth in rural areas as follows:

$$g_t^{rur} = g_t^{rur*} s_{t-1}^{rur*} + g_t^{rur-} s_{t-1}^{rur-}$$

where g_t^{rur*} represents the growth for those rural households that did not experience a loss in consumption, g_t^{rur-}represents growth for rural households that experience a consumption loss, and s_{t-1}^{rur*} and s_{t-1}^{rur-} captures the share of total consumption held by the respective groups in the prior period.

Equation (2R) can then be modified as:

$$g_t^{c,rur} = g_t^{c,agr} + \theta g^{c,ser} = (g_t^{rur*} s_{t-1}^{rur*} + g_t^{rur-} s_{t-1}^{rur-}) \times s_{t-1}^{rur}.$$

As we did for households that experienced an income increase, we will assume that growth rate for households that experienced no loss in consumption is equivalent to expected growth rates forecasted before the COVID-19 pandemic. In particular, we assume $g_t^{rur*} = g_{t,preCOVID}^{c,agr} + \theta g_{t,preCOVID}^{c,ser}$, which allows us modify Equation (3R) to estimate the growth rate of rural households with consumption loss as:

$$g_t^{rur-} = \frac{\left(g_t^{c,agr} + \theta g_t^{c,ser} \right) / s_{t-1}^{rur} - \left(g_{t,preCOVID}^{c,agr} + \theta g_{t,preCOVID}^{c,ser} \right) s_{t-1}^{rur*}}{s_{t-1}^{rur-}}.$$

Following the same logic, we can estimate growth rate for the urban households that experience a consumption loss by:

$$g_{\mathrm{t}}^{urb-} = \frac{\left(g_t^{c,ind} + (1-\theta) g_t^{c,ser} \right) / s_{t-1}^{urb} - \left(g_{t,preCOVID}^{c,ind} + (1-\theta) g_{t,preCOVID}^{c,ser} \right) s_{t-1}^{urb*}}{s_{t-1}^{urb-}}.$$

Appendix B: Additional results

Table B.1: Overview of High-frequency phone surveys used

Country	Region	Question type
Burkina Faso	Sub-Saharan Africa	Consumption
Bulgaria	Europe & Central Asia	Income
Central African Rep.	Sub-Saharan Africa	Consumption
Congo, Dem. Rep.	Sub-Saharan Africa	Consumption
Gabon	Sub-Saharan Africa	Income
Ghana	Sub-Saharan Africa	Income
Guinea	Sub-Saharan Africa	Income
Gambia, The	Sub-Saharan Africa	Income
Guatemala	Latin America & Caribbean	Income
Honduras	Latin America & Caribbean	Income
Croatia	Europe & Central Asia	Income
Kazakhstan	Europe & Central Asia	Income
Kenya	Sub-Saharan Africa	Consumption
Lao PDR	East Asia & Pacific	Income
Mali	Sub-Saharan Africa	Consumption
Myanmar	East Asia & Pacific	Consumption
Mongolia	East Asia & Pacific	Consumption
Mozambique	Sub-Saharan Africa	Income
Mauritius	Sub-Saharan Africa	Income
Malawi	Sub-Saharan Africa	Income
Niger	Sub-Saharan Africa	Consumption
Nigeria	Sub-Saharan Africa	Income
Philippines	East Asia & Pacific	Income
Poland	Europe & Central Asia	Income
West Bank and Gaza	Middle East & North Africa	Income
Romania	Europe & Central Asia	Income
Sudan	Sub-Saharan Africa	Consumption
Senegal	Sub-Saharan Africa	Income
Solomon Islands	East Asia & Pacific	Consumption
El Salvador	Latin America & Caribbean	Income
South Sudan	Sub-Saharan Africa	Consumption
Tajikistan	Europe & Central Asia	Income
Tunisia	Middle East & North Africa	Income
Uganda	Sub-Saharan Africa	Consumption
Uzbekistan	Europe & Central Asia	Income
Zambia	Sub-Saharan Africa	Income
Zimbabwe	Sub-Saharan Africa	Consumption

Note: *Question type* reports either income (preferred) or consumption variable from the phone survey used to calculate the change probabilities reported in Table B.2. The income change question asks whether the household experience a loss, gain, or no change in income since the beginning of the pandemic. The consumption loss question reports whether a household experienced a loss in consumption.

Table B.2: Coefficients from multinomial logit regressions

		Total income increased			Total income decreased		
Country	Sector	Education	HH Size	Age	Education	HH Size	Age
Bulgaria	Rural	-.830	.5449	.6364	-.325	-.147	-.217
Bulgaria		(0.474)	(0.219)	(0.135)	(0.743)	(0.313)	(0.172)
Bulgaria	Urban	-.171	.1211	.4610	-.143	-.278	-.219
Bulgaria		(0.162)	(0.139)	(0.078)	(0.191)	(0.173)	(0.089)
Burkina Faso	Rural					-.031	-.100
Burkina Faso						(0.244)	(0.225)
Burkina Faso	Urban					.3396	.0009
Burkina Faso						(0.128)	(0.128)
Central African Republic	National				-.067	.0923	-.069
Central African Republic					(0.064)	(0.071)	(0.079)
Congo, Dem. Rep.	National					.5096	.0146
Congo, Dem. Rep.						(0.152)	(0.140)
Croatia	Rural	-.694	.0315	-.181	.0306	.5064	-.591
Croatia		(0.228)	(0.195)	(0.171)	(0.203)	(0.178)	(0.143)
Croatia	Urban	-.395	.5510	-.160	.1790	.7276	-.434
Croatia		(0.160)	(0.180)	(0.122)	(0.132)	(0.151)	(0.095)
El Salvador	National	.4418	-.112	.0324	-.096	.0621	-.033
El Salvador		(0.280)	(0.394)	(0.260)	(0.092)	(0.133)	(0.092)
Gabon	Rural		-2.10			.0541	
Gabon			(0.895)			(0.143)	
Gabon	Urban		-.102			.1082	
Gabon			(0.479)			(0.063)	
Gambia, The	Rural		9.720			-1.33	
Gambia, The			(768.489)			(0.899)	
Gambia, The	Urban		.8057			.1842	
Gambia, The			(0.672)			(0.112)	
Ghana	Rural	.0594	-.374	.4006	-.462	.0815	-.076
Ghana		(0.240)	(0.211)	(0.205)	(0.095)	(0.085)	(0.087)
Ghana	Urban	.4454	-.017	-.429	-.467	.0370	-.126
Ghana		(0.201)	(0.166)	(0.165)	(0.072)	(0.068)	(0.066)
Guatemala	National	.2273	.2183	.4855	-.092	.2502	-.132
Guatemala		(0.245)	(0.314)	(0.221)	(0.094)	(0.121)	(0.092)
Guinea	National		.0112	-.038		-.072	-.160
Guinea			(0.231)	(0.198)		(0.086)	(0.074)
Honduras	National	.2588	.3599	.2952	-.115	.1334	.0348
Honduras		(0.271)	(0.318)	(0.268)	(0.096)	(0.118)	(0.097)
Kazakhstan	Rural	.7119	.2198	-.274	-.112	-.284	-.275
Kazakhstan		(0.585)	(0.427)	(0.307)	(0.206)	(0.161)	(0.103)
Kazakhstan	Urban	.8488	.0427	-.137	-.254	.3269	-.314
Kazakhstan		(0.593)	(0.540)	(0.281)	(0.187)	(0.194)	(0.101)
Kenya	Rural					.2513	.0250
Kenya						(0.043)	(0.039)
Kenya	Urban					.1493	.1400
Kenya						(0.049)	(0.050)

