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WORK IN PROGRESS

Abstract

COVID-19 has had catastrophic economic consequences worldwide. This paper tries to quantify the consequences of the pandemic on global inequality and poverty in 2020. To this end, a combination of data sources is used including (i) actual income data from National Statistical Offices, (ii) high-frequency phone surveys, (iii) country-level estimates of the impact of the pandemic on poverty and inequality from the literature, and (iv) sectoral and aggregate GDP growth rates from national accounts. Results suggest that the world in 2020 witnessed the largest increases to global inequality and poverty since at least 1990. These findings are primarily driven by country-level shocks to average incomes and an increase in between-country inequality. Changes to within-country inequality were relatively modest, particularly in high-income countries, many of which saw inequality decline in 2020.

Keywords: Poverty, inequality, COVID-19
JEL codes: D63, I14, I15, I32

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Introduction

Though 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 (United Nations and World Bank 2020). Without the household surveys and other surveys national statistical offices regularly conduct to track economic well-being, information on the magnitude of the economic consequences has been lacking.

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 economics 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 Portal (PIP) as our starting point. To get estimates for 2020 we use published household surveys where available and compliment them with a simulation exercise using High-Frequency Phone Surveys (HFPS) for 46 countries. Though the HFPS 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, sectoral national account data, and a set of assumptions to deduce the impact of the pandemic along countries' distribution. For some countries without HFPS, we rely on estimates from simulations published in the literature. Taken together, we are able to derive estimates of the global distribution of economic welfare in 2020. To isolate the impact of the pandemic, we compare our 2020 distributions with counterfactual 2020 distributions. These counterfactual distributions are created by assuming that countries in 2020 would experience the growth expected by growth forecasts released in 2019 before the pandemic spread.

We aim to contribute to the literature by providing the first empirically driven global estimates of the impact of the pandemic on inequality and poverty that explicitly factor in the differential impacts the pandemic may have had along the distribution. Earlier work has analyzed the impact of the pandemic on global inequality without accounting for within-country inequality (such as Deaton 2021), on global poverty without accounting for within-country inequality (such as Lakner et al. forthcoming, Valensisi 2020, Sumner et al. 2020), and on global poverty accounting for within-country inequality using general equilibrium models (Laborde et al. 2021). Several cross-country studies exist that estimate the impact of the pandemic on poverty and inequality (Clark et al. 2021, Lastunen et al. 2021, Lustig et al. 2021, Palomino et al. 2020).

A secondary contribution is to provide annual estimates of global inequality from 1990 to today. Previous studies, such as Lakner and Milanovic (2016) and Milanovic (2021) utilize household surveys only available in benchmark years. For instance, Milanovic (2021) has 131 countries accounted for in the global distribution benchmarked to 2013. These are the number of surveys available in 2013 or +/- 1 year. Our approach on the other hand is to interpolate and extrapolate household surveys such that we cover all the 218 World Bank economies. This methodology is similar to the methodology used for reporting global poverty by the World Bank (see Prydz et al. 2019 and Ferreira et al. 2016). While our approach requires additional assumptions, it allows us to (i) provide global inequality measures that are consistent with the global poverty measures, and (ii) provide annual estimates of global inequality.

Our estimates of global inequality are referred to as *Concept 3* inequality, which is defined as "inequality between all citizens of the world" (Milanovic 2005). In this concept of global inequality, individuals are ranked according to their personal income no matter the country or region they reside in. This concept is different than Milanovic's *Concept 1* and *2* inequality, both of which use the per capita GDP as the welfare aggregate rather than personal incomes. *Concept 2* differs from *Concept 1* in that the former accounts for the size of populations across countries whereas the latter gives equal weights to all countries. Our objective is to calculate the change in welfare of individuals around the world for which Concept 3 inequality fits best. Our approach is different from the methods that distribute total income from national accounts to households or individuals (for a discussion of one such method, see Piketty et al (2018).

We find that the world in 2020 witnessed the largest increases to global inequality and poverty since at least 1990. The global Gini increased by 1 point due to the pandemic and 143 million more people were living in extreme poverty---measured as having a daily income or consumption below $1.90---because of the pandemic. Both of these findings reverse trends that have taken five years to accomplish. The uptick in global inequality is driven by increases in between-country inequality, reflecting that the shock to mean welfare was larger in poorer countries. Though inequality within countries did increase in many developing countries, inequality decreased in many high-income countries and certain populous developing countries, such as China, India, and Brazil. Likewise, the uptick in extreme poverty was driven by shocks to average incomes and not by changes to inequality within countries. The increases in both inequality and extreme poverty were driven by India, yet the same qualitative results are present without India.

The rest of the paper is organized as follows. Section 2 outlines some of the possible mechanisms that could influence the impact of COVID-19 on poverty and inequality. Section 3 explains the data sources we use. Section 4 details our methodology to recover distributions for 2020. Section 5 covers our main results. Section 6 contains some robustness checks. Section 7 concludes.

1. Potential mechanisms

The pandemic, its economic consequences, and the policy responses to these consequences have impacted poverty and inequality across and within countries in a variety of ways. Several channels pull 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.

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 at the bottom of the distribution. 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 distribution there.

In response to the economic shutdowns, countries around the world implemented emergency transfers and other mitigating economic mechanism 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.

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 increase poverty.

Beyond 2020, different factors have been at play, such as access to vaccines, the elimination of emergency social support, and inflation.

2. Data

We use four different data sources in this paper. Our starting point is the distribution of welfare in each country in 2019 from the Poverty and Inequality Portal (PIP), which contains the World Bank's official country-level, regional, and global estimates of poverty. 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 comes from the Global Monitoring Database, which is the World Bank's repository of multitopic income and expenditure household surveys used to monitor global poverty. PIP contains more than 2000 surveys from 168 countries covering 97.7% of the world's population. The data available in PIP are standardized as far as possible but differences exist with regards to the method of data collection, and whether the welfare aggregate is based on income or consumption.

For 156 of the countries, housing 73% of the world's population, micro data are available. For an additional 8 economies (Australia, Canada, Germany, Israel, Japan, South Korea, Taiwan, and the United States), or 8% of the world's population, grouped 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 are 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

The second data source we use is the High-Frequency Phone Surveys (HFPSs) that the World Bank has collected in collaboration with National Statistical Offices (NSOs). These surveys, as their name indicates, are conducted over the phone and are hence less comprehensive than traditional household surveys. Yet their mode of data collection means that they can be conducted even during strict quarantines and government shutdowns. In many countries, phone surveys are some of the only national surveys available from 2020. At the time of writing, such surveys have been conducted in 72 countries across all developing regions. More than 100 indicators have been harmonized across countries from these surveys.

A challenge with using the HFPSs is that they are not nationally representative for a few reasons. First, households without a phone are outside of 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. Most of the phone surveys have been reweighted, which can partially overcome these problems (Ambel et al. 2021; Brubaker et al. 2021). Yet if conditional on covariates households without any phone are fundamentally different from households with phones, then there is only so much reweighting can do. [2]

A third data source that we use is sectoral and national growth rates from national accounts. For this purpose, we use data from the World Bank's Macro and Poverty Outlook (MPO). We use the most recent vintage from the fall of 2021 (which contains estimates – not forecasts – of growth

[2] We could further post-stratify the weights based on the missing values of our variable of interest. We opt for not doing so. If we had post-stratified, we would have used the variables we use to differentiate probabilities of experiencing increases or declines in incomes, given that these are the variables that likely matter for representativeness and are widely available across countries. All reweighting would do in this case, is to shift the total weight from some household types to others, without affecting the distribution of weights within household types. As we are only using the surveys to get statistics for types of households differentiated by these variables, and not to obtain nationally representative statistics, this would not matter to us.

in 2020) as well as the vintage that just preceded the outbreak the pandemic, from the fall of 2019 (which contains growth forecasts for 2020). We use the latter for our counterfactual 2020 scenario (discussed in Section 4.2).

Finally, we rely on published income and consumption data for 2020, which we retract directly from the websites of national statistical offices.

3. Methodology

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

3.1 Estimating the 2019 welfare distribution

Not all countries conducted household surveys in 2019. For countries that did not, 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 data from national accounts, and that inequality has not changed since the time of the last survey and 2019. Mahler et al. (2021) show that both of these assumptions are relatively accurate. More complicated methods that try to predict growth in the survey mean and/or changes to inequality yield only slight increases to predictive accuracy.

This approach is possible for 168 countries with data available in PIP. For the countries that do not have any prior household surveys, we assume their 2019 distribution equals the 2019 distribution of the region they belong to, using the regions available in PIP. For instance, Afghanistan is not available in the South Asia region. The 2019 distribution we use for Afghanistan is the population-weighted distribution of the rest of the countries in South Asia. Close to 2.5% of the world population is estimated as such for 2019.

3.2 Estimating a counterfactual 2020 welfare distribution

Some countries might have seen poverty decline in 2020 even though they have been negatively impacted by the pandemic. This could happen if the poverty decline would have been greater in the absence of the pandemic. Vice versa, some countries may have seen poverty increase in 2020, yet have been unimpacted by the pandemic if a similarly sized poverty increase would have happened without the pandemic taking place. To control for such patterns and isolate the impact of the pandemic on poverty and inequality, we estimate a counterfactual 2020 welfare distribution that approximates what the income distribution in the country would have looked like in the absence of the COVID-19 pandemic.

To that end, we use the October-2019 per capita GDP growth forecasts for 2020 from the MPOs 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 to the 2019 level. Evidence suggests that there are differences between growth in the mean consumption from household surveys and growth in per capita GDP (Ravallion 2003, Deaton 2005, Lakner et al. forthcoming, Prydz et al. forthcoming). To account for this, we deflate the per capita GDP growth in 2020 by 0.85 (for detail see Lakner et al., forthcoming). This implies that if a country's per capita GDP growth forecast is 1 percent, households' welfare will grow by 0.85 percent.[3]

A concern with our use of a counterfactual estimate is that it may be a poor approximation of what would have happened without COVID for several reasons. For one, the growth forecasts in the MPOs may be inaccurate. While we are unable to test this, the growth forecasts are based on all the information available as of the fall of 2019. Second, even if the growth forecasts are accurate, the counterfactual distribution will only be accurate if welfare in household surveys grows in accordance with growth in real GDP per capita and if inequality would not have changed in the absence of COVID. As we argued when explaining how the 2019 distributions are derived, these two assumptions are on average relatively accurate compared to more sophisticated modeling approaches. Third, the pandemic was not the only thing that happened in 2020. In countries where environmental disasters hit in 2020, where significant economic policies unrelated to COVID were implemented, or where conflict erupted or stopped, the difference between our 2020 estimates and counterfactual estimate captures other elements than the pandemic. We think it is safe 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 effect of the pandemic – that is the difference in 2020 between the one with (discussed in the next section) and one without COVID-19. However, we also report the change in inequality and poverty from 2019 to 2020, which can be thought of as a gross effect.

4.3 Estimating the "actual" 2020 welfare distribution

We rely on various data sources to generate the 2020 pandemic-influenced welfare distribution. In order of preference, these are: (i) household income growth data collected by country NSOs, (ii) HFPSs, (iii) simulations from other papers, and (iv) sectoral and national growth rates from MPOs.

(i) Estimates for countries with household surveys conducted in 2020

For seven countries -- Australia, Canada, China, Russia, South Korea, the U.S, and Vietnam -- we rely on tabulated or grouped data acquired from these countries' NSOs to create the 2020

[3] 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).

distribution. In several cases, we need to make important assumptions to match this data to our 2019 distributions.

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 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 first half of 2019, so we do not have data from the first half of 2020.

For Canada, we rely on experimental estimates of the growth rate in disposable income by quintile for 2020 (Chart 1 of Statistics Canada 2021).

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, which is not available by quintile yet. 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) did produce *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.

For Russia we rely on data received from the Federal State Statistics Service on the share of the population with incomes in 10 prespecified categories in 2019 and 2020. We use this data to back out nine different growth rates consistent with the change in the share of the population with incomes in those 10 categories.

For South 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 U.S. we use data on the changes in post-tax income shares by quintile (Table C-3 in Shrider et al. 2021). To apply this data, we first take the 2019 welfare vector and change each quintile's income share to match the published change. Subsequently, since the growth in mean post-tax income is not made available, we grow (or rather, shrink) the entire distribution such that the change in mean welfare reflects 0.85 of growth in real GDP per capita in 2020 for the US (see the previous section for why we use 0.85).

For Vietnam, we rely on growth rates in consumption 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.

(ii) Estimates for countries with phone surveys

Our next preferred source of data is the HFPSs. At the time of writing, the HFPSs were conducted in 72 developing countries in coordination with the local NSOs. While the phone surveys provide information on whether households gained or lost income or consumption (henceforth income) since the beginning of the pandemic, they do not contain information households' level of income, nor do they report the size of the change in income. To utilize the information in the HFPSs, we need to (a) map the income changes from the HFPSs to the 2019 welfare distributions discussed above and (b) estimate the size of the change in income for each household.