Lao PDR	Rural	-.047	.1092	.0444	-.240	.0651	-.113
Lao PDR		(0.110)	(0.107)	(0.089)	(0.082)	(0.081)	(0.067)
Lao PDR	Urban	-.150	-.106	.0165	-.298	.0765	-.157
Lao PDR		(0.172)	(0.181)	(0.143)	(0.105)	(0.108)	(0.087)
Malawi	Rural	.6577	-.215	.2374	.0721	-.092	.1742
Malawi		(0.269)	(0.221)	(0.177)	(0.154)	(0.117)	(0.094)
Malawi	Urban	-.212	.0694	-.539	-.250	.3160	-.577
Malawi		(0.296)	(0.283)	(0.279)	(0.151)	(0.141)	(0.139)
Mali	Rural					.1652	-.205
Mali						(0.280)	(0.239)
Mali	Urban					.0491	.0137
Mali						(0.151)	(0.150)
Mauritius	National	-.421	.1731	-.480	-.358	.4077	-.669
Mauritius		(0.204)	(0.222)	(0.144)	(0.136)	(0.149)	(0.097)
Mongolia	Rural				.4467	.1235	-.052
Mongolia					(0.222)	(0.213)	(0.171)
Mongolia	Urban				-.221	.4710	-.116
Mongolia					(0.174)	(0.165)	(0.133)
Mozambique	Urban	-.071	-.695	.3474	-.542	.2438	.2219
Mozambique		(0.426)	(0.445)	(0.399)	(0.227)	(0.217)	(0.212)
Myanmar	Rural				.0539	.3773	-.235
Myanmar					(0.112)	(0.130)	(0.098)
Myanmar	Urban				.7647	.8944	.2870
Myanmar					(0.200)	(0.224)	(0.163)
Niger	Rural					.6874	.2612
Niger						(0.298)	(0.254)
Niger	Urban					.7035	-.117
Niger						(0.222)	(0.216)
Nigeria	Rural		-.561	-.176		-.129	-.187
Nigeria			(0.158)	(0.148)		(0.105)	(0.100)
Nigeria	Urban		.6590	.0824		.3388	-.159
Nigeria			(0.322)	(0.288)		(0.117)	(0.100)
Philippines	Rural	-.177	-.333	.0163	-.560	.1687	.0373
Philippines		(0.372)	(0.427)	(0.349)	(0.144)	(0.152)	(0.136)
Philippines	Urban	0.536	0.035	-0.21	-0.27	-0.08	0.454
Philippines		(0.316)	(0.249)	(0.224)	(0.116)	(0.116)	(0.100)
Poland	Rural	0.010	-0.31	-0.30	0.077	0.333	-0.12
Poland		(0.225)	(0.267)	(0.150)	(0.153)	(0.172)	(0.103)
Poland	Urban	-0.05	-0.00	0.147	0.200	0.169	-0.43
Poland		(0.178)	(0.211)	(0.110)	(0.123)	(0.140)	(0.074)
Romania	Rural	-1.55	0.316	-0.66	-0.51	0.387	-0.33
Romania		(0.576)	(0.494)	(0.351)	(0.226)	(0.241)	(0.150)
Romania	Urban	0.038	0.189	-0.08	-0.26	0.302	0.172
Romania		(0.536)	(0.616)	(0.350)	(0.170)	(0.199)	(0.113)
Senegal	Rural		-0.15			0.512	
Senegal			(0.508)			(0.194)	
Senegal	Urban		-0.80			0.280	
Senegal			(0.406)			(0.121)	
Solomon Islands	Rural				0.113	-0.75	0.851

Solomon Islands					(0.111)	(0.112)	(0.098)
Solomon Islands	Urban				0.101	-0.19	0.569
Solomon Islands					(0.062)	(0.065)	(0.053)
South Sudan	National					0.349	0.414
South Sudan						(0.150)	(0.114)
Sudan	Rural					0.134	
Sudan						(0.112)	
Sudan	Urban					0.009	
Sudan						(0.061)	
Tajikistan	Rural				0.125	-0.03	0.296
Tajikistan					(0.222)	(0.229)	(0.203)
Tajikistan	Urban				-0.00	0.438	0.291
Tajikistan					(0.541)	(0.439)	(0.344)
Tunisia	Rural	-0.73	1.139	-0.17	-0.47	-0.14	-0.30
Tunisia		(0.578)	(0.613)	(0.515)	(0.209)	(0.235)	(0.205)
Tunisia	Urban	0.169	0.579	-1.18	-0.29	0.834	-0.32
Tunisia		(0.305)	(0.447)	(0.374)	(0.109)	(0.173)	(0.141)
Uganda	Rural				0.048	0.278	-0.09
Uganda					(0.093)	(0.075)	(0.064)
Uganda	Urban				-0.28	-0.10	0.095
Uganda					(0.136)	(0.129)	(0.118)
Uzbekistan	Rural		0.654	0.217		0.743	0.187
Uzbekistan			(0.172)	(0.129)		(0.177)	(0.133)
Uzbekistan	Urban		-0.37	0.310		-0.05	0.327
Uzbekistan			(0.247)	(0.195)		(0.255)	(0.203)
West Bank and Gaza	Rural		0.494	-0.29		-0.10	-0.23
West Bank and Gaza			(0.220)	(0.162)		(0.046)	(0.030)
West Bank and Gaza	Urban		0.725	-0.02		-0.05	-0.14
West Bank and Gaza			(0.075)	(0.049)		(0.016)	(0.011)
Zambia	National	1.206	1.066	-15.4	0.103	-0.36	0.108
Zambia		(1.449)	(1.192)	(1997.757)	(0.426)	(0.297)	(0.278)
Zimbabwe	Rural					-0.00	-0.07
Zimbabwe						(0.086)	(0.067)
Zimbabwe	Urban					0.037	0.024
Zimbabwe						(0.166)	(0.127)

Note: The baseline category is no change in income. Standard errors are reported in parenthesis. Size of the households are categorized into four bins: 1-person household, 2 to 4-person household, 5 to 7-person household, and 7+ person household. Age of the household head is categorized into five bins: under 18 years of age, 19-30 years of age, 31-45 years of age, 46-65 years of age, 65+ years of age. Education of head of household is categorized into four bins: no education, any primary education, any secondary education, and any tertiary education.

Table B.3a: Changes in inequality (Gini index) for the countries using phone surveys

Country	Region	2019	2020 (COVID-19)	Change, Gini points
Burkina Faso	Sub-Saharan Africa	48.10	48.14	0.04
Bulgaria	Europe & Central Asia	40.19	41.59	1.40
Central African Republic	Sub-Saharan Africa	58.48	55.83	-2.66
Congo, Dem. Rep.	Sub-Saharan Africa	42.42	42.21	-0.21
Gabon	Sub-Saharan Africa	37.89	38.10	0.21
Ghana	Sub-Saharan Africa	43.58	43.09	-0.49
Guinea	Sub-Saharan Africa	29.55	30.88	1.33
Gambia, The	Sub-Saharan Africa	35.88	35.67	-0.22
Guatemala	Latin America & Caribbean	48.13	48.74	0.61
Honduras	Latin America & Caribbean	48.11	48.33	0.22
Croatia	Europe & Central Asia	28.88	30.55	1.68
Kazakhstan	Europe & Central Asia	27.90	27.92	0.02
Kenya	Sub-Saharan Africa	40.32	41.45	1.14
Lao PDR	East Asia & Pacific	39.46	39.04	-0.42
Mali	Sub-Saharan Africa	36.21	37.87	1.66
Myanmar	East Asia & Pacific	31.58	30.92	-0.66
Mongolia	East Asia & Pacific	33.35	33.08	-0.27
Mozambique	Sub-Saharan Africa	54.69	53.78	-0.91
Mauritius	Sub-Saharan Africa	37.24	37.97	0.72
Malawi	Sub-Saharan Africa	39.09	38.42	-0.66
Niger	Sub-Saharan Africa	37.40	37.04	-0.36
Nigeria	Sub-Saharan Africa	35.27	34.90	-0.37
Philippines	East Asia & Pacific	37.92	42.45	4.53
Poland	Europe & Central Asia	30.25	30.24	-0.01
West Bank and Gaza	Middle East & North Africa	33.77	33.95	0.19
Romania	Europe & Central Asia	34.78	36.06	1.28
Sudan	Sub-Saharan Africa	34.28	34.43	0.15
Senegal	Sub-Saharan Africa	38.61	37.78	-0.83
Solomon Islands	East Asia & Pacific	37.60	36.67	-0.93
El Salvador	Latin America & Caribbean	38.90	38.89	0.00
South Sudan	Sub-Saharan Africa	44.40	45.28	0.88
Tajikistan	Europe & Central Asia	33.91	34.29	0.38
Tunisia	Middle East & North Africa	32.88	33.33	0.45
Uganda	Sub-Saharan Africa	42.92	42.67	-0.26
Uzbekistan	Europe & Central Asia	35.46	35.38	-0.08
Zambia	Sub-Saharan Africa	57.38	56.77	-0.61
Zimbabwe	Sub-Saharan Africa	50.59	50.40	-0.19

Note: This table reports the Gini index for each country using the high frequency phone surveys for 2019 and 2020 (observed COVID distribution). The last column captures the Gini points change between 2020 and 2019. Note that the inequality of the counterfactual 2020 distribution is same as the 2019 distribution for each country.

Table B.3b: Changes in extreme poverty for the countries using phone surveys

Country	2019	2020 (counterfactual)		2020 (COVID-19)		Net COVID-19 impact, pp
	Rate, %	Rate, %	Change, pp	Rate, %	Change, pp	
Burkina Faso	30.00	28.90	-1.10	31.50	1.50	2.60
Bulgaria	0.90	0.80	-0.10	1.00	0.10	0.20
Central African Rep.	67.70	66.90	-0.80	67.80	0.10	0.90
Congo, Dem. Rep.	62.30	62.10	-0.20	62.60	0.30	0.50
Gabon	2.40	2.40	0.00	2.70	0.30	0.30
Ghana	22.20	21.20	-1.00	22.00	-0.20	0.80
Guinea	13.40	12.50	-0.90	14.20	0.80	1.70
Gambia, The	10.30	9.80	-0.50	11.00	0.70	1.20
Guatemala	6.90	6.80	-0.10	7.40	0.50	0.60
Honduras	12.70	12.00	-0.70	15.60	2.90	3.60
Croatia	0.20	0.20	0.00	0.40	0.20	0.20
Kazakhstan	0.00	0.00	0.00	0.00	0.00	0.00
Kenya	25.20	24.00	-1.20	25.90	0.70	1.90
Lao PDR	6.60	5.70	-0.90	6.90	0.30	1.20
Mali	14.40	13.70	-0.70	17.20	2.80	3.50
Myanmar	1.10	1.00	-0.10	1.10	0.00	0.10
Mongolia	0.40	0.30	-0.10	0.70	0.30	0.40
Mozambique	63.20	63.00	-0.20	64.40	1.20	1.40
Mauritius	0.00	0.00	0.00	0.20	0.20	0.20
Malawi	69.10	68.50	-0.60	69.10	0.00	0.60
Niger	50.10	48.80	-1.30	49.60	-0.50	0.80
Nigeria	30.90	31.00	0.10	32.30	1.40	1.30
Philippines	4.10	3.50	-0.60	9.70	5.60	6.20
Poland	0.00	0.00	0.00	0.00	0.00	0.00
West Bank and Gaza	0.50	0.50	0.00	1.00	0.50	0.50
Romania	2.10	2.00	-0.10	2.30	0.20	0.30
Sudan	21.20	22.70	1.50	24.00	2.80	1.30
Senegal	9.00	7.90	-1.10	8.20	-0.80	0.30
Solomon Islands	24.80	24.80	0.00	27.10	2.30	2.30
El Salvador	1.40	1.30	-0.10	1.80	0.40	0.50
South Sudan	71.90	70.50	-1.40	72.30	0.40	1.80
Tajikistan	3.50	3.20	-0.30	3.60	0.10	0.40
Tunisia	0.00	0.00	0.00	0.20	0.20	0.20
Uganda	40.50	39.30	-1.20	40.40	-0.10	1.10
Uzbekistan	30.10	28.00	-2.10	30.20	0.10	2.20
Zambia	61.10	61.20	0.10	61.70	0.60	0.50
Zimbabwe	39.70	39.40	-0.30	42.50	2.80	3.10

Note: This table reports the poverty rates (%) for each country using the high frequency phone surveys. For 2020, poverty rates and the percentage points change in poverty from 2019 is reported for both the observed distribution (with COVID) and the counterfactual distribution (no COVID). The last column captures the percentage points difference between the 2020 distribution with COVID-19 and counterfactual distribution. pp - percentage points.

Table B.4: Comparison of poverty and inequality estimates using various θ

		Poverty rate (%)		Gini index	
Country	Region	pop wt	inc wt	pop wt	inc wt
Burkina Faso	Sub-Saharan Africa	26.05	24.87	49.17	48.14
Bulgaria	Europe & Central Asia	0.88	0.85	41.95	41.84
Central African Republic	Sub-Saharan Africa	62.75	62.73	56.17	56.13
Congo, Dem. Rep.	Sub-Saharan Africa	56.71	56.70	42.27	42.19
Gabon	Sub-Saharan Africa	1.80	1.81	38.06	38.06
Ghana	Sub-Saharan Africa	17.83	17.81	43.16	43.14
Guinea	Sub-Saharan Africa	10.03	10.00	31.05	30.88
Gambia, The	Sub-Saharan Africa	7.45	6.87	35.92	35.57
Guatemala	Latin America & Caribbean	5.49	5.38	48.39	48.24
Honduras	Latin America & Caribbean	13.23	12.68	48.69	48.33
Croatia	Europe & Central Asia	0.41	0.41	30.55	30.46
Kazakhstan	Europe & Central Asia	0.01	0.01	27.94	27.92
Kenya	Sub-Saharan Africa	19.90	19.75	40.89	40.74
Lao PDR	East Asia & Pacific	3.90	3.80	39.06	38.97
Mali	Sub-Saharan Africa	12.00	12.01	37.89	37.77
Myanmar	East Asia & Pacific	0.65	0.65	30.83	30.86
Mongolia	East Asia & Pacific	0.22	0.25	33.06	33.06
Mozambique	Sub-Saharan Africa	59.08	58.75	54.00	53.78
Mauritius	Sub-Saharan Africa	0.08	0.15	37.21	38.01
Malawi	Sub-Saharan Africa	62.44	62.40	38.54	38.45
Niger	Sub-Saharan Africa	40.86	40.71	37.01	37.00
Nigeria	Sub-Saharan Africa	25.92	25.78	34.97	34.89
Philippines	East Asia & Pacific	6.53	6.38	42.48	42.40
Poland	Europe & Central Asia	0.00	0.00	30.20	30.19
West Bank and Gaza	Middle East & North Africa	0.69	0.69	33.89	33.89
Romania	Europe & Central Asia	1.89	1.90	36.10	36.05
Sudan	Sub-Saharan Africa	16.93	16.94	34.34	34.32
Senegal	Sub-Saharan Africa	5.29	5.26	37.68	37.56
Solomon Islands	East Asia & Pacific	20.53	20.33	36.73	36.64
El Salvador	Latin America & Caribbean	1.22	1.19	38.90	38.72
South Sudan	Sub-Saharan Africa	67.56	67.50	45.47	45.35
Tajikistan	Europe & Central Asia	2.26	2.26	34.26	34.24
Tunisia	Middle East & North Africa	0.14	0.10	33.61	33.30
Uganda	Sub-Saharan Africa	32.86	32.81	42.69	42.68
Uzbekistan	Europe & Central Asia	22.45	22.51	35.35	35.34
Zambia	Sub-Saharan Africa	58.19	57.80	57.52	56.78
Zimbabwe	Sub-Saharan Africa	37.48	36.35	51.18	50.40

Note: This table compares estimates for poverty (rate, %) and inequality (Gini index) using different θ in equations 3R and 3U. The weight used to split the growth of the service sector into rural and urban area, θ, is either the share of the population (*pop wt*) or share of income (*inc wt*). Poverty and inequality using the latter estimates are reported in the main text.