(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 A.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 for example 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 is of similar type (i.e. shares the same characteristics), we will assign as having experienced an income loss in 2020 with 75% probability, no change with 20% probability, and an income increase with 5% probability.

In the robustness checks section, we test this matching assumption in Nigeria, where we can perfectly map the households in the phone survey sample and the 2019 welfare vector, and hence know which households experienced an income gain, loss, or no change. We show that our matching has little bearing on our results when compared to using the true matching.

(b) Estimate 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. In what follows, we outline the method we use to predict the growth rates of each household in a manner consistent with growth observed in national accounts. As discussed in section 4.2, the growth rates discussed below are adjusted for the passthrough rate unless otherwise noted.

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:

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

We know the share of income pertaining to various groups in the residential areas from the 2019 distributions, however, we do not know the g_t^{rur+}, g_t^{rur-}, g_t^{urb+}, and g_t^{urb-}. Additionally, the growth in national accounts is not disaggregated by growth in rural and urban areas. Hence, further assumptions are necessary.

First, we assume that the sectoral growth rates – from agriculture, industry, and services – in national accounts can be allocated to rural and urban areas. The sectoral growth estimates are available from the Macro and Poverty Outlooks (MPOs) of the World Bank. Denote the contribution to growth from agriculture, industry, and services as $g_t^{c,agr}$, $g_t^{c,ind}$, and $g_t^{c,ser}$, then 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 s_{t-1}^{agr} is the share of total income from the agricultural sector, and likewise for other sectors.

Distributing sectoral growth to urban and rural households is not straightforward. One can perhaps reasonably assume that growth in the agricultural sector pertain to rural households. For most developing countries one can further assume that growth from industry applies to urban households. For the service sector it is less clear. 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 care about growth in service sector income, but the argument likely carries over from levels of service sector income to growth in service sector income. One extreme assumption would be to assign the growth equally to urban and rural areas using population weights, while another extreme would be to assign all service sector growth to urban areas. Here, 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 from 2019 (which we can extract from the 2019 vectors). 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 our baseline assumption is that $\theta = s_{t-1}^{rur}$ (in Table A.4, we show results when θ is defined based on population shares). We can now rewrite equations (1R') and (1U'):

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

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

We still have two unknowns in each equation: the growth rate of rural (urban) households experiencing an income decline or increase. To progress, 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. To make sense of this, notice that all the equations above can be written based on the realized growth rates – which we refer to without any additional notation – as well as based on what was expected prior to COVID-19 spreading. We refer to those growth rates by adding a 'preCOVID' subscript. The time of the growth estimates still refer to 2020, only now they were forecasted before COVID-19 spread. In practice, 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 isolation:

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

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

Similar calculations for urban households' yield

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

To foster some intuition behind these equations, suppose for the moment that all growth rates in them are negative, except for the ones with a preCOVID subscript. 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 larger drops rural households assigned to an income loss will have.
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 greater growth of households experiencing increases in income, and the more of these households there are, the larger drops households with an income loss need to have for the total growth to match national accounts.
3. [The denominator of (3R)]: The more rural households experiencing a decrease in incomes, the smaller decrease the rural households assigned to an income loss will have. This is happening to match total national growth rates. If many households experienced declines, their rate of declines need to be smaller to not overshoot the total (shrinkage of) growth.

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 reality, all urban households with an income decrease will not have lost the same share of their income and so on for the other growth rates. In the robustness section we show that our results do not change notably if we add random noise to the growth rates.

(iii) Estimates for countries without 2020 welfare data or phone surveys

A large part of the global population had neither an actual survey conducted in 2020 (or the data from it has yet to be released) and had not a high-frequency phone survey. For those countries we use four other methods in the following order of preference.

Use estimates from the literature. For a handful of countries, we use estimates of the distributional impact of COVID from other papers. This concerns Brazil, where we use estimates from Lustig et al. (2020), India, where we use estimates from Gupta et al. (2021), and Turkey where we use data from Baez & Celik (2021). For EU 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 of 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.

Apply urban/rural growth rates to the 2019 distribution. When no estimates are available in the literature, we use a more rudimentary approach to recover a 2020 distribution. We use the allocation of sectoral national accounts described above to back out urban and rural growth rates, and apply those growth rates to the 2019 distribution. That is, we assume that households could only experience two different growth rates in 2020. This will obviously only catch a small fraction of the within-country inequality changes that happened in 2020.

Apply national growth rates to the lined-up welfare distribution. For some countries we do not have sectoral national accounts or we lack 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. For these countries we do not recover any within-country distributional changes.

Use the regional distribution. For a few percent of the world's population, 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.

4.4 Coverage

Table 1 reports the share of the population (panel A) and the number of countries (panel B) covered by each method. The methods are reported from the most preferred on the left column (NSO data) to the least preferred on the right (regional average). We only have survey data from

NSOs for 7 countries (covering 27% of the world's population) at the time of writing. Our preferred methods include the first 3 columns – NSO data, data utilizing phone surveys, and data from the literature. This includes 69 countries that cover 73% of the global population.

Table 1A: Population coverage by method (%)

Region	NSO	Phone survey	Data from literature	Rural/ urban	National growth	Regional average
East Asia & Pacific	67	19	0	3	8	3
Europe & Central Asia	16	10	48	26	1	0
Latin America & Caribbean	0	56	33	4	0	7
Middle East & North Africa	0	4	0	69	15	12
North America	100	0	0	0	0	0
South Asia	0	0	74	24	0	2
Sub-Saharan Africa	0	58	0	40	1	0
World	27	20	26	20	4	3

Table 1B: Country coverage by method (number of countries)

Region	NSO	Phone survey	Data from literature	Rural/ urban	National growth	Regional average
East Asia & Pacific	4	6	0	6	8	14
Europe & Central Asia	1	6	24	16	2	9
Latin America & Caribbean	0	13	1	6	4	18
Middle East & North Africa	0	2	0	8	5	6
North America	2	0	0	0	0	1
South Asia	0	0	1	6	0	1
Sub-Saharan Africa	0	19	0	25	2	2
World	7	46	26	67	21	51

Notes: This table reports the population (panel A) and country (panel B) coverage for the various methods used to derive the 2020 welfare distributions for each country. NSO = National statistical office.

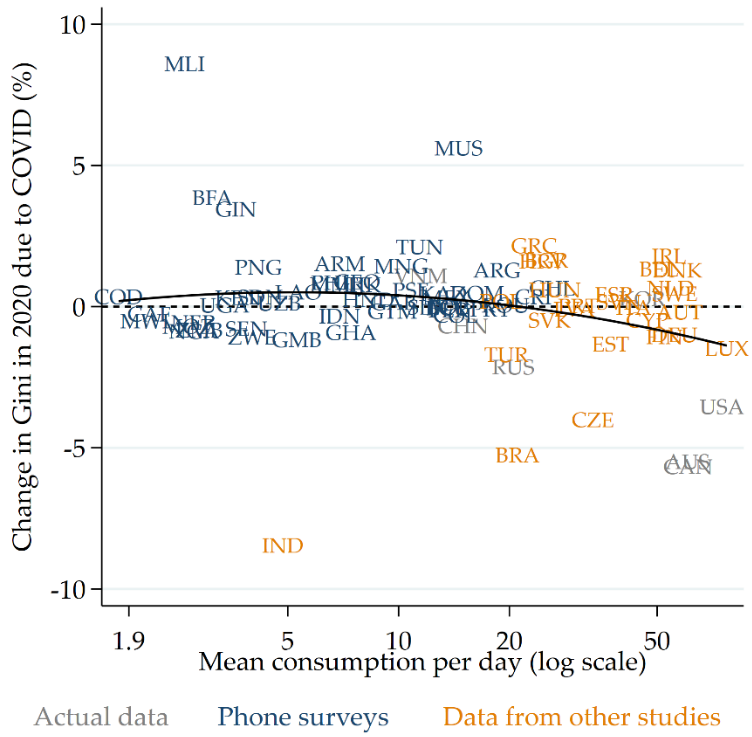
4. Results

In what follows, we first report the changes in poverty and inequality across countries using the three preferred methods – data from NSOs, data from phone surveys, and data from the literature. Then, we report the changes in global inequality and poverty. Finally, we look at the drivers of these changes.

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

Figure 1 shows the percent change in the Gini index in 2020 for all countries with data from our three preferred methods. 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. However, note that most richer countries did experience a decline in inequality in 2020. This is most likely due to the wide-ranging social assistance programs that were implemented in 2020. In the poorest countries, inequality is just as likely to increase as decrease while in middle-income countries, the majority of countries saw an increase in inequality. This may be because these are the countries where the urban low-skilled are in the bottom of the distribution and yet the ability to implement emergency transfers is limited.

Figure 1: Change in inequality across countries

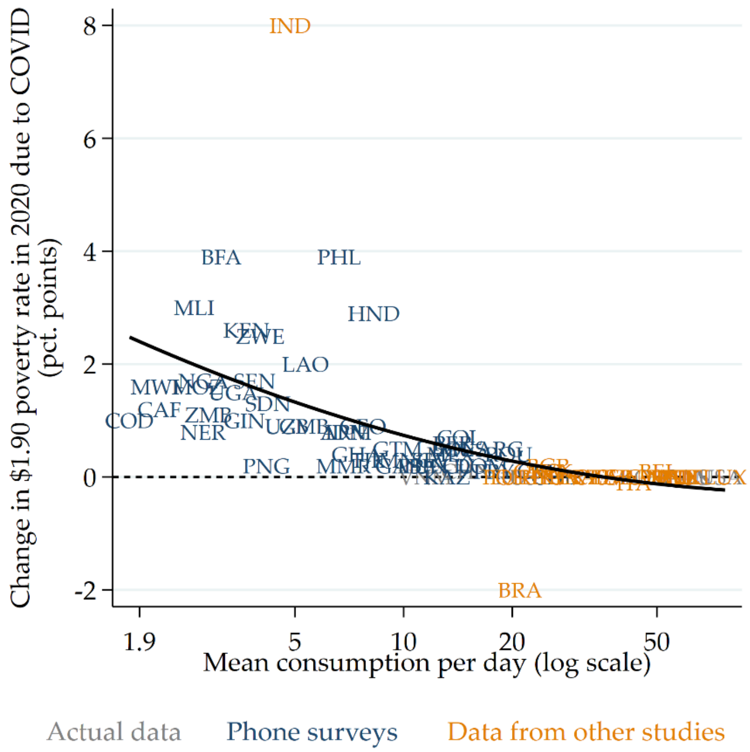


Note: This figure reports the percent change in the Gini index in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). Only countries with estimates based on our three preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. Map A.1 shows a global map of these estimates. See Table A.2 for the inequality estimates for the countries using phone surveys.

Whereas the changes in inequality were mixed, the impact on extreme poverty has been rather consistent and harmful (Figure 2). We find large increases in extreme poverty for countries that were already poor. This could either be because these countries experienced larger shocks to average incomes, or because they have a more people just above the international poverty line.

India experienced the largest increase in extreme poverty, which appears to be for both of these reasons.

Figure 2: Change in extreme poverty across countries

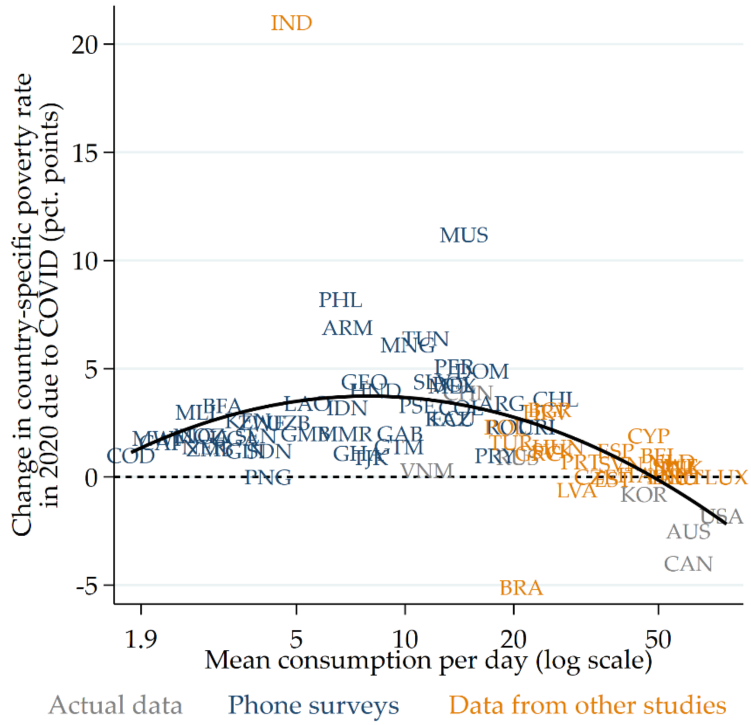


Note: This figure reports the percentage points change in extreme poverty -- those living below the $1.90-a-day poverty line -- in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). Only countries with estimates based on our three preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. Map A.2. shows a map of these estimates. Figure A.1 shows the same plot using 2019 instead of the counterfactual 2020 as the baseline. See Table A.3 for the poverty estimates for the countries using phone surveys.