Table B.5a: Comparison of income inequality from the literature, Gini index and mean log deviation

	This paper				Milanovic (2021)				World Bank (2016)			
		MLD				MLD				MLD		
	Gini index	Total	Between-country	No. of countries	Gini index	Total	Between-country	No. of countries	Gini index	Total	Between-country	No. of countries
1988									69.7	101.4	80.0	73
1993	69.7	98.7	73.7	218					69.3	98.3	75.9	102
1998	69.3	96.7	72.2	218					68.6	94.0	73.5	106
2003	68.4	92.6	70.4	218					68.7	93.9	72.3	135
2008	66.3	85.5	67.8	218	66.4	91.0	61.9	136	66.6	86.3	69.8	136
2013	63.0	75.3	65.6	218	61.6	75.9	59.7	131	62.5	74.5	65.2	101

Table B.5b: Comparison of income inequality from the literature, income shares

	This paper			World Inequality Report (2022)		
	Top 10%	Middle 40%	Bottom 50%	Top 10%	Middle 40%	Bottom 50%
2019	48.8	40.2	10.9	52.2	39.3	8.5
2020	49.5	39.8	10.7	52.3	39.3	8.4

Source: PIP; Milanovic (2021); World Bank (2016); Chancel et al. (2022).

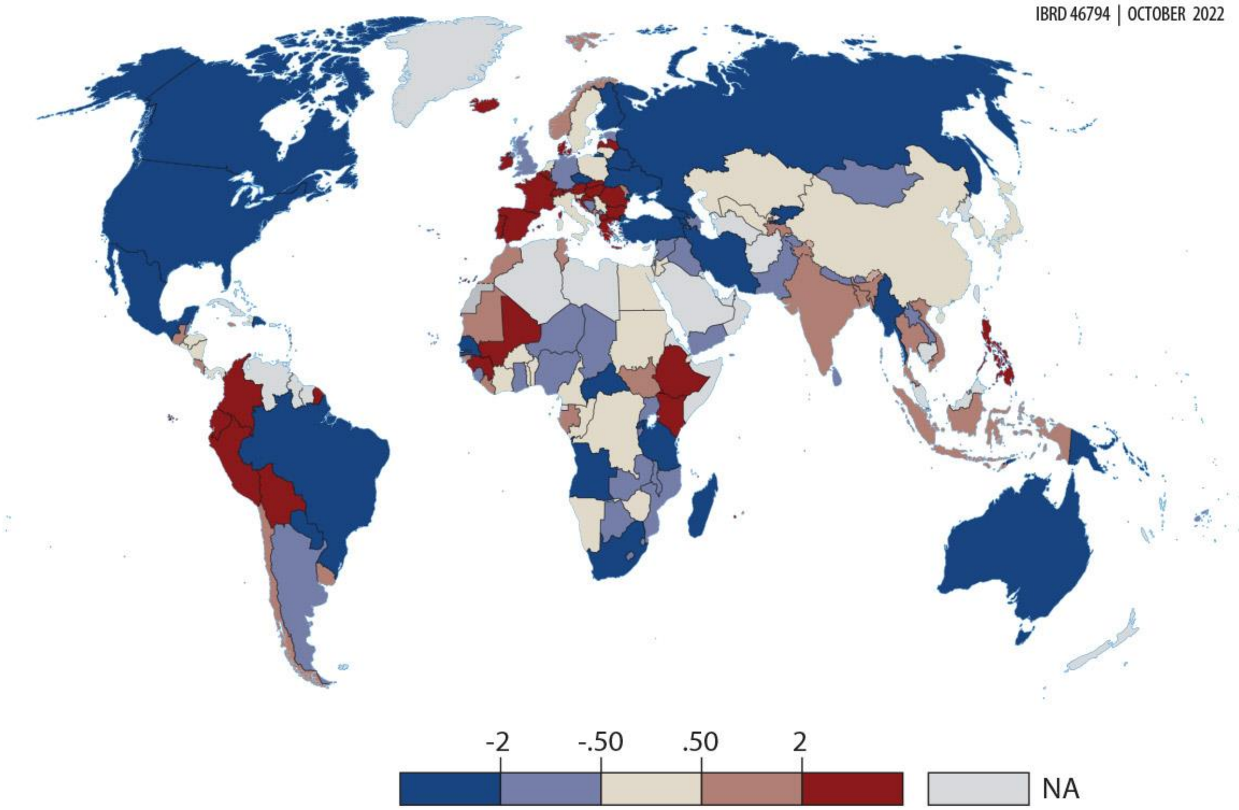
Note: Panel a compares estimates of the Gini index and mean log deviation (x100) from various sources with the current paper. The between-country share (in %) according to the mean log deviation is also reported. Panel b reports the income shares (in %) of the top 10%, middle 40%, and the bottom 50% of the respective income distributions. MLD – mean log deviation.

Table B.6: Poverty rate based on distribution-sensitive and distribution-neutral assumptions

		Poverty rate, %			Millions of poor			Net COVID-19 impact (millions)	
Region	Line	Counter -factual	COVID (base)	COVID (GDP)	Counter -factual	COVID (base)	COVID (GDP)	COVID (base)	COVID (GDP)
East Asia and the Pacific	2.15	0.9	1.4	1.2	20.0	28.6	26.2	8.6	6.2
Europe and Central Asia	2.15	2.2	2.4	2.4	11.0	12.0	12.0	1.0	1.0
Latin America and the Caribbean	2.15	4.1	3.9	4.8	26.8	25.4	30.9	-1.4	4.2
Middle East and North Africa	2.15	8.1	8.4	8.5	32.4	33.6	34.1	1.3	1.7
Rest of the World	2.15	0.6	0.6	0.6	6.1	6.3	6.3	0.2	0.2
South Asia	2.15	7.5	11.4	9.8	138.7	211.7	181.1	73.0	42.4
Sub-Saharan Africa	2.15	34.6	35.3	36.1	393.6	401.1	410.2	7.5	16.6
Global	*2.15*	*8.1*	*9.3*	*9.0*	*628.5*	*718.8*	*700.9*	*90.3*	*72.4*
East Asia and the Pacific	3.65	6.8	8.2	7.7	143.1	172.3	163.2	29.3	20.2
Europe and Central Asia	3.65	6.0	6.4	6.3	29.8	31.6	31.4	1.8	1.7
Latin America and the Caribbean	3.65	10.3	10.1	11.7	66.5	65.5	76.1	-1.0	9.7
Middle East and North Africa	3.65	17.6	17.7	18.4	70.5	71.1	74.0	0.6	3.5
Rest of the World	3.65	0.8	0.7	0.8	8.4	7.8	8.8	-0.6	0.4
South Asia	3.65	39.6	46.0	44.7	735.3	854.8	829.7	119.5	94.4
Sub-Saharan Africa	3.65	61.9	63.4	63.3	703.4	720.5	719.2	17.0	15.7
Global	*3.65*	*22.6*	*24.8*	*24.5*	*1756.9*	*1923.6*	*1902.4*	*166.7*	*145.6*
East Asia and the Pacific	6.85	30.3	33.7	31.9	639.5	712.8	674.7	73.3	35.2
Europe and Central Asia	6.85	14.7	15.5	15.6	72.9	77.0	77.3	4.0	4.4
Latin America and the Caribbean	6.85	27.5	27.9	30.8	178.3	181.1	199.8	2.7	21.4
Middle East and North Africa	6.85	45.1	47.3	47.4	180.9	189.7	190.2	8.9	9.3
Rest of the World	6.85	1.3	1.2	1.4	14.2	13.0	15.2	-1.3	0.9
South Asia	6.85	81.1	84.1	83.4	1505.8	1562.0	1548.3	56.1	42.4
Sub-Saharan Africa	6.85	86.3	87.0	87.0	980.5	988.3	988.7	7.8	8.2
Global	*6.85*	*46.0*	*48.0*	*47.6*	*3572.2*	*3723.7*	*3694.1*	*151.6*	*121.9*