The change in extreme poverty is small for upper-middle-income and high-income countries, as not many people in those countries live close to $1.90-a-day. To gauge the impact of the negative growth shocks on incomes in the lower part of respective country distributions, one would need an absolute poverty line that is more relevant to each country's income level. Jolliffe and Prydz (2019) use a collection of harmonized national poverty lines to find that wealthier countries tend to have higher national poverty lines. They find that a good approximation of a country's national poverty line is $1 plus half of median daily welfare. We calculate this line for each country in 2019 and hold it fixed for 2020. Hence, we create a country-relevant absolute poverty threshold (which is not equivalent to a relative poverty threshold).

Figure 3 reports the changes in these country-specific absolute poverty rates. Using country-specific poverty lines, we find that the middle 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.

Figure 3: Change in country-specific absolute poverty across countries

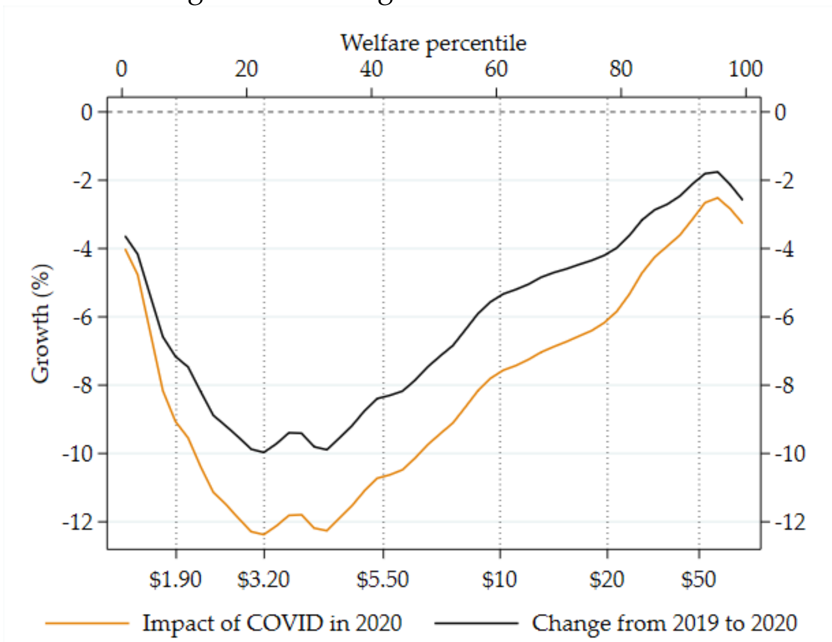


Note: This figure reports the percentage points change in absolute poverty in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). The absolute poverty line for each country is calculated as the median daily income in 2019 plus \$1. Only countries with estimates based on our three preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019. Map A.3 shows a map of these estimates. Figure A.2 shows a similar plot using 2019 instead of the counterfactual 2020 as the baseline.

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 when comparing 2020 with our counterfactual estimates for 2020 (orange line) and with 2019 (black line). On average, every percentile of the global income distribution had a negative income shock in 2020. The largest shocks were reported for those that live approximately between the 10th and the 40th percentile of the global income distribution – equivalent to those that live on approximately between \$3.20-a-day to \$5.50-a-day. The growth incidence curve is upwards sloping over most of the distribution, which suggests that global inequality might have increased due to the pandemic.

Figure 4: Global growth incidence curve



Note: The figure shows an anonymous global growth incidence curve comparing the 2020 distribution with our counterfactual 2020 distribution (orange line) and 2019 (black line). The bottom horizontal axis shows the welfare level of the particular welfare percentile in 2019. The impact of COVID in 2020 reports the difference between the 2020 distribution and the counterfactual 2020 distribution.

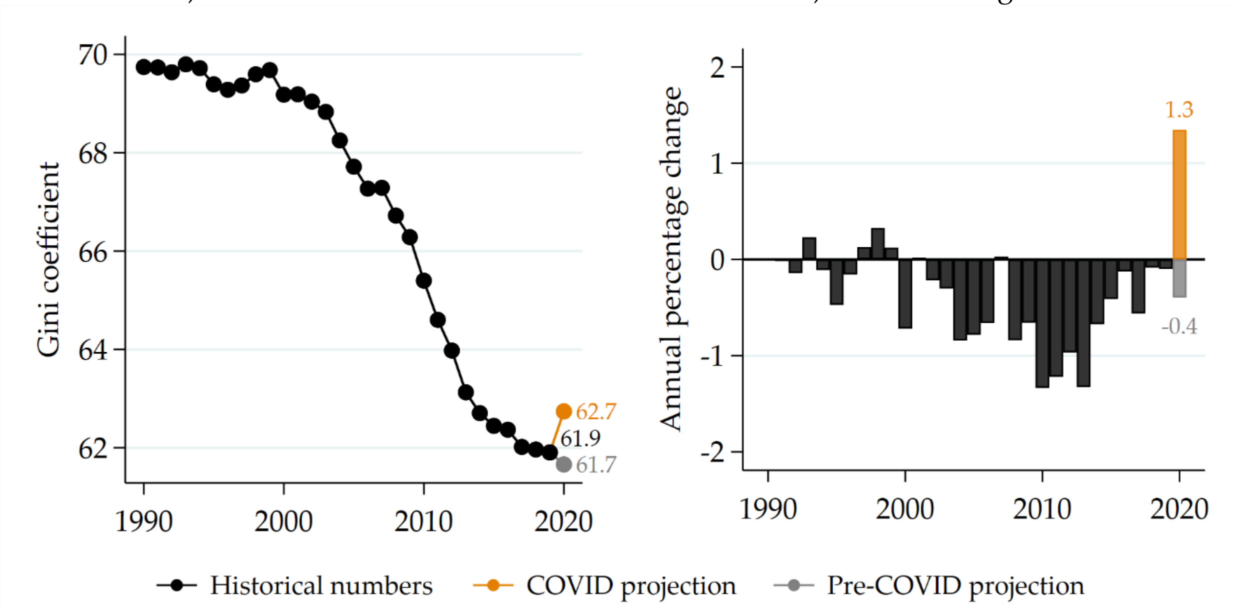
We evaluate the impact of the pandemic on global inequality more formally by looking at the global Gini coefficient over time in Figure 5. We estimate that the global Gini index increased to 62.7 points in 2020 from 61.9 points in 2019 -- a 1.3% increase -- and that the net effect of the pandemic is an increase in global inequality of 1 Gini point. This is the first time in the past three decades that the Gini index has had a marked increase. As is evident from the figure, the decrease in global inequality was slowing in the last 5 years. If we take the trends from 2014-2019, which had an average annual decline in Gini index of 0.3%, it will take us more than five years to wipe out the increase in Gini index due to the COVID-19 pandemic in 2020.

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 held from 40.9% to 41.1% and 10.7% to 10.8% respectively. The crisis reverses the expected gains of both these income groups. Due to the pandemic, we estimate that the top 10% income group increase their income share from 48.4% to 49.1%. The net effect of the pandemic will be to increase the share of income for the top decile by 1 percentage point, reduce the income share of the middle 40% and the bottom 50% by 0.31 and 0.65 percentage points.[4]

[4] 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%

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 (x 100) and the annual percentage change in the Gini from 1990 to 2020, using the global distributions in PIP for the historical series and the simulations conducted in this study for 2020. Table A.5A compares the changes in Gini and GE(0) index to those previously reported in the literature.

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

	2019	**2020 (without COVID)**	**2020 (with COVID)**	**Net COVID change, pp**
Top 10%	48.39	48.09	49.05	0.96
Middle 40%	40.94	41.13	40.82	-0.31
Bottom 50%	10.67	10.78	10.13	-0.65

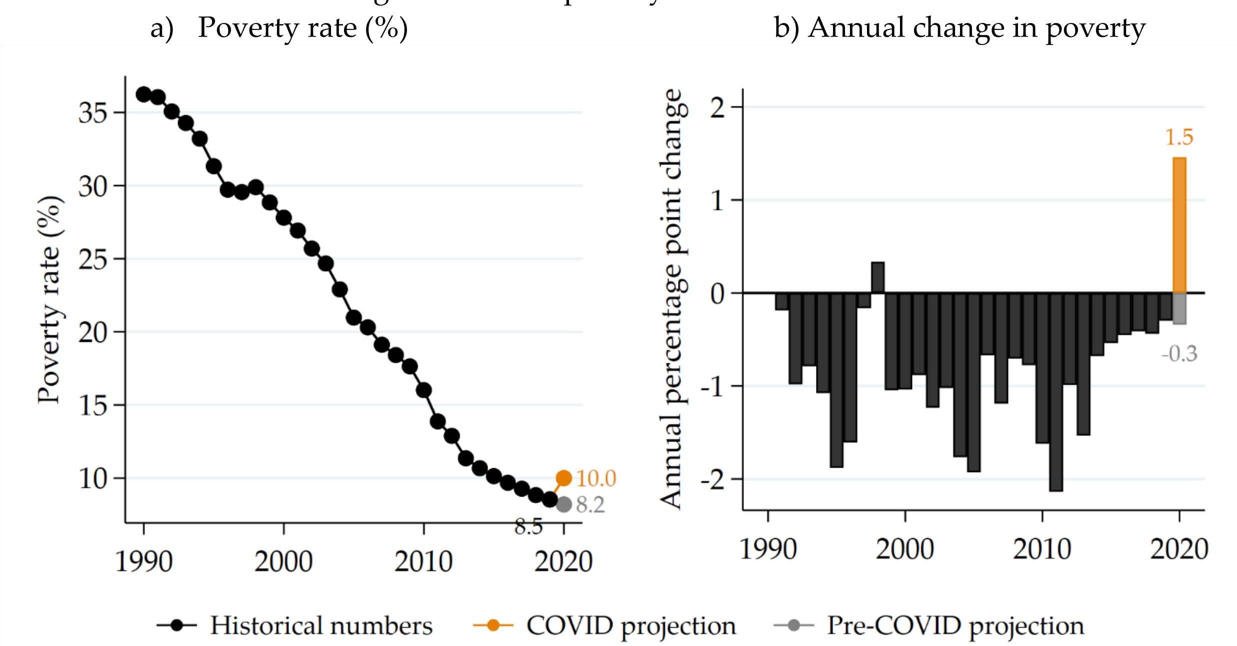
Note: This table reports the share of global income for various income groups. The last column reports the net change in income share in percentage points due to COVID-19. The net change is calculated as the difference between the 2020 estimates with and without the pandemic.

Figure 6 shows the global poverty rate from 1990-2020 and the year-on-year change in the poverty rate from 1991 to 2020. We find that global extreme poverty will increase 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 0.3 percentage points (65 million people) in the years affected

(Chancel et al., 2022). They do not find any change to the income of the middle 40% of their global distribution. See also Table A.5B.

by the Asian financial crisis (i.e., 1997-98). We expect 1.5 percentage points (123 million people) to move 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 percentage terms. This is because the stock of extreme poor 20 years ago was nearly 2.5-times larger than the 655 million estimated for 2019. In percentage terms, the change in number of poor from 2019 to 2020 represents a 19% increase in poverty, whereas the increase from 1996 to 1998 was about 4%. The net COVID-19-induced poverty includes the further 0.3 percentage points (20 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 1.8 percentage points (143 million people) in 2020.

Figure 6: Global poverty from 1990 to 2020



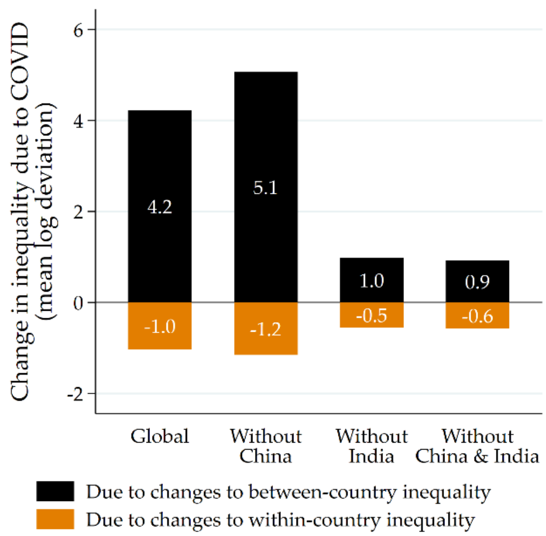
Note: This chart shows the global poverty rate evaluate at the $1.90 line and the annual percentage point change in the global poverty rate from 1990 to 2020, using the global distributions in PIP for the historical series and the simulations conducted in this study for 2020. The net COVID-19-induced factors include both those that entered poverty in 2020 (the orange bar) and those that would have escaped poverty in the absence of the pandemic (the grey bar).

4.3 Decomposing the changes to 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. 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. In so doing, we use the Theil *L* or the Mean Log Deviation (MLD) as it allows for total inequality to be decomposed into these two parts. We estimate the net increase in COVID-19-induced inequality in 2020 to be 3.2 points and that this increase was driven by the differences across countries. Changes to inequality within countries actually decreased overall global inequality by 1 point. Another way to think about this is that had the pandemic hit all individuals within a country equally, the MLD would increase by 4.2 points instead of 3.2. The large negative shock to India's economy is the main driver behind the increase in between-country inequality. Without India, the increase in within-country inequality goes from 4.2 to 1.0. Yet even without India (and/or China), we find that global inequality increased, that inequality between countries increased, and that inequality within countries decreased.

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

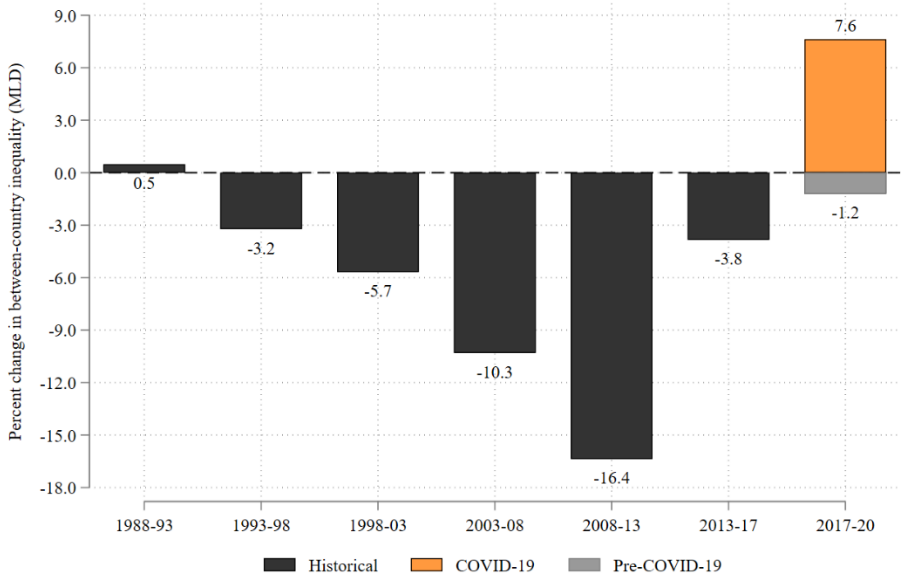


Note: This figure disaggregates the net change in global inequality due to the pandemic into between- and within-country components. The disaggregation of the total is shown for the global estimate with and without China and India. A version looking at the changes from 2019 to 2020 is presented in Figure A.3.

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 change in between-country portion of MLD, from 1988 to 2020. These changes are reported for every five-year interval up to 2013. Then we report the estimated change between 2013 and 2017 and from 2017 to 2020. We breakup the 2013-2020 series in 2017 as the latter is the last year with available global data in PIP.

We find continuous catch-up of the lower and middle-income countries to the richer countries over the last nearly three decades. The income difference between countries decreased by 34% between 1988 and 2017. A significant portion of this overall decrease happened in the five-year period after the financial crisis. We estimate that countries will move further apart for the first time in more than three decades. The inequality between countries is estimated to increase by 7.6% in 2020 compared to 2017. This increase in inequality due to the COVID-19 pandemic (in 3 years) is equivalent to more than 1/5th of the reduction we saw in nearly three decades ending in 2017.

Figure 8: Change in inequality between countries from 1988 to 2020

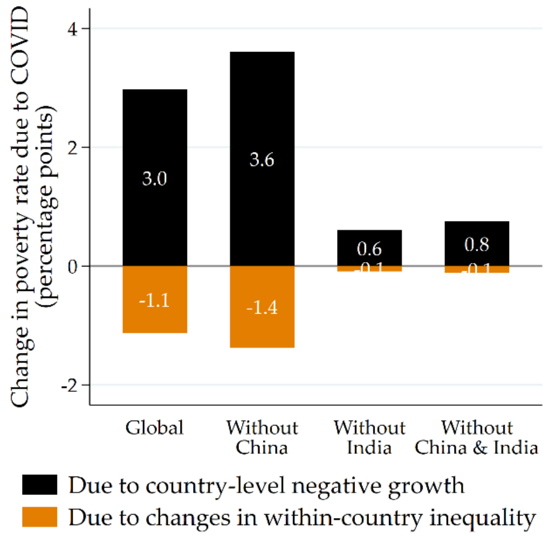


Note: This figure reports the changes in between-country portion of Mean Log Deviation from 1988 to 2020. 2017 is the last year with official global estimates in PIP.

Turning to global poverty, Figure 9 disaggregates the COVID-19-induced net increase in extreme poverty in 2020 by negative country-level shocks and within-country inequality changes. We find that the increase in extreme poverty was a result of the average negative shocks to household incomes and not to the differential income shocks within-countries. In fact, we find that the within-country inequality changes cushioned some of the large shocks to poverty. If rather than using differential growth rates across households within a country, we had applied the same average growth rate to each household, the net increase extreme poverty would have been to 3 percentage points instead of 1.8 percentage points -- 231 million added poor instead of 143 million.

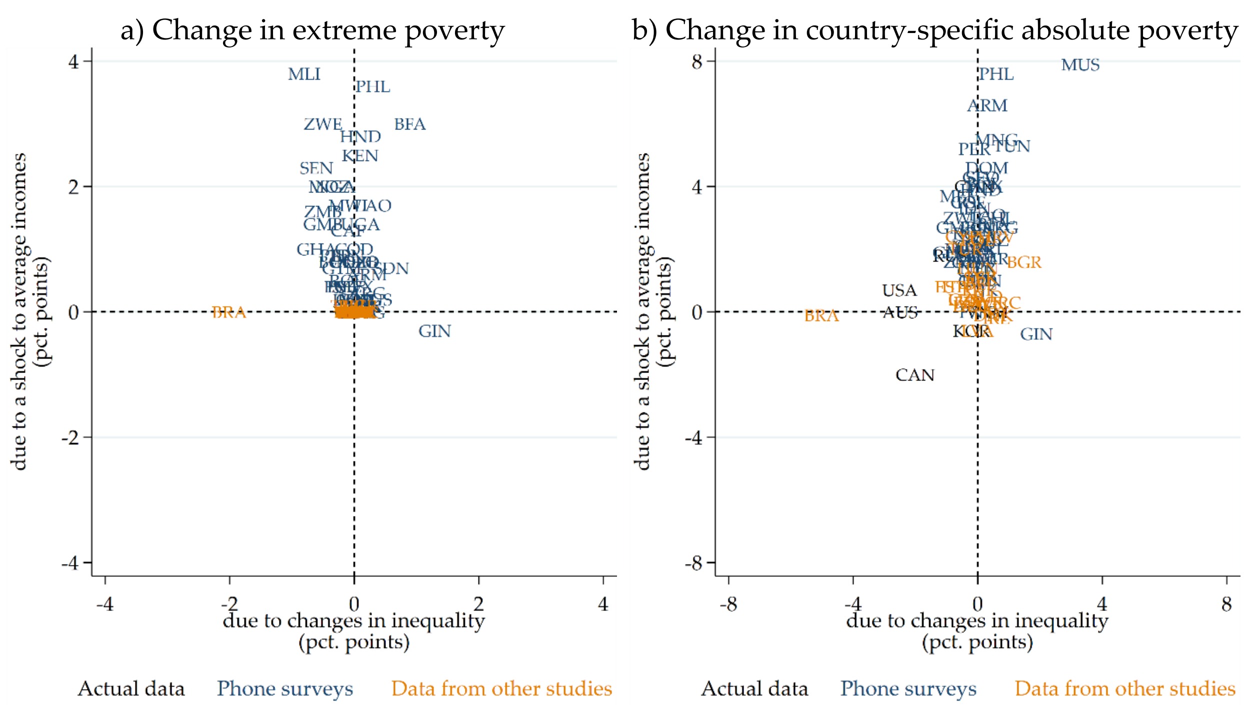
Once again, India is the main driver of the result. Without India, the increase in global poverty would have been 0.5 percentage point. Yet, our qualitative finding remains without India (and/or China): global poverty increased in 2020 due to negative shocks to average incomes while within-country changes mitigated this shock. 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 $1.90 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 change in global extreme poverty in 2020 due to COVID 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. A version looking at the changes from 2019 to 2020 is presented in Figure A.4.

Figure 10: Disaggregation of change in absolute poverty into growth and inequality component



Note: This figure disaggregates the change in absolute poverty into poverty in 2020 caused by the pandemic into negative income shocks and within-country inequality changes, by country. Only countries where we have data with one of our three preferred methods are included. India is excluded from the figure since it is an outlier. A version looking at the changes from 2019 to 2020 is presented in Figure A.5.

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 assumption regarding which household receives 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.

6.1 Which household received income gain, loss, or no change

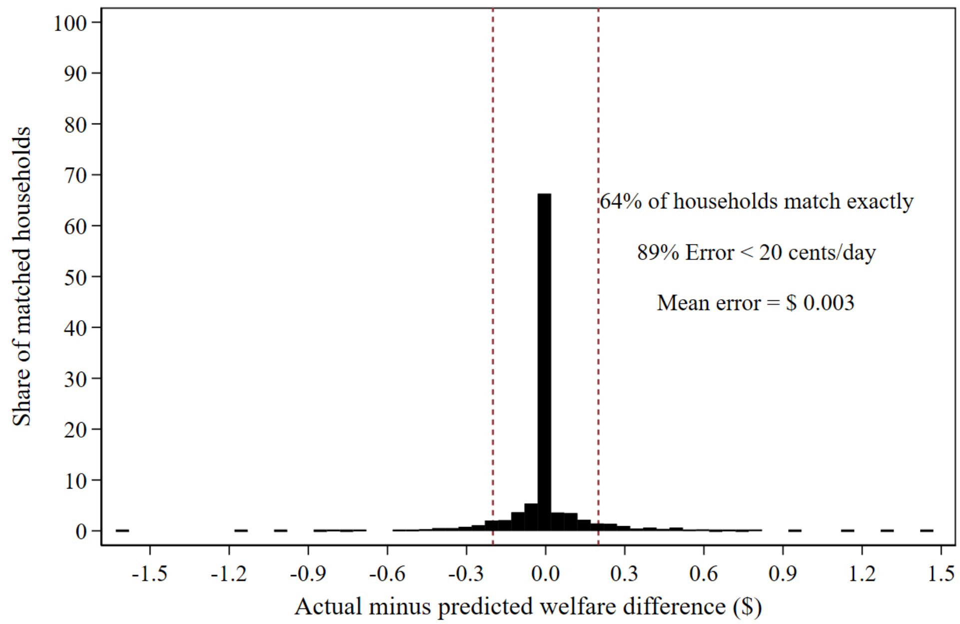
Nigeria is the only country where we can match the households in the phone surveys to an underlying household survey, namely the Generalized Household Survey (GHS). The phone survey sample for Nigeria is a third of the sample of the 2018/19 GHS. There are 1,963 households in the phone survey of which 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 exactly match 64% of households with 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 89% of households, the difference in welfare generated using the two approaches were within 20 cents, and a mean difference for all households of $0.003.

Though we do not match 36% of households correctly 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 $1.95 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 both 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 0.07 percentage points higher and an inequality estimate that is 0.06 Gini points (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.

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



Note: Predicted matching implies estimated poverty/inequality in 2020 using the methodology discussed in Section 4.3. Actual matching are income changes reported in the phone surveys.

Table 3: Comparison of actual and predicted matching for Nigeria

	Number of Households	2019	2020		Covid – no covid difference	Change 2019-2020
			no covid	with covid		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Poverty rate (%)						
Actual matching	1,866	37.6	37.7	39.47	1.76	1.89
Predicted matching	1,866		37.7	39.39	1.69	1.82
(B) Gini index (x100)						
Actual matching	1,866	34.2	34.2	34.05	-0.14	-0.17
Predicted matching	1,866		34.2	33.99	-0.21	-0.23

Note: Predicted matching implies estimated poverty/inequality in 2020 using the methodology discussed in Section 4.3. Actual matching are income changes reported in the phone surveys.