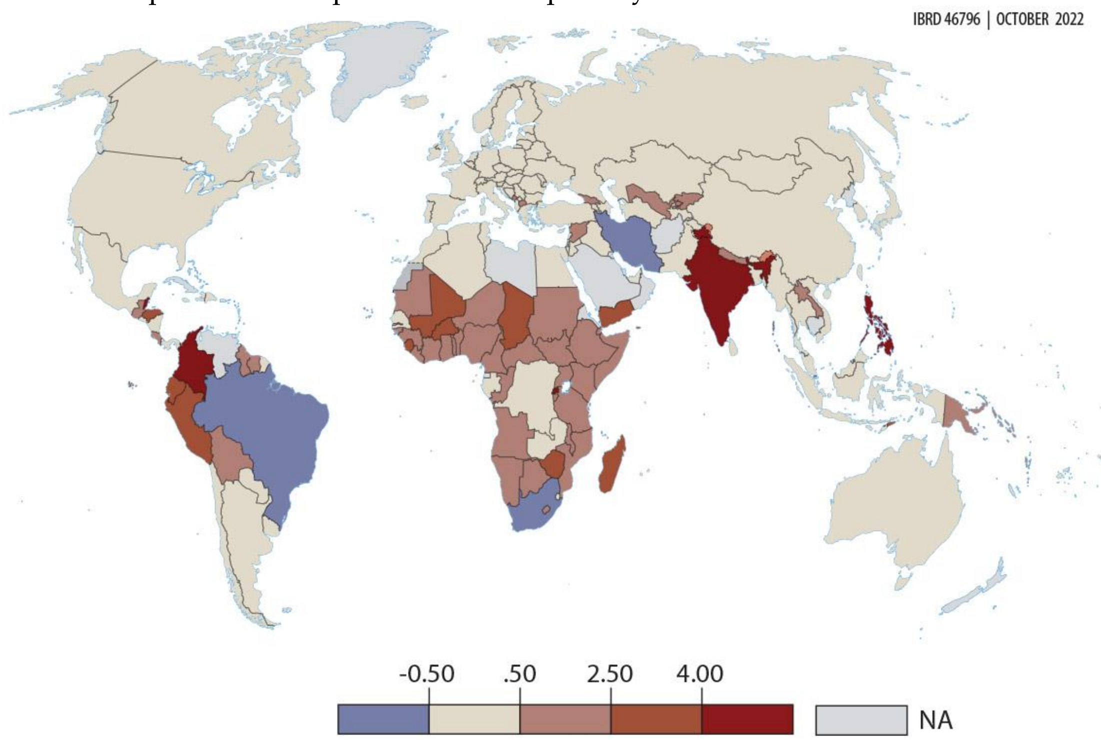
Note: This table reports the global and regional poverty rate (%) and the millions of poor at three poverty lines -- $2.15 a day, $3.65 a day, and $6.85 a day -- for the counterfactual 2020 distribution, and for two COVID-19 scenarios: (a) based on the method discussed in this paper (*baseline*), which accounts for household distributional changes, and (b) based on a distribution-neutral projection using per capita GDP growth in all countries (*GDP*). The last two columns report the *Net COVID-19 impact*, which is the difference between the 2020 distribution with COVID-19 and counterfactual distribution.

Map B.1: Change in within-country inequality from 2019 to 2020, percent

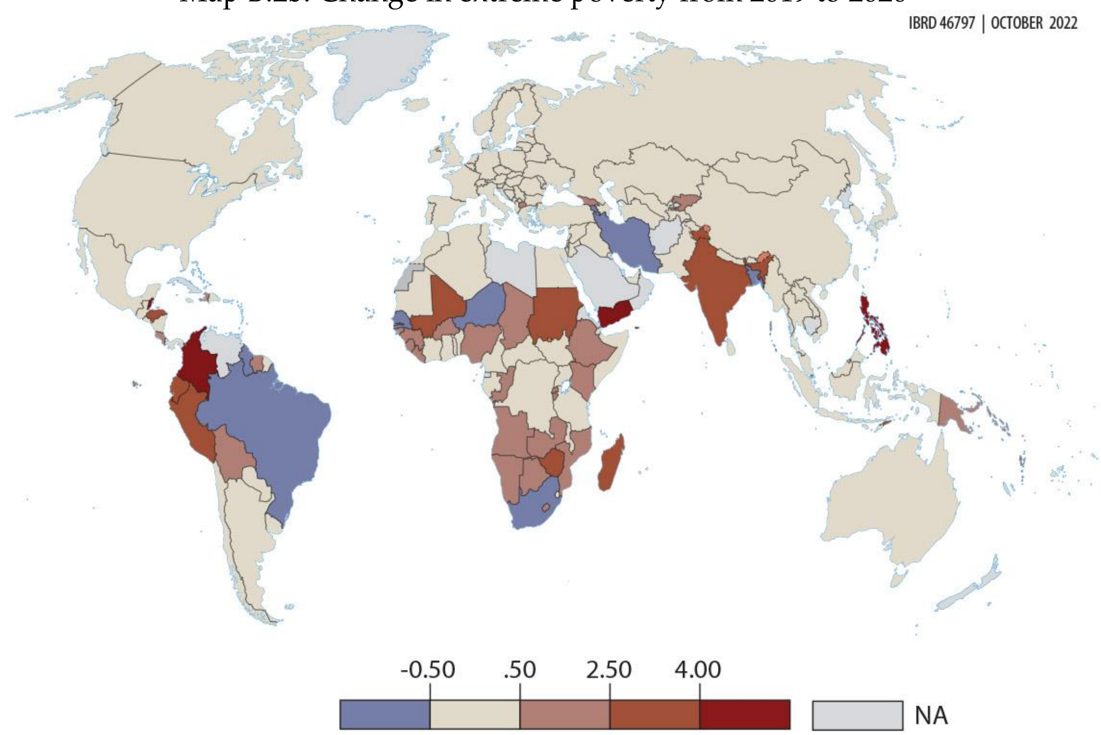


Note: Figure reports the percent change in the Gini index from 2019 to 2020. NA – countries with no micro data in PIP or countries using per capita GDP based distribution-neutral projection.

Map B.2a: Net impact on extreme poverty due to COVID-19 in 2020

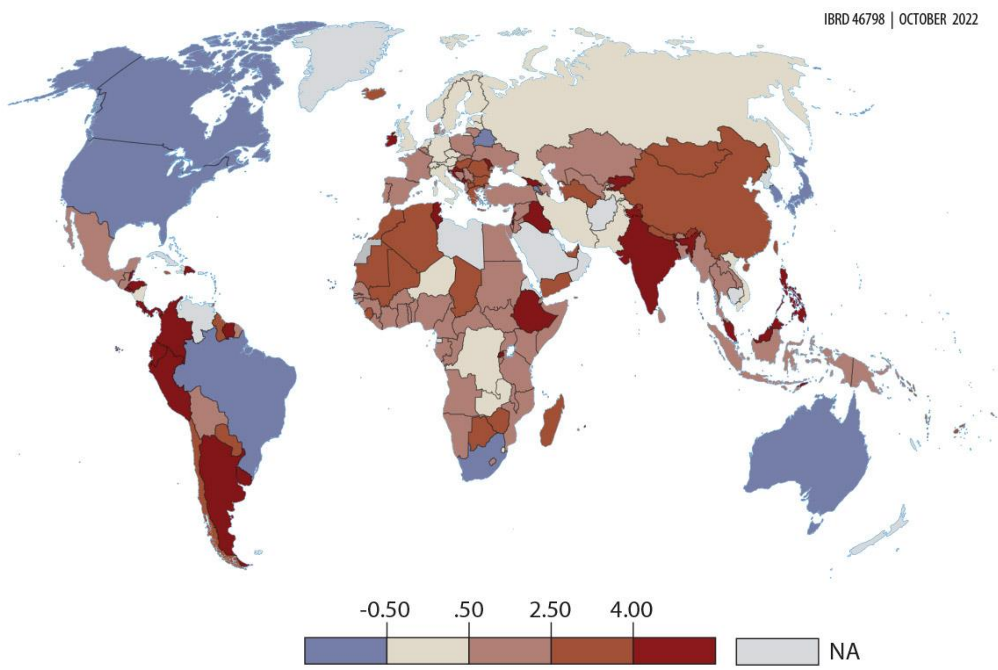


Map B.2b: Change in extreme poverty from 2019 to 2020

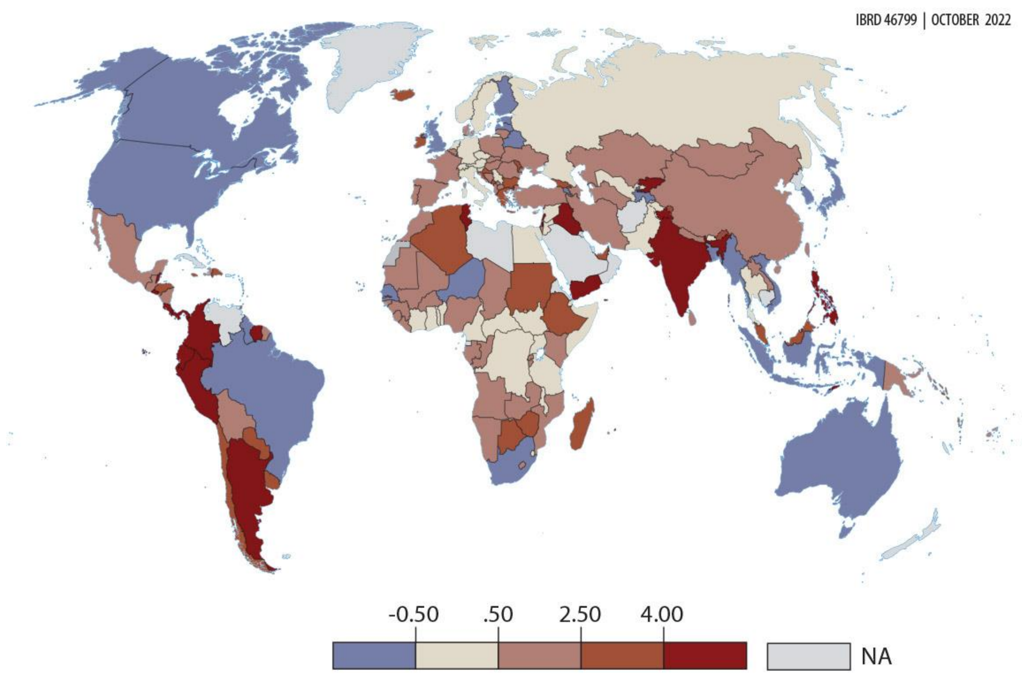


Note: Panel a reports the percentage points change in extreme poverty – those living below the $2.15-a-day threshold -- in 2020 compared to the counterfactual. Panel b reports the same using the 2019 distribution as baseline. NA – countries with no micro data in PIP; pp – percentage point.