6.2 Random allocation of growth rates

In our simulation, we assigned the same growth rates within six groups of households. These six 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 six 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 have the same growth and test how alternative growth realizations impact the poverty and inequality estimates.

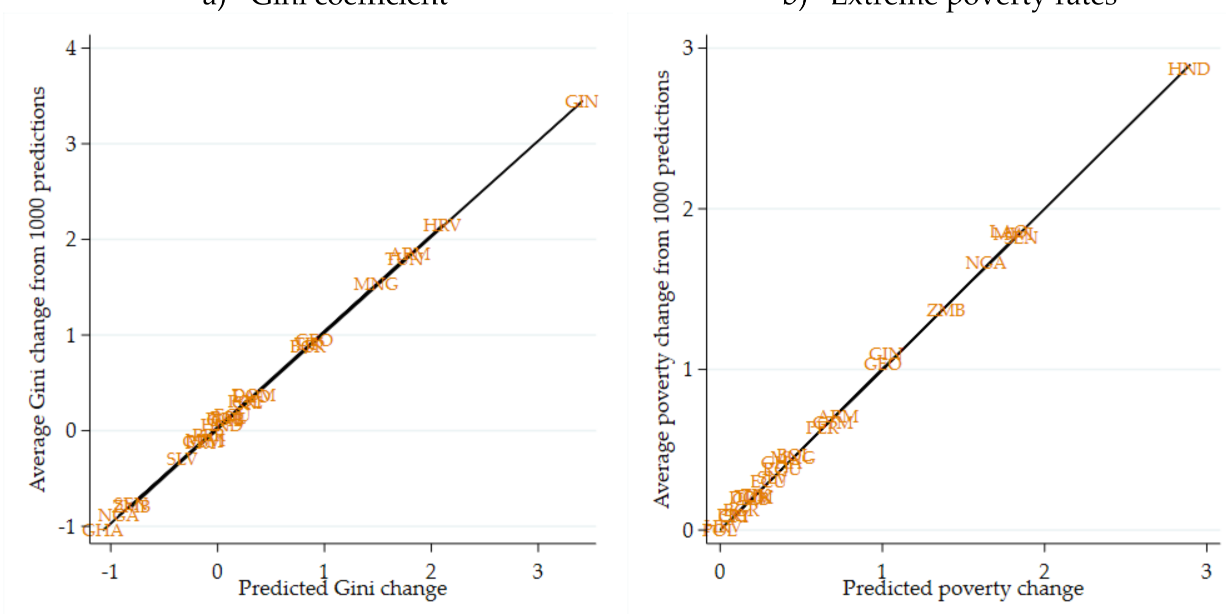
To that end, we generate 1000 different growth rates for each household that each randomly add noise to our baseline growth rates. We do so by first generating a maximum noise parameter, $\pm b$, to add to our baseline growth rates. We limit that bandwidth to 10 percentage points, and across the 1000 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 $g_t^{area} = 3.2$ percent, then the applied growth rates, $g_{t,i}^{area}$, would be uniformly distributed between 1.2 and 5.2 percent with mean 3.2 percent.

From these, we generate 1000 different distributions for each country and calculate the impact of COVID on inequality and poverty 1000 different times. Figure 12 shows the correlation between the mean of these 1000 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 six 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

a) Gini coefficient

b) Extreme poverty rates



Note: The figure compares our estimated impact of the pandemic on the Gini coefficient and extreme poverty rate (x-axis) versus the average impact from 1000 simulations where a random shock is assigned to each household's growth rate. Histograms of the estimates from the 1000 simulations by country are available in Figure A.6 and A.7.

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, we have relied on a combination of data sources and assumptions about how the data materialize in changes to household welfare. In particular, for 46 low- and middle-income countries, we use information from High-Frequency Phone Surveys together with pre-pandemic welfare vectors and national accounts data to model the impact of the pandemic along the countries' income distribution.

In the coming year more welfare data collected during the pandemic will likely be prepared and published. This will allow the construction of global estimates of the pandemic on inequality and poverty with slightly less assumptions. Yet most low- and middle-income countries could not collect data during 2020, and for the ones that could, the mode of collection often changed, challenging comparability with prior estimates. As such, even when all collected data for 2020 are published, simulations like the ones conducted here will be necessary to get a truly global picture of the initial economic consequences of the pandemic

We find that the pandemic caused the largest increase in global inequality and poverty since at least 1990. On both fronts, the pandemic erases about five years of global progress. Concretely, we find that the global Gini increased by more than 1 point and that the number of people living below the international poverty line increased by 143 million people. The increase in poverty is driven by the country-wide 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. Hence, if the pandemic had hit all people within countries equally, its impact on global inequality and poverty had 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 the value of household consumption 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 within-country inequality to increase.

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Appendix

Table A.1: Coefficients from multinomial logit regressions

		Total income increased			Total income decreased		
Country	**Sector**	**Education**	**HH Size**	**Age**	**Education**	**HH Size**	**Age**
Argentina	Rural	-0.244	0.754	-1.19	-0.456	0.421	-0.536
		(0.558)	(0.546)	(0.497)	(0.294)	(0.332)	(0.268)
Argentina	Urban	0.141	-0.511	0.13	0.23	0.288	-0.239
		(0.151)	(0.219)	(0.135)	(0.097)	(0.129)	(0.077)
Armenia	Rural	0.104	-0.146	-0.51	-0.494	0.337	-0.424
		(0.411)	(0.269)	(0.165)	(0.123)	(0.069)	(0.046)
Armenia	Urban	0.128	-0.782	0.428	-0.544	0.525	-0.342
		(0.233)	(0.19)	(0.133)	(0.096)	(0.068)	(0.045)
Bulgaria	Rural	-0.831	0.545	0.636	-0.326	-0.148	-0.218
		(0.474)	(0.219)	(0.135)	(0.743)	(0.313)	(0.172)
Bulgaria	Urban	-0.171	0.121	0.461	-0.144	-0.278	-0.219
		(0.162)	(0.139)	(0.078)	(0.191)	(0.173)	(0.089)
Bolivia	Rural	0.251	0.37	0.318	-0.037	0.149	-0.026
		(0.626)	(0.549)	(0.555)	(0.224)	(0.194)	(0.199)
Bolivia	Urban	-0.223	0.151	-0.471	-0.405	0.149	-0.271
		(0.28)	(0.231)	(0.216)	(0.127)	(0.107)	(0.095)
Chile	Rural	-0.281	0.854	0.238	-0.122	1.057	-0.325
		(0.444)	(0.52)	(0.341)	(0.246)	(0.308)	(0.183)
Chile	Urban	-0.669	-0.817	0.273	-0.172	0.402	-0.222
		(0.242)	(0.291)	(0.19)	(0.119)	(0.128)	(0.083)
Colombia	Rural	0.118	0.506	0.954	-0.276	-0.17	0.058
		(0.523)	(0.533)	(0.48)	(0.204)	(0.221)	(0.175)
Colombia	Urban	0.069	0.749	-0.432	0.268	0.472	-0.212
		(0.31)	(0.325)	(0.262)	(0.121)	(0.145)	(0.101)
Costa Rica	Rural	-0.206	-0.037	-0.451	-0.424	0.831	-0.188
		(0.394)	(0.719)	(0.458)	(0.121)	(0.213)	(0.138)
Costa Rica	Urban	0.371	1.634	-0.468	0.046	0.465	-0.347
		(0.326)	(0.43)	(0.325)	(0.106)	(0.177)	(0.108)
Dominican Republic	Rural	0.515	0.363	0.618	0.384	0.462	0.24
		(0.475)	(0.523)	(0.382)	(0.268)	(0.294)	(0.206)
Dominican Republic	Urban	-0.316	0.243	-0.075	-0.084	0.358	-0.097
		(0.207)	(0.254)	(0.173)	(0.108)	(0.137)	(0.092)
Ecuador	Rural	0.397	-0.067	-1.444	0.17	0.575	-0.377
		(0.781)	(0.686)	(0.624)	(0.245)	(0.223)	(0.189)
Ecuador	Urban	0.679	-0.339	-1.04	0.106	0.5	-0.414
		(0.733)	(0.727)	(0.533)	(0.108)	(0.119)	(0.08)
Ethiopia	Rural		0.304	0.135		0.008	-0.026
			(0.157)	(0.125)		(0.115)	(0.091)

Ethiopia	Urban		0.187	-0.313		0.008	-0.149
			(0.098)	(0.089)		(0.07)	(0.06)
Gabon	Rural		-2.102			0.054	
			(0.895)			(0.143)	
Gabon	Urban		-0.102			0.108	
			(0.479)			(0.063)	
Georgia	Rural	0.279	0.341	-0.289	-0.158	0.448	-0.488
		(0.452)	(0.307)	(0.231)	(0.25)	(0.162)	(0.122)
Georgia	Urban	-0.203	0.000	-0.442	-0.101	0.271	-0.512
		(0.305)	(0.231)	(0.162)	(0.15)	(0.111)	(0.081)
Ghana	Rural	0.059	-0.375	0.401	-0.462	0.082	-0.076
		(0.24)	(0.211)	(0.205)	(0.095)	(0.085)	(0.087)
Ghana	Urban	0.445	-0.018	-0.429	-0.467	0.037	-0.126
		(0.201)	(0.166)	(0.165)	(0.072)	(0.068)	(0.066)
Guinea	National		0.011	-0.038		-0.073	-0.161
			(0.231)	(0.198)		(0.086)	(0.074)
Gambia, The	Rural		9.72			-1.331	
			(768.489)			(0.899)	
Gambia, The	Urban		0.806			0.184	
			(0.672)			(0.112)	
Guatemala	National	0.227	0.218	0.486	-0.093	0.25	-0.133
		(0.245)	(0.314)	(0.221)	(0.094)	(0.121)	(0.092)
Honduras	National	0.259	0.36	0.295	-0.115	0.133	0.035
		(0.271)	(0.318)	(0.268)	(0.096)	(0.118)	(0.097)
Croatia	Rural	-0.694	0.032	-0.181	0.031	0.506	-0.592
		(0.228)	(0.195)	(0.171)	(0.203)	(0.178)	(0.143)
Croatia	Urban	-0.396	0.551	-0.16	0.179	0.728	-0.435
		(0.16)	(0.18)	(0.122)	(0.132)	(0.151)	(0.095)
Kazakhstan	Rural	0.712	0.22	-0.274	-0.113	-0.284	-0.275
		(0.585)	(0.427)	(0.307)	(0.206)	(0.161)	(0.103)
Kazakhstan	Urban	0.849	0.043	-0.137	-0.255	0.327	-0.314
		(0.593)	(0.54)	(0.281)	(0.187)	(0.194)	(0.101)
Cambodia	Rural		-0.033	-0.702		-0.193	-0.163
			(0.627)	(0.462)		(0.187)	(0.143)
Cambodia	Urban		-1.073	1.196		0.269	-0.173
			(1.736)	(1.398)		(0.287)	(0.236)
Lao PDR	Rural	-0.047	0.109	0.044	-0.241	0.065	-0.114
		(0.11)	(0.107)	(0.089)	(0.082)	(0.081)	(0.067)
Lao PDR	Urban	-0.15	-0.106	0.017	-0.298	0.077	-0.157
		(0.172)	(0.181)	(0.143)	(0.105)	(0.108)	(0.087)
St. Lucia	Rural		2.158	-0.423		0.309	-0.391
			(0.561)	(0.628)		(0.154)	(0.145)
St. Lucia	Urban		0.488	-0.115		0.638	-0.354
			(1.127)	(1.017)		(0.135)	(0.115)