Map B.3a: Net impact on societal poverty due to COVID-19 in 2020

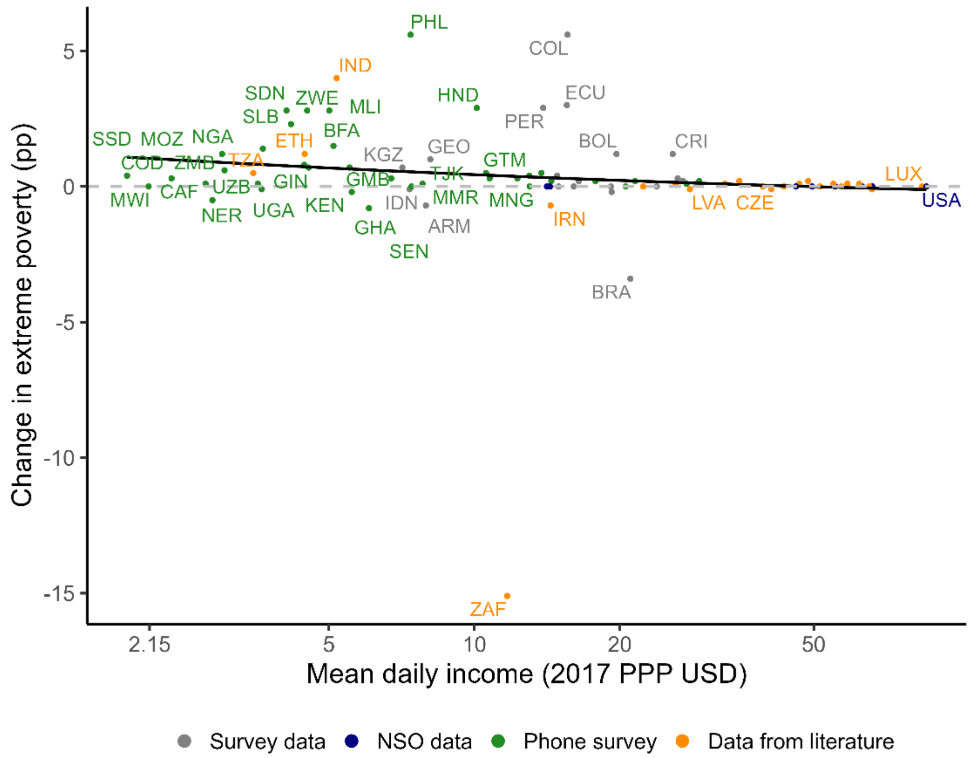


Map B.3b: Change in societal poverty from 2019 to 2020



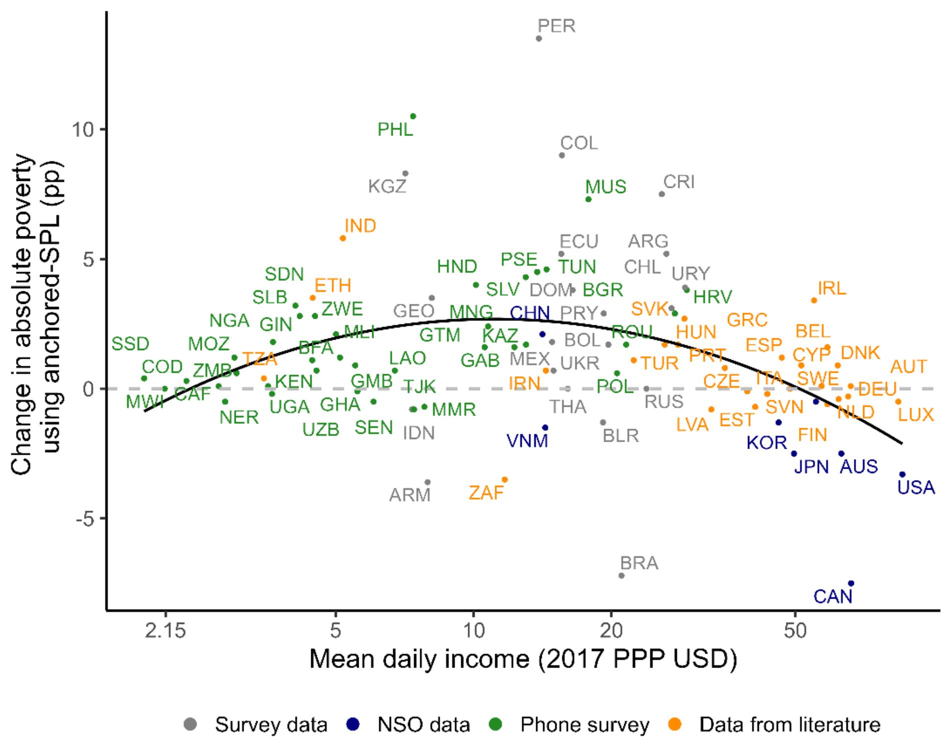
Note: Panel a reports the percentage points change in societal poverty in 2020 compared to the counterfactual. Panel b reports the same using the 2019 distribution as baseline. The anchored societal poverty line (SPL) for each country is calculated as max($2.15, $1.15 + 0.5 x median daily income in 2019). The color coding for Taiwan, China represents data value for China, which is 3.8 in panel a and 2.1 in panel b. The corresponding data values for Taiwan, China are -0.5 and -1.0. NA – countries with no micro data in PIP; pp – percentage point.

Figure B.1: Change in extreme poverty from 2019 to 2020, by country



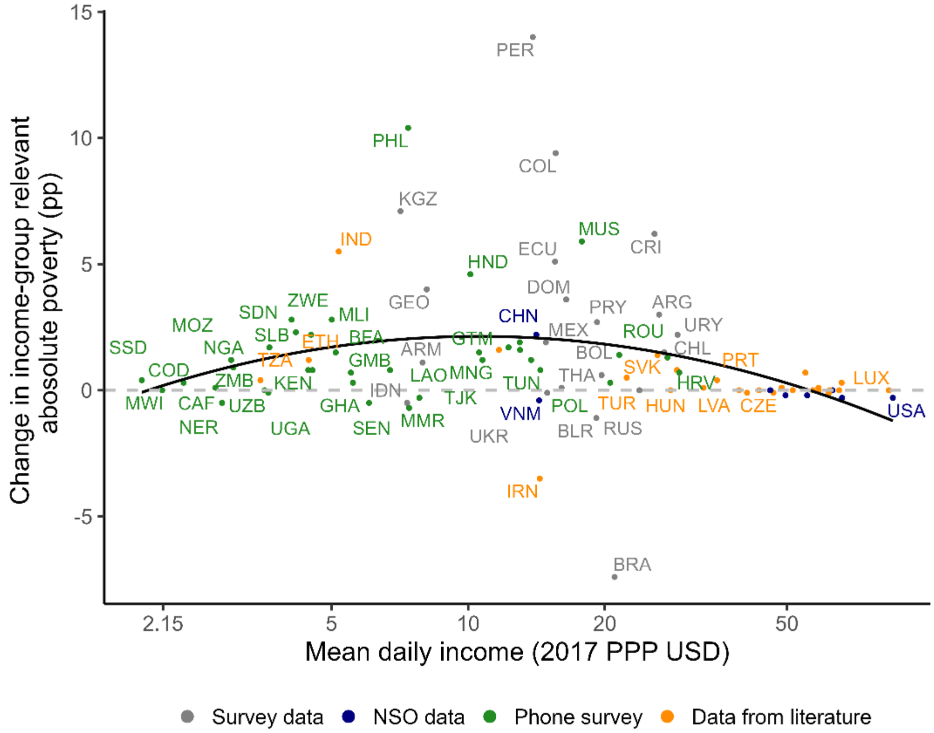
Note: This figure reports the percentage points change in the extreme poverty rate from 2019 to 2020. Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. The solid line is fitted using a quadratic specification. PPP – purchasing power parity; pp – percentage point.

Figure B.2: Change in societal poverty from 2019 to 2020, by country



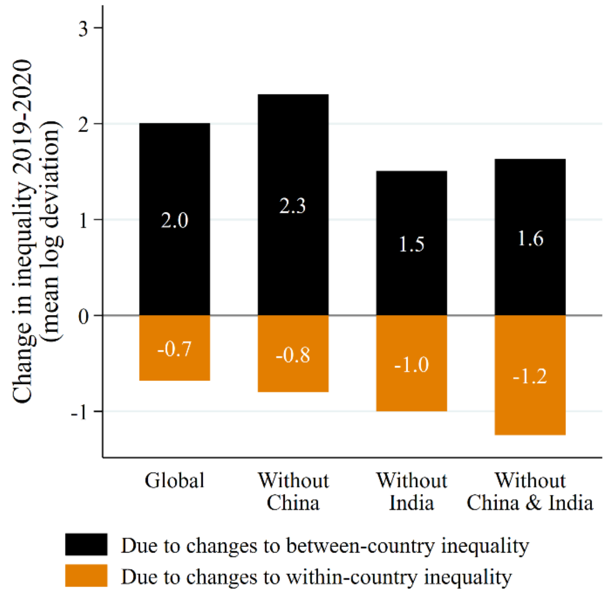
Note: This figure reports the percentage points change in societal poverty from 2019 to 2020. Poverty for each country is calculated using the societal poverty line (SPL) anchored to 2019. This anchored-SPL is calculated as max($2.15, $1.15 + 0.5 x median daily income in 2019). Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. The solid line is fitted using a quadratic specification. PPP – purchasing power parity; pp – percentage point.

Figure B.3: Change in absolute poverty from 2019 to 2020, using income-group poverty lines



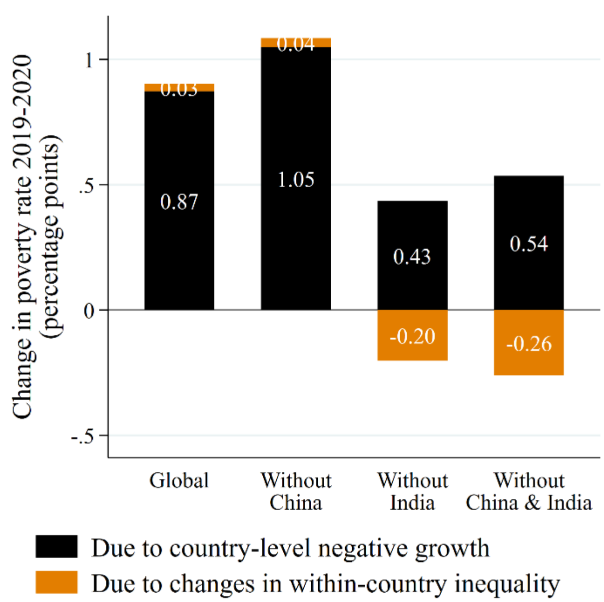
Note: This figure reports the percentage points change in absolute poverty from 2019 to 2020. The absolute poverty for each country is calculated using income-group specific poverty lies, which are $2.15 a day for the low-income countries, $3.65 a day for lower-middle income countries, and $6.85 a day for the rest. Only countries with estimates based on the four preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. The solid line is fitted using a quadratic specification. PPP – purchasing power parity; pp – percentage points.

Figure B.4: Disaggregation of global inequality into within and between country inequality



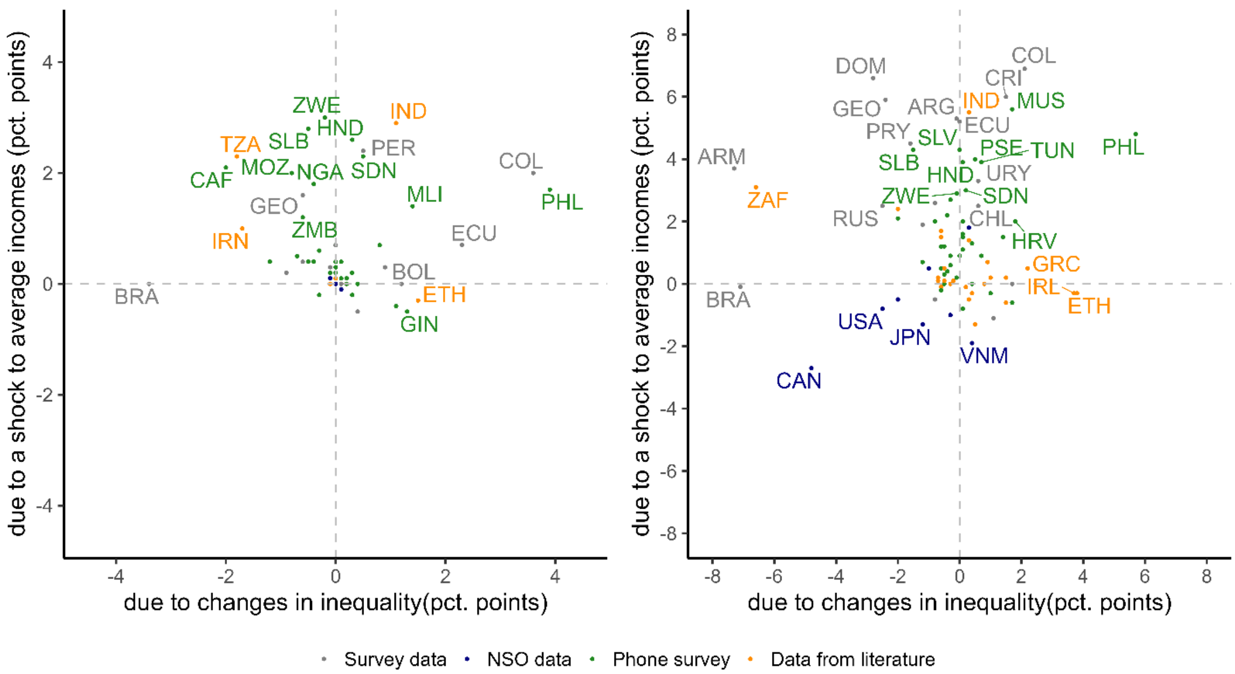
Note: This figure shows the disaggregation of the change in global inequality from 2019 to 2020 into between- and within-country components. The disaggregation of the total is shown for the global estimate with and without China and India.

Figure B.5: Disaggregation of global extreme poverty into growth and inequality components



Note: This figure shows the disaggregation of the change in global extreme poverty from 2019 to 2020 into poverty caused by negative income shocks and within-country inequality changes. The disaggregation of the total is shown for the global estimate with and without China and India.

Figure B.6: Disaggregation of change in absolute poverty into growth and inequality component



Note: This figure disaggregates change in poverty (using anchored-SPL) from 2019 to 2020 into negative income shocks and within-country inequality changes, by country. See also Figure 3. Only countries where we have data with one of the four preferred methods are included. South Africa is excluded from panel a as it is an outlier.

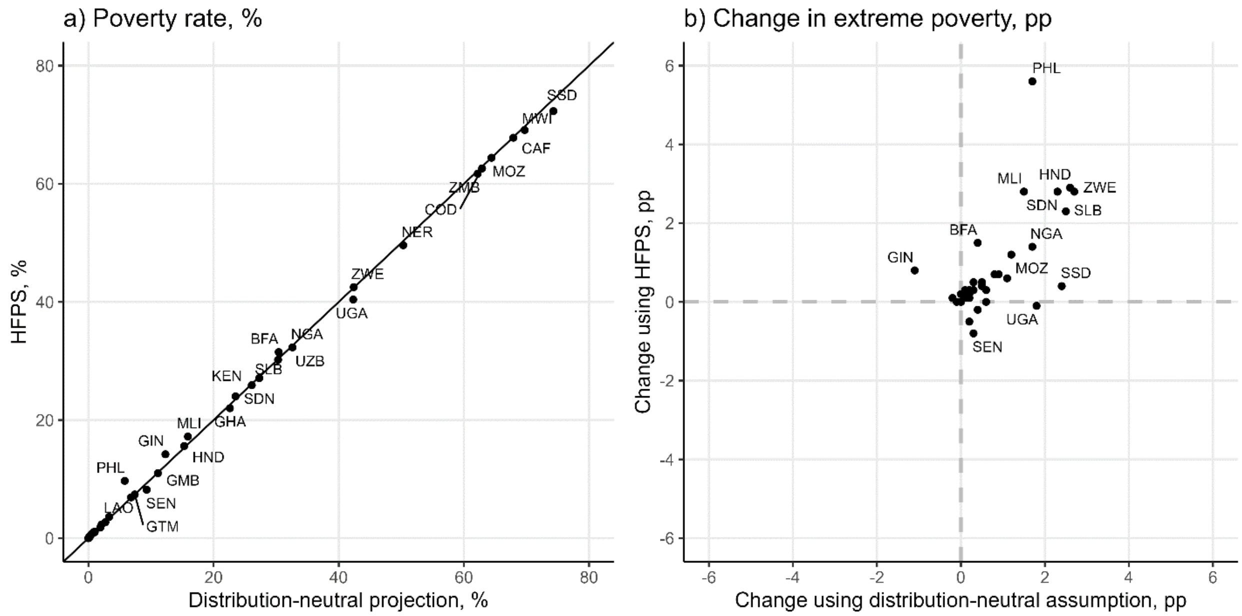
Figure B.7: Distribution of impacts of COVID-19 on inequality with 1000 simulations

Note: This figure shows the distribution of the impact of COVID-19 on inequality in 2020 from 1000 simulations for each country utilizing the high frequency phone surveys. Each simulation adds some random noise to our preferred growth rate for each household. The impact on inequality is the percent difference in the projected Gini index for the 2020 welfare distribution and counterfactual 2020 welfare distribution. The dashed vertical line represents the impact with the constant growth assumption used in the paper.

Figure B.8: Distribution of impacts of COVID-19 on poverty with 1000 simulations

Note: This figure shows the distribution of the impact of COVID-19 on poverty in 2020 from 1000 simulations for each country utilizing the high frequency phone surveys. Each simulation adds some random noise to our preferred growth rate for each household. The impact on poverty is the percentage point difference in the projected extreme poverty rate for the 2020 welfare distribution and counterfactual 2020 welfare distribution. The dashed vertical line represents the impact with the constant growth assumption used in the paper. pp – percentage points.

Figure B.9: Comparison of poverty using phone survey and per capita GDP



Note: This figure compares the projected poverty rates in 2020 (panel a) and the 2019-2020 change in poverty rate (panel b) using the high-frequency phone survey compared to using the growth in per capita GDP. HFPS – high-frequency phone survey; pp – percentage points.