Mexico	Rural	1.09	-2.639	-0.102	0.161	0.101	-0.245
		(0.85)	(0.956)	(0.538)	(0.158)	(0.159)	(0.108)
Mexico	Urban	-0.392	-0.096	-0.562	-0.074	0.27	-0.211
		(0.289)	(0.33)	(0.215)	(0.071)	(0.079)	(0.054)
Mozambique	Urban	-0.071	-0.696	0.347	-0.542	0.244	0.222
		(0.426)	(0.445)	(0.399)	(0.227)	(0.217)	(0.212)
Mauritius	Rural	-0.421	0.173	-0.481	-0.358	0.408	-0.67
		(0.204)	(0.222)	(0.144)	(0.136)	(0.149)	(0.097)
Malawi	Rural	0.658	-0.216	0.237	0.072	-0.093	0.174
		(0.269)	(0.221)	(0.177)	(0.154)	(0.117)	(0.094)
Malawi	Urban	-0.212	0.069	-0.54	-0.25	0.316	-0.577
		(0.296)	(0.283)	(0.279)	(0.151)	(0.141)	(0.139)
Nigeria	Rural		-0.561	-0.177		-0.129	-0.188
			(0.158)	(0.148)		(0.105)	(0.1)
Nigeria	Urban		0.659	0.082		0.339	-0.16
			(0.322)	(0.288)		(0.117)	(0.1)
Peru	Rural	-0.044	-1.039	-0.849	0.068	-0.282	0.055
		(0.954)	(1.054)	(0.93)	(0.267)	(0.27)	(0.233)
Peru	Urban	0.119	-0.814	0.758	-0.233	0.08	-0.436
		(0.668)	(0.695)	(0.476)	(0.151)	(0.138)	(0.109)
Philippines	Rural	-0.178	-0.333	0.016	-0.56	0.169	0.037
		(0.372)	(0.427)	(0.349)	(0.144)	(0.152)	(0.136)
Philippines	Urban	0.536	0.035	-0.215	-0.272	-0.083	0.455
		(0.316)	(0.249)	(0.224)	(0.116)	(0.116)	(0.1)
Poland	Rural	0.011	-0.313	-0.304	0.078	0.334	-0.127
		(0.225)	(0.267)	(0.15)	(0.153)	(0.172)	(0.103)
Poland	Urban	-0.054	-0.008	0.147	0.2	0.169	-0.436
		(0.178)	(0.211)	(0.11)	(0.123)	(0.14)	(0.074)
Paraguay	Rural	-0.032	-1.007	0.022	-0.391	0.312	-0.008
		(0.47)	(0.818)	(0.438)	(0.246)	(0.314)	(0.231)
Paraguay	Urban	-0.666	-0.539	0.301	-0.177	0.332	0.116
		(0.477)	(0.542)	(0.408)	(0.13)	(0.133)	(0.111)
West Bank and Gaza	Rural		0.495	-0.293		-0.108	-0.238
			(0.22)	(0.162)		(0.046)	(0.03)
West Bank and Gaza	Urban		0.726	-0.023		-0.055	-0.143
			(0.075)	(0.049)		(0.016)	(0.011)
Romania	Rural	-1.559	0.316	-0.661	-0.52	0.388	-0.337
		(0.576)	(0.494)	(0.351)	(0.226)	(0.241)	(0.15)
Romania	Urban	0.039	0.19	-0.085	-0.264	0.302	0.172
		(0.536)	(0.616)	(0.35)	(0.17)	(0.199)	(0.113)
Senegal	Rural		-0.157			0.513	
			(0.508)			(0.194)	
Senegal	Urban		-0.803			0.28	
			(0.406)			(0.121)	

El Salvador	National	0.442	-0.113	0.032	-0.096	0.062	-0.033
		(0.28)	(0.394)	(0.26)	(0.092)	(0.133)	(0.092)
Tunisia	Rural	-0.736	1.139	-0.172	-0.475	-0.142	-0.301
		(0.578)	(0.613)	(0.515)	(0.209)	(0.235)	(0.205)
Tunisia	Urban	0.169	0.579	-1.189	-0.297	0.834	-0.32
		(0.305)	(0.447)	(0.374)	(0.109)	(0.173)	(0.141)
Uzbekistan	Rural		0.654	0.217		0.744	0.188
			(0.172)	(0.129)		(0.177)	(0.133)
Uzbekistan	Urban		-0.372	0.311		-0.054	0.328
			(0.247)	(0.195)		(0.255)	(0.203)
Zambia	National	1.206	1.066	-15.43	0.103	-0.368	0.109
		(1.449)	(1.192)	(1997.7)	(0.426)	(0.297)	(0.278)

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, 2-4 person household, 5-7 person household, and 7+ person household. Age of the head household 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 A.2: Changes in inequality (Gini index) for the countries using phone surveys

Country	**Code**	**2019**	**2020 (with covid)**	**Net COVID change 2020, Gini points**
Argentina	ARG	42.90	43.48	0.58
Armenia	ARM	29.88	30.42	0.54
Burkina Faso	BFA	35.30	36.50	1.20
Bolivia	BOL	41.65	41.69	0.05
Central African Republic	CAF	56.24	56.11	-0.13
Chile	CHL	44.44	44.74	0.30
Congo, Dem. Rep.	COD	42.10	42.25	0.15
Colombia	COL	51.33	51.18	-0.15
Costa Rica	CRI	48.19	48.32	0.13
Dominican Republic	DOM	41.92	42.06	0.14
Ecuador	ECU	45.71	45.78	0.07
Gabon	GAB	38.02	38.05	0.03
Georgia	GEO	35.95	36.28	0.33
Ghana	GHA	43.52	43.06	-0.47
Guinea	GIN	33.73	34.88	1.15
Gambia, The	GMB	35.92	35.51	-0.41
Guatemala	GTM	48.28	48.21	-0.06
Honduras	HND	48.17	48.19	0.02
Indonesia	IDN	36.97	36.86	-0.11
Kazakhstan	KAZ	27.79	27.95	0.16
Kenya	KEN	40.78	40.75	-0.03

Lao PDR	LAO	38.80	38.93	0.12
Mexico	MEX	45.38	45.54	0.17
Mali	MLI	33.04	35.92	2.88
Myanmar	MMR	30.70	30.94	0.24
Mongolia	MNG	32.74	33.23	0.49
Mozambique	MOZ	54.00	53.68	-0.32
Mauritius	MUS	36.76	38.70	1.94
Malawi	MWI	44.69	44.64	-0.05
Niger	NER	34.28	34.17	-0.11
Nigeria	NGA	35.13	34.80	-0.32
Peru	PER	41.51	41.48	-0.03
Philippines	PHL	42.27	42.71	0.44
Papua New Guinea	PNG	41.85	42.91	1.06
Paraguay	PRY	45.65	45.58	-0.07
West Bank and Gaza	PSE	33.69	33.83	0.14
Romania	ROU	36.02	36.05	0.03
Sudan	SDN	34.24	34.34	0.09
Senegal	SEN	40.29	39.96	-0.32
El Salvador	SLV	38.78	38.65	-0.13
Tajikistan	TJK	34.00	34.29	0.29
Tunisia	TUN	32.82	33.39	0.58
Uganda	UGA	42.75	42.77	0.02
Uzbekistan	UZB	35.27	35.33	0.06
Zambia	ZMB	57.14	56.68	-0.46
Zimbabwe	ZWE	50.37	50.08	-0.29

Note: This table reports the Gini index (x 100) for each country using the high frequency phone surveys for 2019 and 2020 ("actual" covid distribution). The Net COVID change column captures the Gini points change between the 2020 and the 2019 distributions. Note that the inequality of the counterfactual 2020 distribution is same as the 2019 distribution for each country.

Table A.3: Changes in poverty for the countries using phone surveys

	2019	**2020 (no covid)**		**2020 (with covid)**		**Net COVID change 2020, pp**
Country	**Rate, %**	**Rate, %**	**Change, pp**	**Rate, %**	**Change, pp**	
Argentina	1.46	1.51	0.06	2.05	0.59	0.54
Armenia	1.08	0.76	-0.32	1.49	0.41	0.73
Burkina Faso	32.82	30.66	-2.16	34.78	1.96	4.12
Bolivia	3.24	3.18	-0.06	3.64	0.40	0.46
Central African Republic	70.76	69.95	-0.81	71.06	0.30	1.10
Chile	0.28	0.27	0.00	0.30	0.03	0.03
Congo, Dem. Rep.	70.99	70.73	-0.27	71.64	0.64	0.91
Colombia	4.94	4.80	-0.14	5.56	0.62	0.77

Costa Rica	1.01	1.01	0.00	1.10	0.08	0.08
Dominican Republic	0.57	0.50	-0.06	0.70	0.13	0.20
Ecuador	3.58	3.63	0.05	3.93	0.35	0.30
Gabon	3.42	3.39	-0.03	3.58	0.16	0.19
Georgia	3.78	3.53	-0.26	4.53	0.75	1.01
Ghana	10.70	9.97	-0.73	10.35	-0.35	0.38
Guinea	21.26	20.03	-1.23	21.06	-0.20	1.03
Gambia, The	7.98	7.47	-0.51	8.26	0.28	0.80
Guatemala	6.64	6.47	-0.17	7.17	0.53	0.70
Honduras	14.78	14.36	-0.42	17.26	2.48	2.90
Indonesia	2.70	2.18	-0.51	3.06	0.36	0.87
Kazakhstan	0.01	0.01	0.00	0.01	0.00	0.00
Kenya	31.25	29.46	-1.79	32.10	0.84	2.64
Lao PDR	9.35	8.00	-1.35	9.79	0.43	1.78
Mexico	1.74	1.74	-0.01	2.12	0.37	0.38
Mali	42.26	41.23	-1.03	44.09	1.83	2.86
Myanmar	0.87	0.70	-0.17	0.83	-0.04	0.13
Mongolia	0.24	0.12	-0.12	0.57	0.33	0.45
Mozambique	62.29	62.02	-0.27	63.67	1.38	1.65
Mauritius	0.13	0.11	-0.02	0.47	0.35	0.37
Malawi	67.55	66.75	-0.80	68.56	1.01	1.81
Niger	39.29	38.05	-1.24	38.88	-0.41	0.83
Nigeria	39.20	39.47	0.28	41.12	1.92	1.64
Peru	2.19	2.08	-0.11	2.71	0.52	0.63
Philippines	6.92	6.01	-0.92	10.10	3.17	4.09
Papua New Guinea	26.18	26.78	0.60	27.06	0.88	0.28
Paraguay	0.95	0.88	-0.07	0.96	0.01	0.09
West Bank and Gaza	0.89	0.96	0.06	0.96	0.07	0.00
Romania	2.24	2.05	-0.19	2.44	0.20	0.39
Sudan	13.62	14.86	1.24	16.41	2.79	1.55
Senegal	27.50	25.78	-1.72	27.64	0.14	1.86
El Salvador	1.25	1.16	-0.09	1.49	0.24	0.33
Tajikistan	2.21	1.95	-0.26	2.17	-0.04	0.22
Tunisia	0.22	0.21	-0.01	0.42	0.20	0.21
Uganda	38.02	36.85	-1.17	38.11	0.09	1.26
Uzbekistan	10.68	9.78	-0.89	10.76	0.08	0.98
Zambia	58.52	58.54	0.02	59.94	1.42	1.40
Zimbabwe	39.53	38.98	-0.55	41.33	1.80	2.35

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 "actual" distribution (with covid) and the counterfactual distribution (no covid). The *Net COVID change* column captures the percentage points change in poverty between the "actual" and the counterfactual scenarios in 2020.

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

	Poverty rate (%)		Gini index	
Country	**pop share**	**inc share**	**pop share**	**inc share**
Argentina	2.01	2.05	43.42	43.48
Armenia	1.52	1.49	30.44	30.42
Burkina Faso	35.02	34.78	37.28	36.50
Bulgaria	1.02	0.92	40.90	40.72
Bolivia	3.81	3.64	41.77	41.69
Central African Republic	70.99	71.06	56.16	56.11
Chile	0.30	0.30	44.76	44.74
Congo, Dem. Rep.	71.61	71.64	42.39	42.25
Colombia	5.71	5.56	51.35	51.18
Costa Rica	1.11	1.10	48.41	48.32
Dominican Republic	0.70	0.70	42.08	42.06
Ecuador	3.97	3.93	45.91	45.78
Gabon	3.62	3.58	38.06	38.05
Georgia	4.57	4.53	36.32	36.28
Ghana	10.43	10.35	43.08	43.06
Guinea	21.25	21.06	34.99	34.88
Gambia, The	8.89	8.26	35.94	35.51
Guatemala	7.30	7.17	48.34	48.21
Honduras	17.52	17.26	48.48	48.19
Croatia	0.49	0.49	31.04	30.99
Indonesia	3.06	3.06	36.87	36.86
Kazakhstan	0.01	0.01	27.98	27.95
Kenya	32.36	32.10	40.94	40.75
Lao PDR	9.93	9.79	39.03	38.93
Mexico	2.21	2.12	45.67	45.54
Mali	44.05	44.09	36.03	35.92
Myanmar	0.83	0.83	30.90	30.94
Mongolia	0.57	0.57	33.24	33.23
Mozambique	63.87	63.67	53.96	53.68
Mauritius	0.23	0.47	37.42	38.70
Malawi	68.70	68.56	44.84	44.64
Niger	38.81	38.88	34.16	34.17
Nigeria	41.17	41.12	34.91	34.80
Peru	3.15	2.71	41.93	41.48
Philippines	10.27	10.10	42.78	42.71
Papua New Guinea	27.06	27.06	42.90	42.91
Poland	0.00	0.00	30.35	30.32
Paraguay	0.96	0.96	45.66	45.58
West Bank and Gaza	0.96	0.96	33.82	33.83
Romania	2.44	2.44	36.01	36.05
Sudan	16.39	16.41	34.34	34.34

Senegal	28.14	27.64	40.23	39.96
El Salvador	1.51	1.49	38.81	38.65
Tajikistan	2.17	2.17	34.31	34.29
Tunisia	0.56	0.42	33.77	33.39
Uganda	38.12	38.11	42.80	42.77
Uzbekistan	10.84	10.76	35.35	35.33
Zambia	60.51	59.94	57.60	56.68
Zimbabwe	41.98	41.33	50.51	50.08

Note: This table compares estimates for poverty (rate, %) and inequality (Gini index x100) using different θ in equations 3R and 3U. The weight used to split growth of service sector into rural and urban area, θ, is either population share (pop share) or income share (inc share). Poverty and inequality using the latter estimates are reported in the main paper.

Table A.5A: Comparison of income inequality from the literature, Gini index and Theil 0

	MYL				**Milanovic (2021)**				**World Bank (2016)**			
		Theil 0				Theil 0				Theil 0		
	Gini index	Total	Between-country	# of countries	Gini index	Total	Between-country	# of countries	Gini index	Total	Between-country	# of countries
1988	61.2		72.4	162					69.7	101.4	81.2	73
1993	61.8		72.8	163					69.3	98.3	74.6	102
1998	61.4		70.4	163					68.6	94.0	69.1	106
2003	60.1		66.4	165					68.7	93.9	67.9	135
2008	57.5		59.6	167	66.4	91.0	56.3	136	66.6	86.3	60.2	136
2013	53.1		49.8	168	61.6	75.9	45.3	131	62.5	74.5	48.6	101
2017	51.8		47.9	167								
2020	53.1		51.6	218								

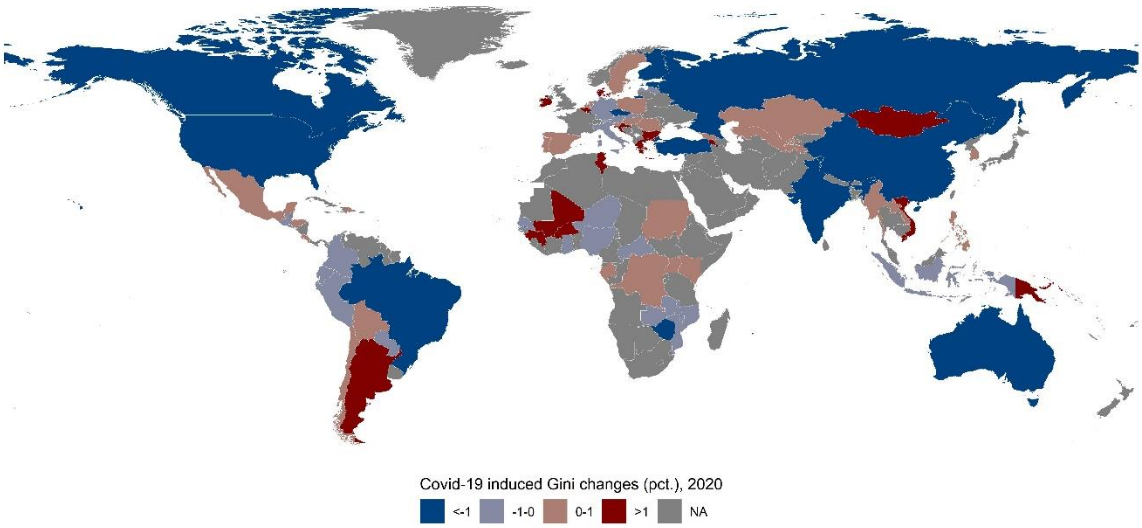
Table A.5B: Comparison of income inequality from the literature, income shares

	MYL			**World Inequality Database**		
	Top 10%	Middle 40%	Bottom 50%	Top 10%	Middle 40%	Bottom 50%
2019	48.4	40.9	10.7	52.2	39.3	8.5
2020	49.1	40.8	10.1	52.3	39.3	8.4

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

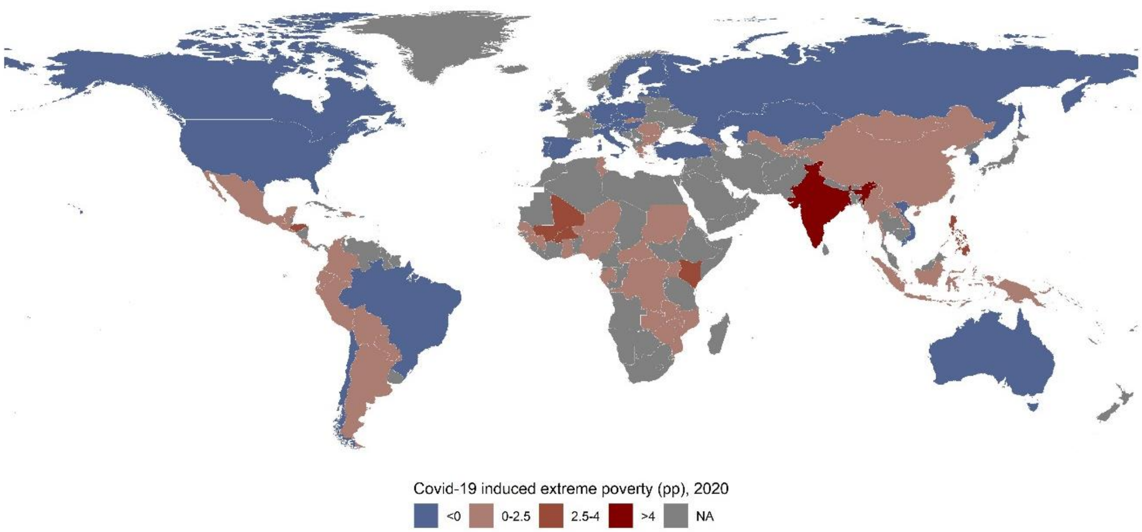
Note: Panel A compares estimates of Gini index (x100) and Theil 0 coefficient (x100) from various studies with the current paper (MYL). The panel also reports the between-country Theil 0 coefficient. Panel B reports the income share of the top 10%, middle 40%, and the bottom 50% of the respective income distributions.

Map A.1. Inequality changes due to COVID



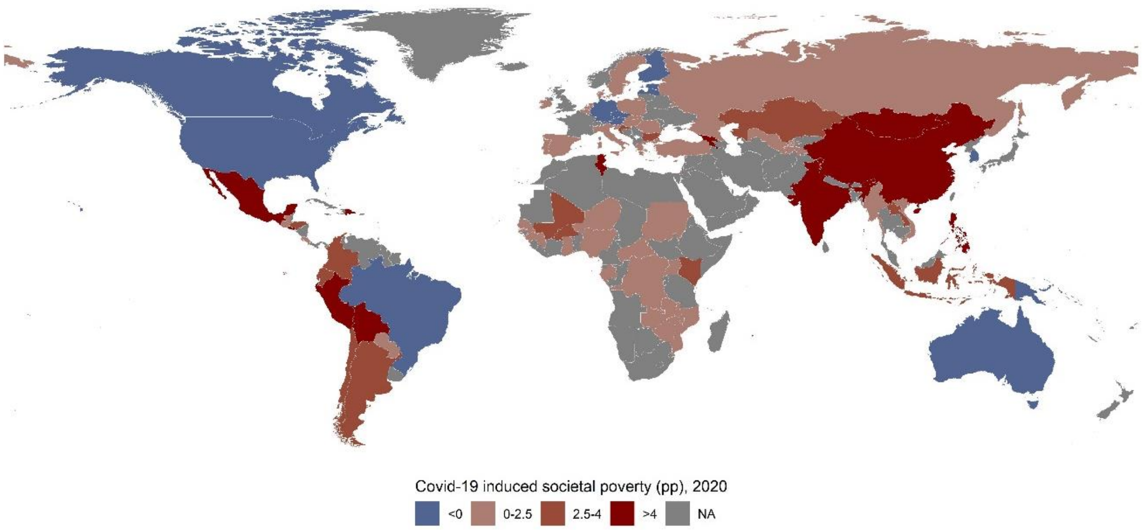
Note: This map reports the percentage change in the Gini index in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). Only countries for which we have estimates with one of our three preferred methods are included.

Map A.2. Extreme poverty changes due to COVID



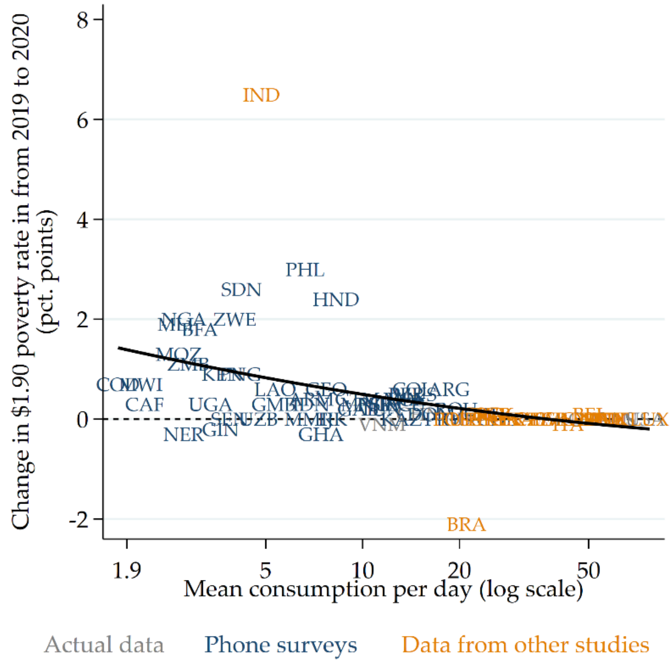
Note: This map reports the percentage points change in extreme poverty (those living below the $1.90-a-day poverty line) in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). Only countries for which we have estimates with one of our three preferred methods are included. The first bin includes those countries with both no change or decreases in extreme poverty.

Map A.3: Country-specific absolute poverty changes due to COVID



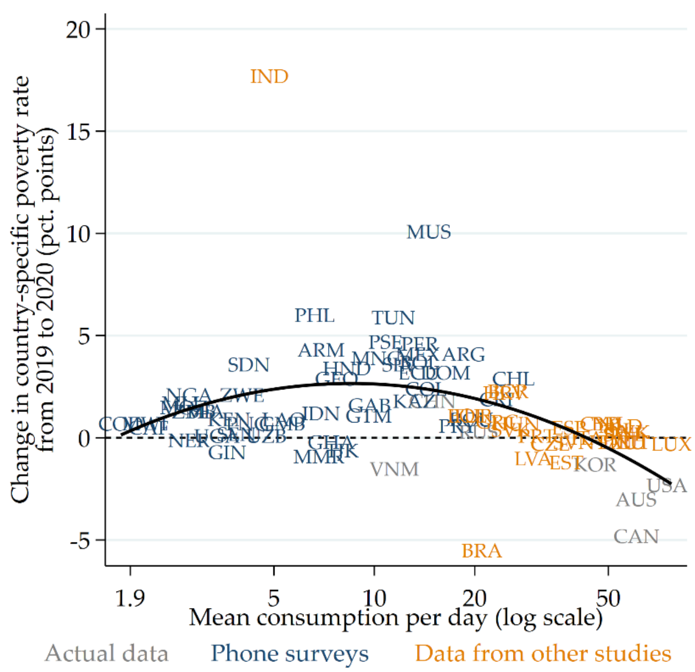
Note: This map reports the percentage points change in absolute poverty (where the poverty line for each country is the median income in 2019 minus $1those living below the $1.90-a-day poverty line) in 2020 due to the pandemic (i.e. comparing our 2020 estimate with our counterfactual 2020 estimate). Only countries for which we have estimates with one of our three preferred methods are included. The first bin includes those countries with both no change or decreases in extreme poverty.

Figure A.1: Change in extreme poverty across countries, 2019-2020



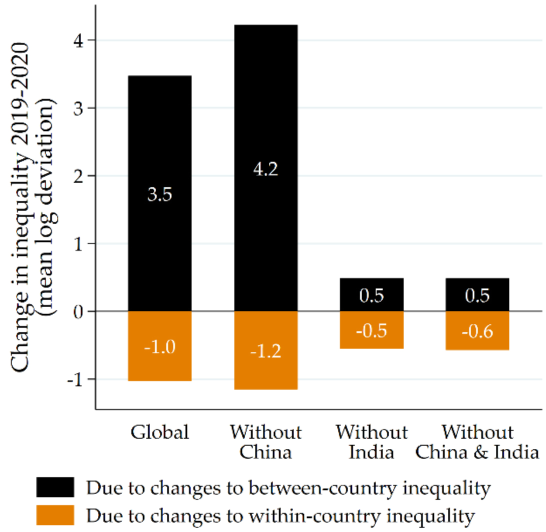
Note: This figure reports the percent change in the extreme poverty from 2019 to 2020. Only countries with estimates based on our three preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019.

Figure A.2: Change in country-specific absolute poverty across countries, 2019-2020



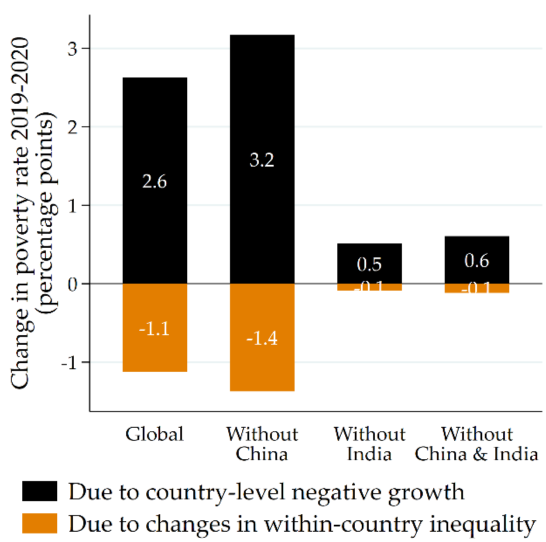
Note: This figure reports the percentage points change in absolute poverty from 2019 to 2020. The absolute poverty line for each country is calculated as the median income in 2019 plus $1. Only countries with estimates based on our three preferred methods are included. On the horizontal scale, countries are ordered by their daily mean income or consumption in 2019.

Figure A.3: Disaggregation of global inequality into within and between countries



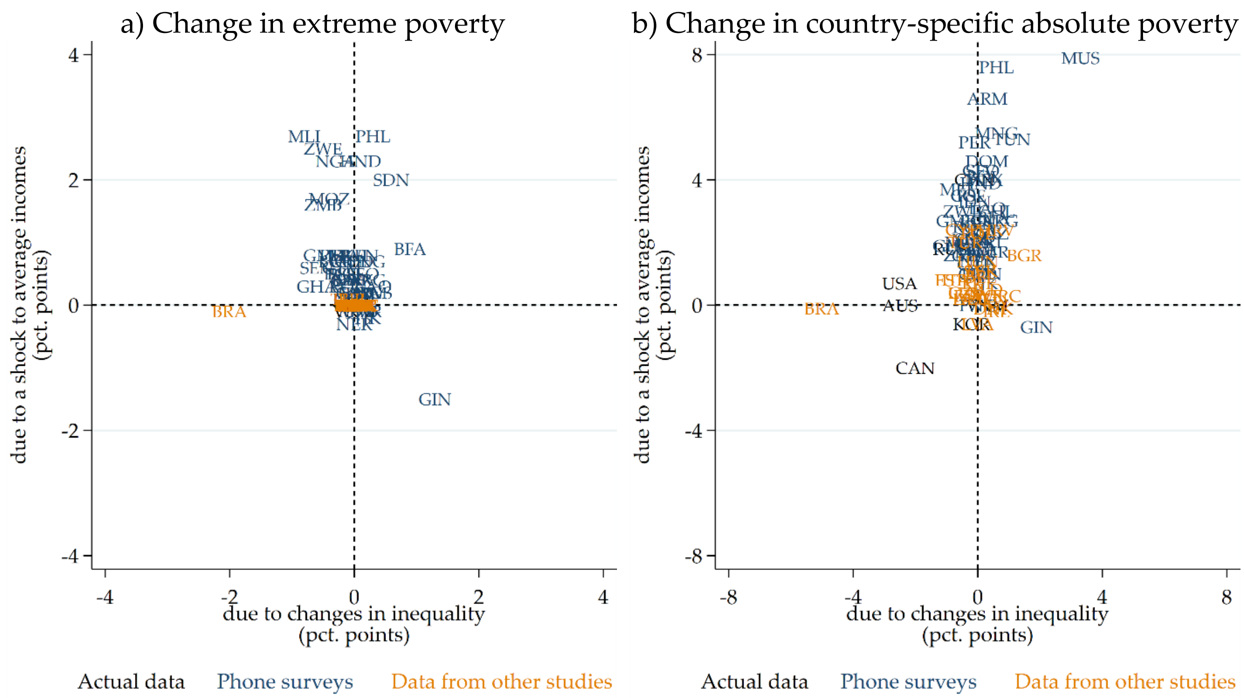
Note: This figure shows the disaggregation of the net change in global inequality from 2019 to 2020 into between- and within-country components. The disaggregation of the total is shown for the global estimate with and without China and India.

Figure A.4: Disaggregation of global extreme poverty into growth and inequality components



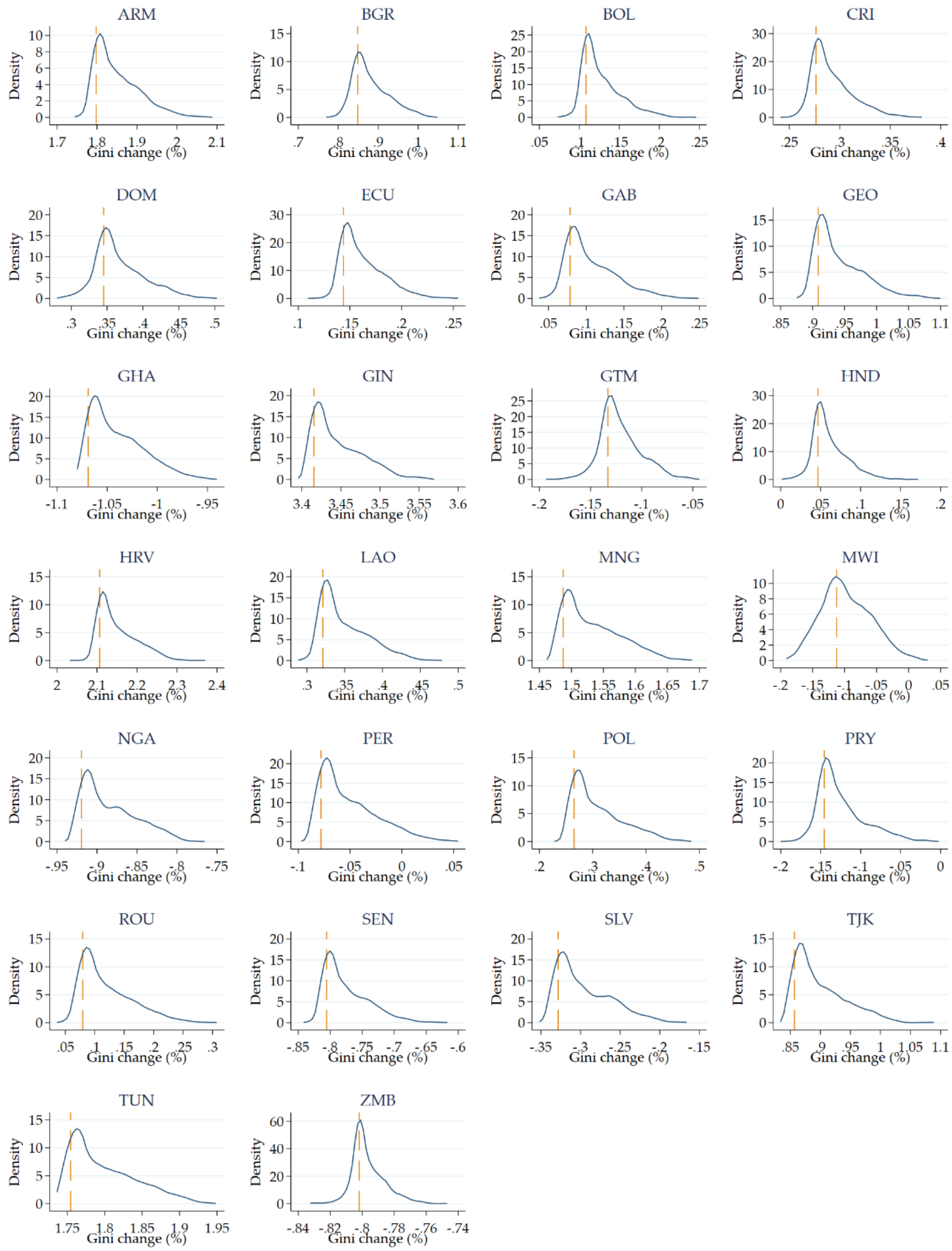
Note: This figure shows the disaggregation of the net change in global extreme poverty from 2019 to 2020 into poverty caused by negative income shocks and within-country inequality changes. The disaggregation of the total is shown for the global estimate with and without China and India.

Figure A.5: Disaggregation of change in absolute poverty into growth and inequality component



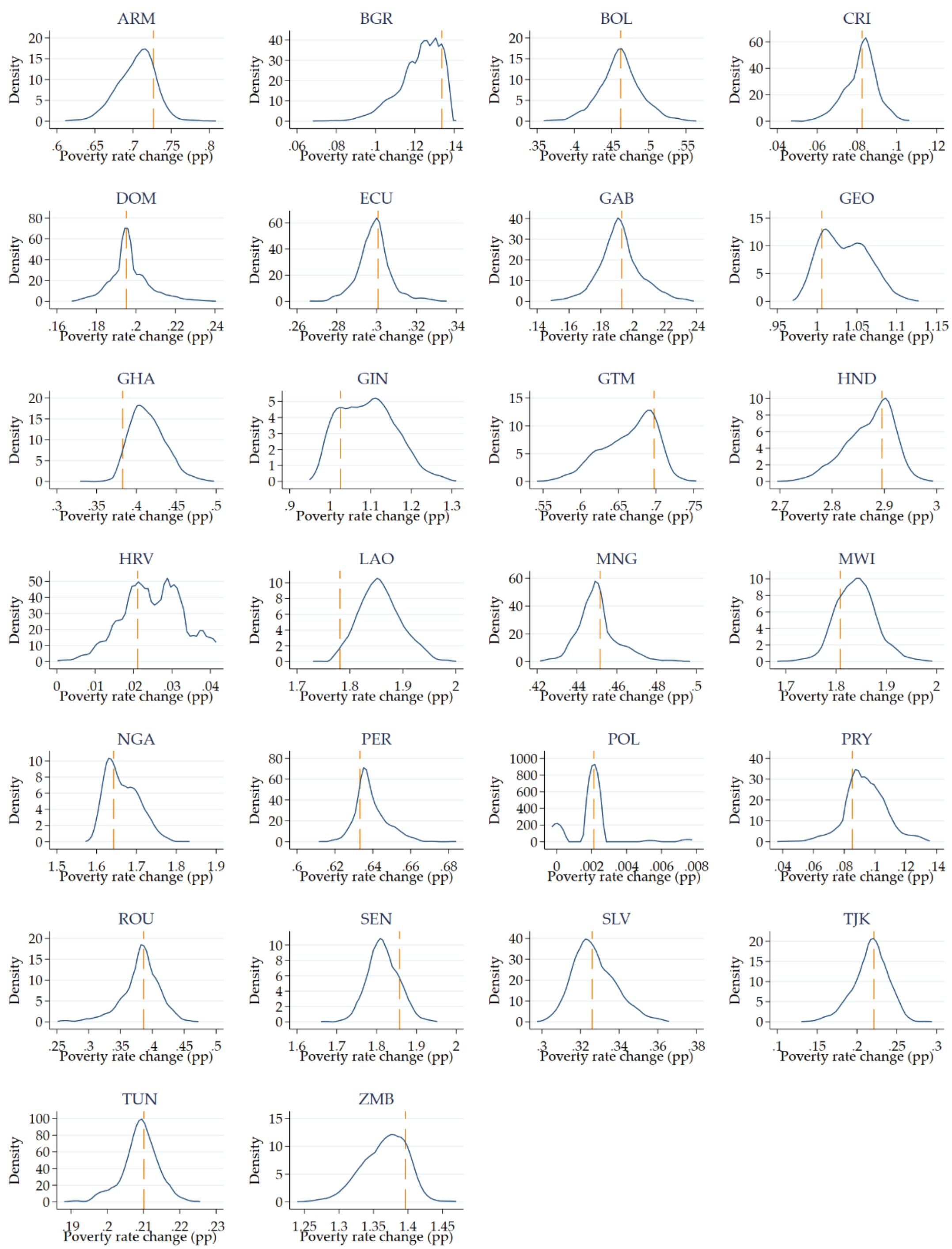
Note: This figure disaggregates change in absolute poverty into poverty from 2019 to 2020 into negative income shocks and within-country inequality changes, by country. Only countries where we have data with one of our three preferred methods are included. India is excluded from the figure since it is an outlier.

Figure A.6: 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. 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 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 A.7: 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. 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.